
Chapter Twenty

A Statistical Framework for Modeling Homogeneity and Interdependence in Groups

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Social behavior can be explained at many different levels. Some questions elicit explanations at the “group” level (e.g., Why are Canadians so reserved?). Other questions elicit explanations at the “individual” level (e.g., Why is Jim Carrey, a Canadian, so wild and crazy?). And other questions seem to elicit explanations at multiple levels of explanation: Why do people obey the law? What makes a marriage last? What makes a family dysfunctional? How do social norms shape an individual’s behavior? These and many other central questions in social psychology require analysis at multiple levels – an individual level, a group level, and possibly higher social levels as well (Doise, 1986).

Social psychology is the study of the “individual within the group.” In this chapter, we present a framework for conceptualizing and analyzing social behavior as a joint function of individual and group-level forces. The chapter is organized into three sections. The first section discusses several areas of research in social psychology that have focused on group-level phenomena. From that review we extract a necessary feature for group-level phenomena – homogeneity among members of a group. The second section discusses how to conceptualize, measure, and analyze (theoretically as well as statistically) this necessary feature. The intraclass correlation will serve as a conceptual and statistical building block. The final section extends the framework to include interdependent processes, processes that are at a “higher level” than individual processes but are not group-level processes in that they do not require homogeneity. Our goal in this chapter is to present a framework for conceptualizing multi-level social psychological processes, a framework that leads naturally into a data-analytic strategy.

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The Individual and the Group

There are therefore Agents in Nature able to make the Particles of Bodies stick together by very strong Attraction. And it is the Business of Experimental Philosophy to find them out.

(Isaac Newton, 1717)

The question of what attracts "particles" to each other and binds them together has been a central problem in science. Over a century ago, chemists used the concept of cohesiveness: "by cohesive attraction . . . we mean that force which binds together the particles of a body" (Daubeny, 1850), e.g., the force that binds together atoms to form a molecule. Modern chemists now favor the term bond over cohesive attraction, and several types of bonds have been identified (e.g., covalent, ionic, hydrogen). Chemists attempt to understand the behavior of a molecule, an aggregate entity, from the behavior of individual atoms and the bonds between those atoms. Chemists also acknowledge the existence of the aggregate entity (e.g., molecules, proteins) and consider the aggregate worthy of study in its own right.

Social psychology has been concerned with forces that bind individuals to create an aggregate, or a group. Since the very founding of the discipline, social psychologists have been at odds about how to allocate priority to the different levels of analysis. Should the behavior of individuals be used to explain group processes? Should group processes be used to explain the behavior of individuals? The individual or the group – which is the independent variable and which is the dependent variable? What "holds" individuals together in a group? What are the predictors of cohesiveness? Is the group more than the sum of its parts? These are deep questions which, for the most part, remain unanswered. Much as Isaac Newton called for scientists of the day to study attraction between particles, Floyd Allport (1924, 1962) identified the issue of individuals and groups as the "master problem of social psychology."

Some theorists such as George Herbert Mead placed explanatory priority on the group – the group provides the context against which the behavior of individuals can be understood. Mead wrote, ". . . the behavior of an individual can be understood only in terms of the behavior of the whole social group of which he is a member, since his individual acts are involved in larger, social acts which go beyond himself and which implicate the other members of that group" (1934, pp. 6–7). Similarly, Durkheim, in his influential sociological treatise (1974, English translation), also placed explanatory priority on the group and Comte placed priority on the family. See Turner and Killian (1957) and Milgram and Toch (1969) for reviews; see Coleman (1990) for a contemporary theory.

Other theorists, such as Floyd Allport, placed explanatory priority on the individual. "All theories which partake of the group fallacy have the unfortunate consequence of diverting attention from the true focus of cause and effect, namely, the behavior mechanisms of the individual" (Allport, 1933, p. 9). When a group-level process is translated into a theory, he argued, the concept needs to be defined in terms of an aggregation of individuals in a way that does not produce a tautology or a personification of the group. "There is no psychology of groups which is not essentially and entirely a psychology of individuals" (Allport, 1933, p. 4).

We agree that individual-level psychology must mediate all group processes, but argue that individual-level explanations are not sufficient. We believe that it is possible to study both levels simultaneously, and that interesting social psychological questions can be asked at each level (see also Kenny & La Voie, 1985). That is, as well as asking questions at the individual level (e.g., does an infant's babbling behavior correlate with the infant's attachment?), we can and should ask questions at higher group levels, such as the levels of the dyad, family, or team (e.g., does a mother-infant dyad that jointly exhibits high emotional expressivity tend to be a dyad that jointly exhibits high behavioral responsivity?).

Emergent processes that operate at higher levels of analysis occur in other areas of psychological research. For example, in connectionist modeling prototypes can be conceptualized as constructs that emerge through the pattern of weights – a higher-level construct built from lower-level processes (e.g., Rumelhart & McClelland, 1986). In evolutionary models, there has also been utility in thinking about separate processes at different levels of analysis (e.g., Wilson & Sober, 1994).

Many social psychologists who study interaction tend to strip away “non-independent” interdependent processes from their experiments and data analysis. For instance, to make studies easier to manage, an investigator examining heterosexual dating couples may focus only on the female partner. To return to the analogy with chemistry, one of our colleagues once criticized our focus on multi-levels of analysis. He claimed that if a chemist is interested in studying salt, she studies sodium chloride, but if she is interested in studying sodium, she studies sodium in isolation. There is a sense in which this critique makes exactly our point. If the chemist interested in sodium can only observe sodium in the context of salt, then the understanding of sodium is qualified by the presence of the element chlorine. Rather than eliminating the effects of chlorine, it is possible to learn much more about sodium by also studying how it interacts with chlorine. The connection to the study of dating couples, and the costs of only studying one partner of the dating couple, should be immediate. Does it make sense to study, for instance, dating relationships by examining only the behavior of one individual, even though the behavior of that individual is confounded with that of the partner as well as with any synergistic effects that may result from the interaction of both individuals?

While there is certainly useful information to be gained by studying an individual in the group, there is additional information that can be extracted at the higher level of the group. We suggest that a complete understanding of dating, for instance, requires an assessment of both individuals as well as of the couple, and by extension we claim that any study purporting to be about social interaction must examine both individual-level and group-level processes.

In previous work, we identified four common errors that occur in social psychological research involving multiple levels of analysis (Gonzalez & Griffin, 1997). These errors are: (1) the *assumed independence error* where the analyst ignores the interdependency between interacting individuals, (2) the *deletion error* where only one individual in a social group is studied (this was described in the two previous paragraphs), (3) the *levels of analysis error* where measures such as dyad or group means are used to denote a supra-individual process, and (4) the *cross-level generalization error* where inferences about one level of analysis are made from analyses at a different level (e.g., Robinson, 1950).

This last error has received renewed interest through the work of King (1997), who has

developed a technique to infer bounds on individual-level parameters when only aggregate group-level data are available. However, even with the new developments in statistical procedures, researchers should be careful of inferring processes at one level of analysis from processes observed at a different level. To illustrate, we turn to an example given by Asch (1952, p. 175). He referred to the workings of a firefighting "bucket brigade" to illustrate emergent property of the group. The efficiency of a bucket brigade working well together to extinguish a fire far exceeds the capacity of a similar number of individuals working alone. In Asch's words, "the final accomplishment is more than, and different from, the sum of the individual effort." A cross-level generalization would lead to a faulty inference when, for example, a researcher incorrectly infers the properties of an effective bucket brigade from the properties that make an individual effective at putting out a fire.

Examples of multiple levels and interdependence in social psychological research

We offer several examples of social psychological research questions that can be modeled within a multi-level, interdependent approach. Our intention is to provide examples of the kinds of theoretical problems that can be addressed with the present framework, so the list should not be viewed as exhaustive.

One research question involves whether dyads or groups have "personalities" or "minds" of their own (e.g., Le Bon, 1903). Are these group personalities unique and separate from the individual members' own personalities? This notion of a group mind was attacked decades ago with the reasoning that groups are made up of individuals and thus "the whole is equal to the sum of its parts" (Allport, 1962). Even Allport, who criticized the notion of the group mind, acknowledged that aggregates can be perceived as having personalities, such as "the spirit of a meeting," but, as discussed earlier, he placed explanatory priority on the individuals making up the aggregate. Allport notwithstanding, the notion that there is psychological reality to group-level constructs is becoming popular again as seen in the following (partial) list of research topics: socially-shared cognition (Resnick, Levine, & Teasley, 1991); relationship awareness (Acitelli, 1993); culture and mind (Markus, Kitayama, & Heiman, 1996); group cohesiveness (Bollen & Hoyle, 1990; Cota, Evans, Dion, Kilik, & Longman, 1995; Hogg, 1993; Mullen & Copper, 1994); and social norms (Miller & Prentice, 1996).

We present below a data-analytic approach that is consistent with Allport's critique because group-level processes are modeled as latent (unmeasured) variables underlying individual-level measurements (hence, "made up" of individuals). Moreover, there is a sense in which the group-level effect is orthogonal to the individual-level effect allowing for a decomposition of individual- and group-level much like sums of squares in an ANOVA (analysis of variance). In this sense, the framework is also consistent with the synergistic arguments of Durkheim (1974), Lewin (1940), and others, that the group is "more than the sum of its parts," or perhaps more appropriately, the group is *different from* the sum of its parts.

Recently, we have seen an increase in research on the "group-level" topic of "entitativity" (e.g., Hamilton & Sherman, 1996; McConnell, Sherman, & Hamilton, 1997). Entitativity is a term coined by Campbell (1958) to denote the perception of group structure. The

data-analytic framework we present permits a comparison of the subjective estimates of entitativity of the type assessed by McConnell et al. with a more "objective" statistical estimate, permitting studies of accuracy and calibration of entitativity judgments. Frey and Smith (1993) conducted an analogous study comparing the perception of interdependence with objective estimates based on Kenny's social relations model.

The study of cohesiveness has recently received new momentum. Bollen and Hoyle (1990) suggested group members perceive cohesiveness along two dimensions: "sense of belonging" and "feelings of morale." Clearly, for a group to be called "cohesive" its members should have a high "sense of belonging" and all members should have a high "feeling of morale" in relation to the group. Cohesiveness appears to be related to several variables measuring group process and function (e.g., Shaw, 1971). However, the measurement of cohesiveness (both perceived and actual) has been debated and some claim that it has not been well-defined (see, for example, Bollen & Hoyle, 1990, as well as Cota et al., 1995). Some investigators have attempted to sidestep the measurement issue by manipulating cohesiveness (e.g., Festinger, Gerard, Hymovitch, Kelley, & Raven, 1952; Schachter, Ellertson, McBride, & Gregory, 1951), but the measurement problem still exists whenever manipulation checks are attempted.

The work on "intersubjective" social cognition (Ickes & Gonzalez, 1994) is also relevant. Much of the research in social cognition has focused on the cognitive mechanisms of individuals devoid of social interaction. Extending social cognition to social interaction, and separating the effects of the individual and group influences, would lead to a new set of empirical phenomena to observe and understand. This work may have implications for topics such as group decision making and majority/minority influence, as well as specific theories such as Aron and Aron's self-expansion theory (e.g., Aron, Paris, & Aron, 1995), Williams's (1997) recent work on social ostracism, and in the social psychology of organizations (e.g., Allmendinger & Hackman, 1996; Schriesheim, 1995).

Another relevant research problem involves misperceptions related to different levels of analysis — a process may operate at one level but the social perceiver is using another level to make inferences. For example, in a study of how managers at a manufacturing facility make decisions about salary raises, Markham (1988) found evidence for a group-level correlation between pay increase and performance evaluation of the workgroup (that is, higher-performing work groups received higher joint pay awards), but no evidence emerged for an individual-level correlation (higher-performing individuals within a work team were not differentially rewarded). As Markham suggested, the manager may view their raise decisions as fair because they were based on group-based merit. However, the individuals within the work team were not privy to the group-level analysis (i.e., performance observations and talk around the water cooler may be primarily with members of one's own workgroup). The individuals have better information about performance variability within the workgroup than across workgroups, so the individuals may have a difficult time making the connection between merit and raise, which could lead to misunderstandings between management and labor. Studying questions such as these could open new theoretical problems regarding the accuracy of group perceptions.

Related observations can be made about other aggregates and levels of analysis: aggregates of cues, behavior versus genetic levels, and aggregates of variables. For example, the "lens model" has seen renewed interest in the judgment and decision-making literature

(e.g., Gigone & Hastie, 1997) as well as the accuracy literature in personality (e.g., Funder, 1995). Without getting into details, this model attempts to capture judgment in the context of noisy cues. The fundamental equations of the lens model are related to the decomposition of individual- and group-level effects (see Castellan's, 1973, derivation of the lens model). Thus, the present framework can be extended to models in the judgment literature whose parameters are commonly estimated without reference to any statistical theory. The pairwise approach described below provides standard errors for those parameters (hence confidence intervals and statistical tests).

Another example is in behavioral genetics, where there is an interest in separating genetic and environmental effects of particular behaviors. For instance, is a trait (whether it be physical, behavioral, or psychological) related to another trait at a genetic level, an environmental level, or both. It turns out that some of the estimators we present below have counterparts in the behavioral genetics literature (such as measures of "familial resemblance"), and one of our contributions is to give standard errors for those estimators. Indeed, we use a method initially developed by Elston (1975) to derive standard errors for genetic correlations. Interest in behavioral genetics (and also the related, though not identical, area of evolutionary psychology) has grown recently among social psychologists. The present techniques will be useful in addressing the theoretical and empirical issues that may emerge as those areas gain popularity. By replacing the terms *genetic* and *environmental* with "method" effects and "trait" effects, the same model applies to problems in personality measurement using the multi-trait multi-method matrix (see Kenny, 1976). Dependence of the type seen in diary studies can also be modeled by the pairwise multi-level approach.

These are but a few research problems that could benefit from using the techniques reviewed in this chapter. What may be more important, though, are the new theoretical questions that could emerge once researchers have new tools in their common tool chest. As one of our colleagues noted, "Invention is the mother of necessity."

A Necessary Property of Group-level Phenomena: Homogeneity

The list of research examples given above highlights a necessary feature of group-level phenomena: *homogeneity*. By homogeneity we mean similarity in the thoughts, behavior, or affect of interacting individuals. The two individuals in a married couple can be homogeneous in their ratings of satisfaction of the marriage (e.g., both partners rate satisfaction as high or both rate as low). Members of a workgroup can be homogeneous in their level of respect for each other (e.g., all members of the workgroup share a common level of respect). Of course, the specific variables on which homogeneity is defined depend on the particular application. The general point is that similarity on each variable of interest is required in order to examine group-level processes. Deal, Wampler, and Halverson (1992) made an analogous observation that the perception of shared values, shared goals, and shared perspectives are critical for the existence of group-level processes in marital relationships. Similarly, Klein, Dansereau, and Hall (1994) argued that in organizational psychology homogeneity of group members is a "prerequisite" for group level processes to be

invoked. Other terms besides homogeneity that could be used to convey the same notion are *concordance* and *uniformity*.

Cartwright and Zander (1956, pp. 305–318) make the case that homogeneity is not sufficient for group-level phenomena because, for instance, a group goal may fail to emerge even when individuals share similar goals. For example, “. . . the members of a committee might each individually want to get home after a long day of meetings, but it would not seem useful to assert that the committee had a goal of going home” (p. 309). Within our framework, however, we want to study the case where individuals share goals and compare that, say, to groups where individuals do not share the same goal. We will model the shared goal as a latent variable that can then be related to other variables; we do not need to equate the shared goal (as indexed by the similarity of the individuals’ goals) with the concept of the “group goal.” It is this step that avoids the problem that Allport raised. Cartwright and Zander provide another example to suggest that homogeneity may not be necessary at all. Three boys successfully construct a lemonade stand (group goal) but the individual goals differ: one boy wants to earn money to buy a baseball glove, another wants to use his new carpentry tools, and a third simply wants to be included because the other two rarely allow him to play with them. We agree with their analysis that this example illustrates the power of interdependence in social interaction and, thus, that not all social interaction requires notions of group-level phenomena (however, we still argue that group-level phenomena require homogeneity). Below we generalize the framework to include the concept of interdependence, which according to Cartwright and Zander is “a more promising basis for a definition of a group goal” (p. 313).

Notions of homogeneity appear in several treatments of group behavior. Homans (1950), as well as Simon’s (1957) mathematical model of the Homans framework, defines “activity within the group” in terms of homogeneity of behavior. Lewin (1935) in his cross-cultural comparison of Germany and the United States referred to differences in homogeneity of behavior. In the study of language and communication, a quintessential social act, the concept of homogeneity is also invoked. At minimum, there must be a shared sense of meaning in order for communication to occur (e.g., Clark, 1996; Quine, 1960). Homogeneity was also central to classic theories of crowd and mob behavior (McDougall, 1920; Milgram & Toch, 1969).

There are several mechanisms through which homogeneity of group members can develop. It could develop through self-selection because people may be attracted to groups whose members are similar to them (e.g., Byrne, 1997; Hinde, 1997). Homogeneity could also be achieved through social norms exerting pressure leading to a “convergence process” (e.g., Newcomb, 1961; Newcomb, Turner, & Converse, 1965; Sherif, 1936), through contagion processes in which information is propagated through group members (e.g., Coleman, 1964; Le Bon, 1903; McDougall, 1920), or through cohesiveness and communication (Back, 1950; Festinger & Thibaut, 1950; Festinger, Schachter and Back, 1950). Common goals can exert pressure to homogeneity (e.g., Asch’s discussion of the bucket brigade) as can the perception of common fate (e.g., Campbell, 1958). The mechanism by which homogeneity is achieved is of interest in its own right (e.g., studies by Festinger, his colleagues and students; see, e.g., Cartwright and Zander, 1956), and is in the spirit of understanding the development of group processes. Here we are concerned with the measurement of homogeneity, rather than its development. Further, we want to be consistent

with Allport's (1924) mandate that group-level processes be explainable by individual-level variables, even if the process cannot be explained by reference to a single individual. The specific measure of homogeneity we consider below takes individual-level measurements as the building block, and thus is consistent with Allport's mandate. Curiously, Allport speculated that homogeneity may lead an observer to falsely perceive a group mind (Allport, 1924).

We now turn to a statistical framework, the *multi-level pairwise approach*, that both measures homogeneity and builds upon homogeneity as a necessary feature of group-level process. The multi-level part of the approach provides a clear statistical criterion for indexing group- and individual-level effects. The pairwise part of the approach offers two types of goods: it provides parameters that measure homogeneity and it provides statistical corrections for nonindependence of data. We first present an introduction to the pairwise approach and review the intraclass correlation, which serves as the building block for the rest of the model. We then show how to use the pairwise model to assess multiple levels simultaneously. The intraclass correlation will serve as the basis for a latent-variable approach to model group-level processes independently from individual-level process. We will then show how the pairwise approach can be extended to include regression models that tackle the issue of interdependence.

A Statistical Implementation of Homogeneity: The Pairwise Approach

Social interaction presents statistical problems because data from individuals within an aggregate are not independent. As Kenny said, nonindependence is the "very stuff" that makes up social interaction and should be modeled rather than ignored or treated as a nuisance. The pairwise approach presented here deals with nonindependence in two ways: the multi-level or latent variable version models interdependence directly so that individuals are "nested" within higher levels of analysis and individual effects are estimated separately from other levels, such as group levels; the regression version accounts for the nonindependence in the estimation and testing of the relevant parameters, but does not model the hierarchical nature of the data. (Note, however, that the two versions can be combined into more general models, as we discuss near the end of this chapter.) By formalizing the concepts in terms of statistical parameters we hope to clarify the issues, and thus avoid another of Allport's critiques: that writers of group-level phenomena "speak in a babble of tongues" (Allport, 1933, p. 13).

Currently, there are several pockets of methodological research on the statistical problem of nonindependence but there has been relatively little interaction between them. It is possible to handle some of the problems created by nonindependence through structural equations modeling (e.g., Bollen, 1989), by modeling individual scores as a function of an underlying group-level latent variable. It is also possible to handle quite complex problems created by nonindependence (e.g., multiple measures on multiple individuals over multiple times) through hierarchical linear modeling (e.g., Bryk & Raudenbush, 1992), by creating linear models at the lowest levels of analysis (e.g., a regression analysis between variables measured on a single individual over multiple times). The parameters are then entered

from the low-level analysis into a higher-level linear model. Sometimes special "tricks" are needed to alter the existing models in just the right way to handle specific problems of non-independence, but these tricks are not widely known and sometimes difficult to implement (e.g., Kaplan & Elliott, 1997; Longford & Muthen, 1992; McArdle & Hamagami, 1996; Muthen, 1994). When there is overlap between the pairwise approach and either structural equations modeling or hierarchical equations modeling, both lead to identical parameter estimates when maximum likelihood estimation is used and all groups have equal sizes.

We will relate the parameters of the pairwise model to substantive constructs in social psychology, and will label the parameters of the model with theoretically meaningful terms. To the typical researcher, our efforts, and those of colleagues such as David Kenny, may appear to be about correct ways to analyze data in the presence of nonindependence. While we certainly are interested in "correct" data-analytic techniques, we are more interested in finding new ways of mining social science data to address psychological questions about social interaction. We view the statistics of nonindependence as an opportunity to study social processes rather than as additional constraints placed on researchers.

Another advantage of the pairwise approach is that it is accessible to researchers from varied backgrounds. One of our goals has been to express the parameters of the statistical estimation in terms that are familiar to researchers (e.g., a Pearson-type correlation, a regression slope) and do the "dirty work" behind the scenes through the standard error, statistical significance test, and the confidence interval. Most of our techniques involve standard estimators and computations that can be performed using widely available computer software (even spreadsheets). Thus, a benefit of the pairwise approach is that researchers can concentrate on their "substantive" domains of interest rather than esoteric statistical procedures and programs.

There has been recent interest in comparing gay/lesbian relationships to heterosexual relationships (e.g., Kurdek, 1997b, for relationship commitment; Kurdek, 1997a, for distress after separation). These comparisons involve delicate statistical issues because they compare dyads whose members are exchangeable (same sex) with dyads whose members are distinguishable (opposite sex). The approach in this chapter extends other models (e.g., Kenny, 1996; Kraemer & Jacklin, 1979) and presents a simple way to analyze these complicated designs.

There are other modeling approaches that investigators have pursued. One approach is to model the social interaction over time as a dynamic process (Coleman, 1964, 1990; Simon, 1957; Stasser, Kerr, & Davis, 1980; Suppes & Atkinson, 1960; Thomas & Malone, 1979; Thomas & Martin, 1976). Another approach is to model the structural properties of the interaction using concepts from graph theory and network analysis (e.g., Harary, Norman, & Cartwright, 1965; Wasserman & Faust, 1994). For a general review of some of these models see Abelson (1967).

Kenny and associates (e.g., Kenny & La Voie, 1984) have worked on round-robin models where, for example, an individual interacts with every other individual. This design feature differs from the present one because we consider the case where group members interact only with group members (e.g., a husband and wife interact with each other, not with other husbands and wives in the sample) and all possible dyads within a group need not interact (e.g., data from a family of five can be collected without requiring family members to interact in various combinations of dyads or triads).

A few social psychologists have used “independence as the null hypothesis” in the sense that if individuals in a group behave differently than a simple probabilistic model based on independence (i.e., non-independence of interacting individuals), then it is assumed that there is some higher-level psychological process that needs to be explained. The simple chance model has usually been of the type that accounts for the “probability of at least one person” exhibiting the behavior. This “independence as null hypothesis” approach has been used in the bystander intervention literature (Latane & Darley, 1969) and in recent work on group discussion (e.g., Stasser & Titus, 1985; see Larson, 1997, for an extension). The limitation of this approach is that even though it identifies situations where nonindependence might be present, it does not model the type nor the degree of nonindependence.

The intraclass correlation: The building block for measures of homogeneity, multiple-levels, and interdependence

The framework we use is the pairwise correlation, which dates back to Pearson (1901; see also Fisher, 1925). The intraclass correlation is simple, even basic, but it serves as the basis of virtually all statistical models designed to capture nonindependence. The intraclass indexes the absolute similarity of scores; in contrast, the more familiar interclass or Pearson correlation indexes the relative similarity of scores around the group mean.

In the pairwise approach, the structure of nonindependence is built directly into the organization of the data matrix, and common estimators are computed on the reorganized data matrix with appropriate corrections to the standard error. The pairwise correlation is so named because each possible within-group pair of scores is used to compute the correlation. For example, with individuals Adam and Amos in the first dyad, there are two possible pairings: Adam in column 1 and Amos in column 2; or Amos in column 1 and Adam in column 2. This coding is represented symbolically in table 20.1. Thus with $N = 3$ dyads, each column contains $2N = 6$ scores because each individual is represented in both columns. The two columns (i.e., variables X and X') are then correlated using the usual product-moment correlation. This correlation is denoted $r_{xx'}$, and is called the *pairwise intraclass correlation*. It is an estimate of the intraclass correlation of one person's score with his or her partner's score. The pairwise intraclass correlation is the maximum likelihood estimate of the intraclass correlation and therefore is endowed with the usual properties of maximum likelihood estimators (such as consistency).¹ For theoretical development of the exchangeable case, formulas, and examples see Griffin and Gonzalez (1995).

The correlation $r_{xx'}$ indexes the absolute similarity between two exchangeable partners in a dyad. This can be seen in a simple scatterplot of X against X' . On this plot each dyad is represented twice, once as the point (X_i, X_i') and again as the point (X_i', X_i) . We draw line segments between points from the same dyad. These line segments will be bisected by the identity line and will have a slope of -1 . The summed squared length of these line segments is inversely proportional to $r_{xx'}$; it is in this sense that the pairwise intraclass is a measure of homogeneity between dyad members – the longer the line segment for a pair, the less similar are the two scores. Note that when the two individuals in the dyad perfectly

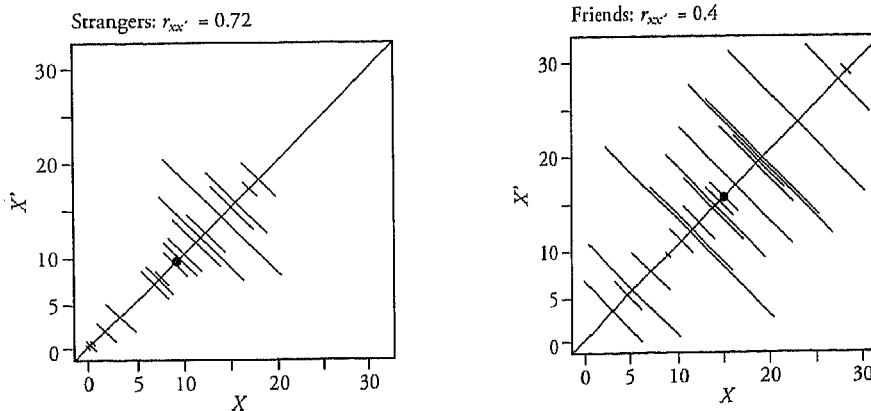


Figure 20.1 Graphical display of the pairwise intraclass correlation. Data are from Stinson and Ickes (1992) and represent the frequency of smiles and laughter for same-sex dyads where both members are either friends or strangers. The point on the identity line represents the mean frequency for strangers and the mean frequency for friends; the length of the line segments is related to the similarity in the within-dyad scores.

agree, then the line segments will have length 0 (i.e., all points will be on the identity line), and the pairwise intraclass correlation $r_{xx'}$ will equal 1. An analogous plot was proposed in the context of calibration and resolution of judgment (Lieberman & Tversky, 1993).

Two examples of these plots appear in figure 20.1. The data, from Stinson and Ickes (1992), are the frequency of smiles and laughter between dyad members, separately for dyads consisting of strangers and dyads consisting of friends. For dyads of strangers the pairwise intraclass $r_{xx'}$ was .72 whereas for dyads of friends $r_{xx'}$ was .40. The plot highlights an interesting difference in interaction between friends and strangers. It appears that the interaction pattern between strangers involves matching each other's frequency of smiling to a higher degree than for dyads of friends. That is, for strangers both partners' frequency of smiling was more similar than the frequency of smiling between friends. For friends, the interaction pattern consisted of pairs where one partner smiled relatively much more than the other. This matching difference was independent of the mean level of smiling. The closed circle on the identity line represents the mean frequency of smiles. Dyads of friends had a higher frequency of smiles than dyads of strangers, yet dyads of strangers had a higher degree of matching (as indexed by the pairwise intraclass). Simply reporting mean differences between friends and strangers misses an interesting part of the interaction involving the matching process.

It is important to remember that the correlation $r_{xx'}$ is computed over $2N$ pairs. Because the correlation $r_{xx'}$ is based on $2N$ pairs rather than on N dyads as in the usual case, the test of significance must be adjusted. The sample value $r_{xx'}$ can be tested against the null hypothesis $\rho_{xx'} = 0$ using the asymptotic test,²

$$Z = r_{xx'} \sqrt{N} \quad (1)$$

Table 20.1 Symbolic representation for the pairwise data setup in the exchangeable case

Dyad	Variable	
	X	X'
1	X_{11}	X_{12}
	X_{12}	X_{11}
2	X_{21}	X_{22}
	X_{22}	X_{21}
3	X_{31}	X_{32}
	X_{32}	X_{31}
4	X_{41}	X_{42}
	X_{42}	X_{41}

Note: The first subscript represents the dyad and the second subscript represents the individual. Categorization of individuals as 1 or 2 is arbitrary.

where N is the number of dyads and Z follows a standardized normal distributed.

The pairwise intraclass correlation indexes the similarity of individuals within dyads, and is closely related to other estimators of the intraclass correlation such as the ANOVA estimator (Fisher, 1925; Haggard, 1958). However, the pairwise method has several important advantages in the present situation. Most important, it is calculated in the same manner as the usual Pearson correlation: the two “reverse-coded” columns are correlated in the usual manner, thus offering ease of computation, flexibility in the use of existing computer packages, and an intuitive link to general correlational methods. It also has certain statistical properties that make it ideal to serve as the basis for more complicated statistics of interdependence (e.g., it is the maximum likelihood estimator of the intraclass correlation on groups of equal size). Moreover, the pairwise method used to compute the intraclass correlation within a single variable can be used to compute the “cross intraclass correlation” across different variables, an important index discussed below. Thus, the pairwise approach can extend to multivariate situations.

The previous example on dyads (table 20.1) was defined implicitly on dyads where the members are “exchangeable”; that is, there is no a priori way to classify an individual in a dyad. Examples of exchangeable dyads include gay couples, same-sex roommates, and identical twins. However, examples of distinguishable dyads (such as heterosexual couples where individuals within a dyad can be classified by sex) also occur. The calculation of the *partial pairwise intraclass correlation* in the distinguishable case follows the same general pattern. In the distinguishable case the pairwise correlation model requires one extra piece of information: a grouping code indexing the dyad member. This extra information is needed because each dyad member is distinguishable according to some theoretically meaningful variable, which is indexed by the grouping code. One simply computes the usual partial correlation between the two reversed columns, i.e., partialing out the variable of the grouping code. This partial correlation is the maximum likelihood estimator of the pairwise intraclass correlation for the distinguishable case. For the theoretical background underly-

ing the distinguishable case, relevant formulae, computational examples, and extensions to a structural equations modeling framework, see Gonzalez and Griffin (1999).

The intraclass correlation can also measure divergent processes in a dyad, which would be indicated by a negative intraclass correlation. A negative intraclass correlation is interpretable in dyads but becomes difficult to interpret in groups of three or more because then the intraclass correlation is asymmetric.

Extensions to groups

For simplicity we will focus much of the discussion in this chapter on dyads, but the framework can easily be extended to groups of any size. Here we show how to extend the pairwise approach to situations where all groups are of size k . The direct extension is to perform the pairwise coding for all possible combinations of dyads. For instance, in a group of size 3 with members denoted A, B, and C, the possible combinations are AB, AC, BA, BC, CA, and CB. For each of the six combinations, data from the person coded on the left (e.g., A in AB) is entered into column X and data from the person coded on the right (e.g., B in AB) is entered into column X' . Thus, for groups of size 3 columns X and X' will contain $6N$ data points, where N is the number of groups. The Pearson correlation between columns X and X' is the pairwise intraclass correlation for the exchangeable case.

Obviously, with large groups the pairwise framework becomes cumbersome because of the many combinations that need to be coded, but it still maintains its interpretational simplicity. A computational shortcut to the pairwise framework for groups is given by using a traditional analysis of variance source table. Compute a one-way ANOVA using the grouping code as the single factor (e.g., if there are 20 groups of size 4, then there will be 20 cells in the ANOVA, each cell having four observations). Denote the sum of squares between groups as SSB , the sum of squares within groups as SSW , and the corresponding mean square terms as MSB and MSW , respectively. The exchangeable pairwise intraclass correlation is identical to

$$r_{xx'} = \frac{(k-1)SSB - SSW}{(k-1)(SSB + SSW)} \quad (2)$$

where k is the group size (Haggard, 1958). Contrast this definition of the pairwise with the ANOVA-based intraclass correlation (e.g., Shrout & Fleiss, 1979), which is

$$r_{xx'} = \frac{MSB - MSW}{MSB + (k - 1)MSW} \quad (3)$$

where k is the group size. For a comparison of these two different formulations of the intraclass correlation, see Gonzalez and Griffin (1999). The setup is similar for the distinguishable case: include a second factor indexing each member of the group and compute the source table for the two-way ANOVA.

Extensions of the intraclass correlation with closed-form expressions (either in pairwise or ANOVA-based formulations) are not straightforward for situations where the size of

the groups varies within the same study. For example, a study on families may have some families of size 3, some of size 4, etc. For preliminary treatments of this problem see Karlin, Cameron, and Williams (1981), and Donner (1986).

Another way to express the intraclass correlation is in terms of a random effects linear model. For the exchangeable case each observation is modeled as an additive function of the grand mean, a group effect and error, where the group effect and the error term each are random variables. The variances of each of these two random variables (V_g and V_e respectively) leads to the intraclass correlation through the simple formula

$$\frac{V_g}{V_g + V_e} \quad (4)$$

With equal size groups, if one uses maximum likelihood to estimate these variance components, then the resulting intraclass correlation is identical to equation (2) (the pairwise estimate); if one uses restricted maximum likelihood to estimate the variance components, then the resulting intraclass correlation is identical to equation (3) (the ANOVA estimate). This random effects formulation can be extended to more complicated situations involving nested factors and can include cases with unequal group sizes. This general framework is called hierarchical linear modeling and there are now several commercial computer packages available (e.g., Bryk & Raudenbush, 1992).

Levels of Analysis

We now apply the pairwise framework to address different levels of analysis present in dyad research. A researcher studying dyads can ask questions at the level of the individual, of the dyad, or of both (Kenny & La Voie, 1985). For instance, a researcher can ask the question: Do *individuals* who gesture more also verbalize more? A researcher can also ask the question: Are *dyads* where both individuals gesture more also the dyads where both individuals verbalize more? These two questions differ in their level of analysis: individuals or dyads.

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

The problem of separating the individual-level analysis from the dyad-level analysis has troubled methodologists for a long time. Robinson (1950) pointed out that the correlation between two aggregated variables (e.g., mean educational attainment and mean income correlated *across* states) is not equivalent to the correlation between the same two variables measured on individuals (e.g., educational attainment and average income *within* a state). The erroneous generalization from one level to another has been termed the “ecological correlation fallacy” (Hauser, 1974; Robinson, 1950; Schwartz, 1994; Susser, 1994a, 1994b). A similar problem arises in cultural psychology: “[a]n ecological fallacy is committed when a researcher uses a culture-level correlation to interpret individual behavior . . . [a] reverse ecological fallacy is committed when researchers construct cultural or ecological indices based upon individual-level measurements (Kim, Triandis, Kagitcibasi, Choi, & Yoon, 1994, p. 4). The need for statistical techniques that permit analysis at different levels (“multi-level analysis”) has led to a cottage industry of different viewpoints and statistical programs (see Bock, 1989; Bryk & Raudenbush, 1992; Goldstein, 1987; Goldstein & McDonald, 1988; Kreft, de Leeuw, & van der Leeden, 1994).

The pairwise correlation can be extended to handle analyses at different levels. Figure 20.3 shows a simple latent variable model for the exchangeable dyadic design. In this model, each measured variable is coded in a pairwise fashion so that the variables X and X' (and, by the same logic, Y and Y') are identical except for order. There are four unique correlations on these six variables because $r_{xy} = r_{x'y'}$ and $r_{xy'} = r_{x'y}$ (these correlations are depicted in figure 20.2).

The variance of a given observed variable is assumed to result from two different latent sources: a dyadic component representing the portion of that variable that is shared and an individual component representing the portion of that variable that is not shared, or is unique, between dyadic partners. Here shared variance within a variable refers to homogeneity and is indexed by the intraclass correlation. As figure 20.3 illustrates, there are two levels at which the variables X and Y can be correlated: (1) the shared dyadic variance of X and Y can be related through the dyadic correlation r_d , and (2) the unique individual variance of X and Y can be related through the individual-level correlation r_i . The model depicted in figure 20.3 permits simultaneous estimation and testing of r_d and r_i .

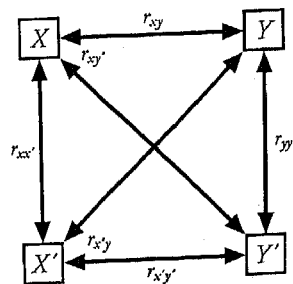


Figure 20.2 All possible pairwise correlations between variables X , Y , and their corresponding “reverse codes.” Note that in the exchangeable case $r_{xy} = r_{x'y'}$ and $r_{xy'} = r_{x'y}$.

The individual-level correlation r_i and the latent dyad-level correlation r_d can be computed directly from the four pairwise correlations as follows:

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

and

$$r_d = \frac{r_{xy'}}{\sqrt{r_{xx'}}\sqrt{r_{yy'}}} \quad (6)$$

These values are maximum likelihood estimates for the case of equal group sizes, such as dyads. The numerator of the individual-level correlation r_i is the difference between the observed correlation r_{xy} , which combines dyad-level and individual-level effects, and the cross intraclass correlation $r_{xy'}$, which contains only dyad-level effects. Thus r_i is a measure of the individual-level relation uncontaminated by dyad-level effects. The numerator of the dyad-level correlation r_d is simply the pairwise cross intraclass correlation $r_{xy'}$, and in this model corresponds to the direct measure of the dyad-level relations. The denominators, too, are conceptually straightforward: they correct the scale of the correlations for the fact that only "part" of each observed variable is being correlated. When the individual components of variables X and Y are correlated, the denominator adjusts for the proportions of variance in the observed X and Y that correspond to the *non-shared* effects ($\sqrt{1 - r_{xx'}}$ and $\sqrt{1 - r_{yy'}}$, respectively). Similarly, when the *dyadic* components of the variables X and Y are correlated, the denominator adjusts for the proportions of variance in the observed X and Y that correspond to the shared dyadic effects ($\sqrt{r_{xx'}}$ and $\sqrt{r_{yy'}}$, respectively). Note that r_d can be interpreted as $r_{xy'}$ that has been disattenuated (i.e., divided by the geometric mean of the intraclass correlations representing the proportion of dyadic variance). Thus, if one of the intraclass correlations is negative, then r_d is not defined and the present latent variable model will not apply. The latent variable correlation r_d is equivalent to the maximum likelihood group-level correlation suggested by Gollob (1991). Kenny and La Voie (1985) proposed an analogous model based on ANOVA rather than maximum likelihood estimators.

For the special case of exchangeable dyads, r_i can be computed either by equation (5) or equivalently by correlating the deviation scores on X and on Y . That is, the dyad mean on X is subtracted from each X score and the dyad mean on Y is subtracted from each Y score, and then the $2N$ deviations on X are correlated with the $2N$ deviations on Y . For dyads, equation (5) and the deviation method yield identical values for r_i . The correlation r_i can be tested using the usual Pearson correlation table (or the associated t -test formula) with $N - 1$ degrees of freedom (Kenny & La Voie, 1985).

When either of the intraclass correlations $r_{xx'}$ or $r_{yy'}$ (or both) are small, r_d will tend to be large and may even exceed 1.0. Because the dyadic model is based on the assumption of dyadic similarity, the model should only be tested when *both* intraclass correlations are significantly positive.³ In psychological terms, the dyadic model should only be applied when there is homogeneity within each variable, which translates into positive intraclass correlations. The latent variable correlation r_d may be interpretable when both intraclass correlations are negative, but adjustments would have to be made to deal with the asym-

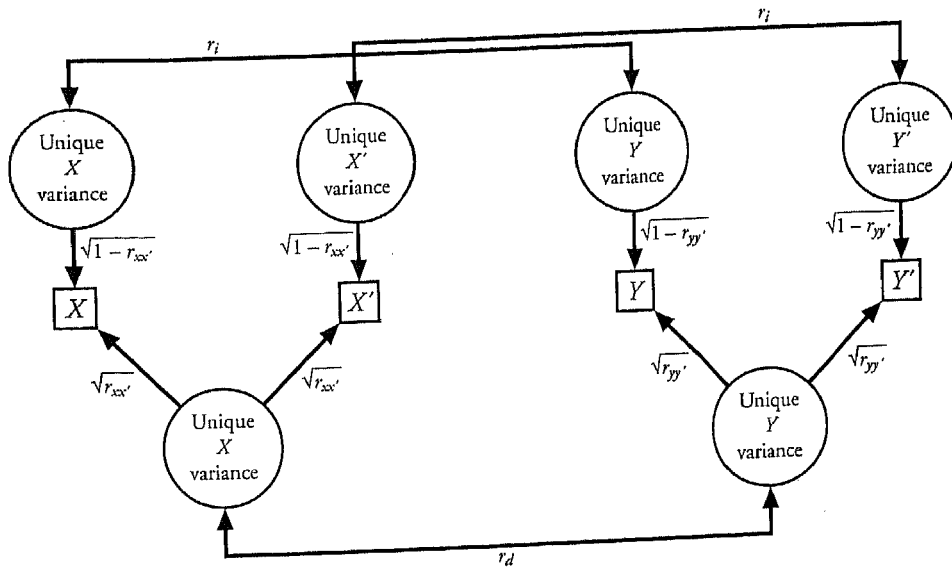


Figure 20.3 A latent variable model separating individual-level (unique) and dyad-level (shared) effects.

metry of negative intraclass correlations. In general, the practice of restricting the application of this model to cases when both intraclass correlations are significantly positive should reduce the occurrence of out-of-bounds values for r_d (see also Kenny & La Voie, 1985).

A significance test for r_d is reported in Griffin and Gonzalez (1995). Under the null hypothesis that population $\rho_d = 0$, the standard error of r_d is

$$\sqrt{\frac{1 + r_{xx'}r_{yy'} + r_{xy}^2}{2Nr_{xx'}r_{yy'}}} \quad (7)$$

Interestingly, the p -value associated with r_d is identical to the p -value associated with r_{xy} . Therefore, when both intraclass correlations are significant, implying significant dyad-level variance (homogeneity) in both X and Y , we recommend interpreting r_{xy} as the raw-score version of r_d because r_d is a disattenuated version of r_{xy} . For computational details, theoretical background and numerical examples, see Griffin and Gonzalez (1995); for extensions of the latent variable model to the distinguishable case, see Gonzalez and Griffin (1999).

Extensions to groups: The latent variable model

When groups consist of three or more individuals and all groups are of equal size, then the computation of the individual-level and group-level correlations proceeds in a manner similar to that described for the group intraclass (equation (2)). One computes the SSB and SSW separately for variable X and for variable Y . In addition, one must compute cross-product sum of squares SSB_{xy} and SSW_{xy} where subscripts denote variables (see Kenny & La Voie, 1985, for computational details). The individual-level r_i is equivalent to

$$\frac{SSW_{xy}}{\sqrt{SSW_x SSW_y}} \quad (8)$$

This is also identical to the ANOVA-based r_i given in Kenny and La Voie (1985). The pairwise cross intraclass correlation $r_{xy'}$ is

$$\frac{SSB_{xy} - \frac{SSW_{xy}}{k-1}}{\sqrt{SSB_x SSB_y}} \quad (9)$$

where k is the group size. The group version of the group-level r_d , which we denote r_g , is equation (6) where one plugs in the group versions of $r_{xy'}$ (equation (9)), $r_{xx'}$ (equation (2)), and $r_{yy'}$ (equation (2)).

The mean-level correlation. It may appear that the correlation between the means for each dyad on the two variables should yield an estimate of the dyad-level correlation. Contrary to this intuition, the "mean-level" correlation (denoted r_m) reflects both individual and dyad-level processes (under the model in figure 3); it can best be thought of as a "total" correlation. The correlation between dyad means can be expressed as a function of pairwise correlations:

$$r_m = \frac{r_{xy} + r_{xy'}}{\sqrt{1 + r_{xx'}}\sqrt{1 + r_{yy'}}} \quad (10)$$

The mean-level correlation r_m should not be used as an index of dyad-level relations because it can be significantly positive or negative even when the dyad-level correlation $r_d = 0$. According to the model in figure 20.3, a positive dyad-level correlation exists only when the tendency for *both* dyad members to be high on X is matched by the tendency for *both* dyad members to be high on Y . However, this is only one of several circumstances that can lead to a positive value of r_m . For example, a positive mean-level correlation will result when the tendency of one member to be extremely high on X is matched with the tendency of that same member to be extremely high on Y , which is an individual-level effect.

A Regression Model for Separating Actor and Partner Effects

We presented above a latent variable dyadic design that decomposed the relationship between two pairwise coded variables into dyadic-level and individual-level relations. However, this particular decomposition is only one of a number of possible models that can be applied in this situation (Kenny, 1996). Another useful way to model social interaction within a dyad is as a combination of two paths linking X and Y : an actor effect, which represents the extent to which a dyad member (the "actor") standing on variable X determines that actor's standing on variable Y , and a partner effect, which represents the extent to which the partner's standing on X determines the actor's standing on Y . We now turn to an example of this actor-partner model, which models interdependence directly without the hierarchy of group and individual effects.

In the Stinson and Ickes example, we might ask: "What predicts an individual's verbalization frequency?" An individual actor's speech frequency might be influenced by the joint effect of the individual's own gazes and his or her partner's gazes. Following the structural model illustrated in figure 20.4 leads to the interpretation of the (semi-partial) pairwise r_{xy} as the "actor correlation" and the (semi-partial) pairwise $r_{xy'}$ as the "partner correlation." To obtain the actor and partner effects in the exchangeable case, it is necessary to partial out the shared component of the actor and partner variance – which means partialling out r_{xx} , the pairwise intraclass correlation on X . The comparison of this model (depicted in figure 20.4) with the decomposition presented earlier in this chapter (figure 20.4) illustrates the importance of a theoretical model in guiding and formulating how an analysis should be conducted. Under different models the same correlations r_{xy} and $r_{xy'}$ carry different interpretations and can be modeled differently.

Thibaut and Kelley (1959; see also Kelley & Thibaut, 1978; Kelley, 1979) proposed a theory of close relationships focusing in particular on interdependence between individuals. The model begins with an economic approach in that it assumes each person in the relationship maximizes "outcomes." Some of these outcomes are under the control of the

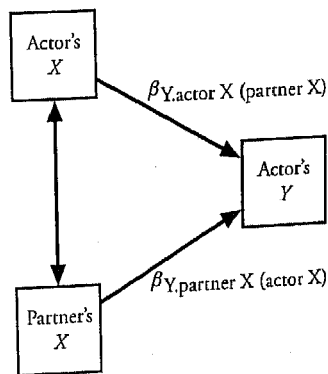


Figure 20.4 Representation of the actor-partner regression model.

individual actor, some are under the control of the partner, and some are under the joint control of the actor and the partner. A particular outcome may be a result of any combination of these three influences. The theory also introduced additional mechanisms such as attributions and goals, and these mechanisms influence the process by which the outcomes are maximized. For instance, an individual may have a "maximize other" goal where he is trying to maximize his partner's outcomes and neglect his own, or a "maximize joint" goal where she is trying to maximize the sum of both her outcomes and her partner's outcomes. The theory attempts to model which situations are subject to different types of outcome influences and outcome goals, and an extension of their model uses a "transition list" structure to model sequential aspects of interdependence (Kelley, 1984). See Rusbult and Van Lange (1996) for a recent review.

Empirical tests of the Kelley and Thibaut model have been limited in part because it is not clear how one would analyze data that emerge from research that brings interdependence into the laboratory, nor is it clear how to implement their analogy to game-theoretic payoff matrices with the typical variables used in social psychological research (see Hinde, 1979, for a similar point). The analytic techniques reviewed in this chapter permit tests for which responses are, and which responses are not, interdependent in dyadic and group interaction. The techniques implement the Kelley and Thibaut framework in a way that allows an investigator to categorize different types of interdependence. By adding the X by X' interaction term to the regression in figure 20.4, it is possible to build a regression model that includes terms for the actor's control, the partner's control, and the joint control. One advantage of the present extension is that it is not necessary to stay within the framework of "outcome matrices" as Kelley and Thibaut did. Instead, a researcher can ask whether an individual's Y variable is a function of her X variable, her partner's X variable, and some suitably defined interaction term (there are several ways of conceptualizing this interaction, see, e.g., Kenny, 1996). We note that Kelley and Thibaut (1978) proposed an "index of correspondence" to measure the similarity of payoffs; this index is identical to the pairwise intraclass correlation.

Some examples of the types of research questions that can be addressed within the Kelley and Thibaut framework include: Does a person's trust of the partner relate to the partner's satisfaction in the relationship? Does a person's trust of the partner relate to her own satisfaction? Does the joint level of both members' trust relate to a given individual's satisfaction? A priori knowledge of the "outcome matrix" would not be needed because the proposed technique estimates (from data) the various sources of influence. Thus, theories that make specific predictions about which behaviors and which outcomes should be interdependent (such as the theory of Kelley and Thibaut) can be tested. These techniques will help our understanding of conflict in relationships (e.g., Holmes & Murray, 1996), aid in understanding applied problems such as identifying the relationship patterns that predict divorce, and could be extended to the study of conflict within and between larger groups.

Necessary properties revisited

Earlier in the chapter we argued that a necessary property of group-level phenomena is homogeneity. The multilevel model is somewhat restrictive because in order to model a

higher level (e.g., group) there must be homogeneity at the lower level (e.g., individual). There is a different way to conceptualize social interaction that does not involve multiple levels, hence does not require homogeneity. This alternative model involves the concept of interdependence.

Kurt Lewin, writing 16 years after Allport's critique of the group mind, argued that "a group can be characterized as a 'dynamic whole'; this means that a change in the state of any subpart changes the state of any other subpart" (1940, p. 68). The degree to which individuals influence each other, i.e., a change in one subpart leading to a change in another subpart, is what we refer to as *interdependence*. Interdependence occurs when the actions and feeling of one individual influence the actions and feelings of another. Indeed, the subjective feeling of "closeness" may be dictated, in part, by how much interdependence there is between the individuals. This interdependence need not occur face-to-face as illustrated by the Yogi Berra quip: "We have a good time together, even when we're not together."

Thibaut & Kelley (1959) had a more specific operationalization of interdependence involving three components: how an actor influences his/her own behavior, how an actor influences his/her partner, and how the actions of the pair as a joint entity influence the actor. This operationalization can be implemented in a regression-like model, which we do below in a manner that preserves the statistical nonindependence of the data. Related terminology, though emphasizing different features of interaction, was used by Newcomb, Turner, and Converse (1965) when they distinguished three types of interpersonal influence: unilateral effects, reciprocal effects, and mutual adaptation. Kenny & La Voie (1984) used the terms *actor effect*, *partner effect*, and *relationship effect*. Allport (1924) used the term *circular reaction* for the iterative process where one person influences another, who in turn influences the first person, who in turn . . .

McDougall (1920), in his classic but underappreciated work on collective psychology, recognized the two necessary conditions of homogeneity and interdependence.

The essential conditions of collective mental action are, then, a common object of mental activity, a common mode of feeling in regard to it, and some degree of reciprocal influence between the members of the group. (p. 23)

He argued that without these conditions, an aggregate of individuals is merely that – an aggregation. In order for an aggregate to acquire emergent properties (such as a "group spirit" or a "national character," issues McDougall was concerned with), homogeneity (a common object and a common mode) and interdependence (reciprocal influence) must be in place.

Note that homogeneity and interdependence are logically independent concepts. For example, individuals in an aggregate could influence each other by their "mere" presence (see Zajonc's, 1980, review of social facilitation), demonstrating interdependence, but the behaviors need not be homogeneous. Likewise, group members may exhibit homogeneity in their behavior because of common fate (a common third variable) and not be interdependent. Even though the two concepts are logically independent, in real world groups the two are probably positively correlated (in ordinal language, high homogeneity goes with high interdependence).

Statistical implementations of interdependence

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

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

$$\frac{s_y(r_{xy} - r_{xy'}r_{xx'})}{s_x(1 - r_{xx'}^2)} \quad (11)$$

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

$$V(\beta_{\text{actor}}) = \frac{s_y^2(r_{xx'}^2 r_{xy'}^2 - r_{xx'} r_{yy'} + 1 - r_{xy}^2)}{2Ns_x^2(1 - r_{xx'}^2)} \quad (12)$$

The test of significance for the actor effect is computed with a Z test using $\frac{\hat{\beta}}{\sqrt{V(\hat{\beta})}}$. The test for the partner effect is analogous, except that r_{xy} appears in equation (12) in place of $r_{xy'}$.

For the Stinson and Ickes data that we have been using throughout this chapter, the actor correlation r_{xy} between gaze and verbalization was .386. In the context of the model shown in figure 20.4, the standardized regression coefficient was 0.173 ($Z = 0.97$). This standardized regression coefficient is interpreted as the influence on an actor's frequency of verbalization given one standard deviation change on the actor's frequency of gaze, holding constant the partner's frequency of gaze. In this case, the actor effect was not statistically significant. Similarly, the partner correlation $r_{xy'}$ between gaze and verbalization was 0.471. The standardized regression coefficient was 0.372 ($Z = 2.09$). In other words, the influence on the actor's frequency of verbalization given one standard deviation change on the partner's frequency of gaze, holding constant the actor's frequency of gaze, was statistically significant. The partner's gaze frequency was a more powerful predictor of the actor's verbalization frequency than the actor's own gaze frequency. For one possible theoretical

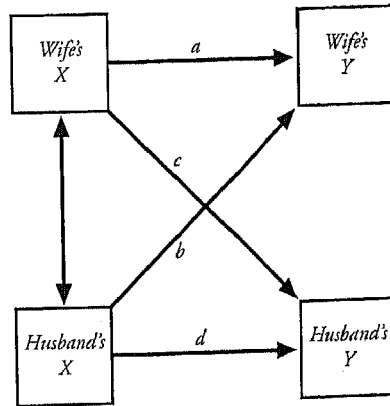


Figure 20.5 Representation of the actor-partner regression model for testing differences in regression coefficients between two classes.

analysis of these results, see Duncan and Fiske (1977).

A more complicated form of the actor-partner regression model is used for analyzing data from distinguishable dyads because when there are two different types of dyad members it is usually of interest to examine whether the actor effects and the partner effects vary across the two types of individuals. For example, consider the model presented in figure 5, adapted from Murray, Holmes, and Griffin's (1996) study of married couples. In this model, a woman's image of her partner is determined by two causes: her own self-image (the "projection" path labeled a , which is an actor effect) and her partner's self-reported self-image (the "matching" path labeled b , which is a partner effect). A man's image of his partner is similarly determined by an actor effect d and a partner effect c .

In such a model it is of central interest to test whether the actor (projection) paths are equal across sexes, or whether the partner (matching) paths are equal across sexes. This can be most easily done using structural equation modeling, as in the Murray et al. (1996) study, where the fit of the model under equality constraints is compared to the model where the constraints are not imposed. If both the actor and the partner effects are equal across the two classes, then a and d can be pooled and b and c can be pooled. In a simple model such as this, the pooled structural equation model is essentially equivalent to carrying out the pairwise regression model adjusted for distinguishable dyads because there the parameters are also averaged across the two types of people. The structural modeling approach can be extended to estimate much more complex models, as illustrated in the Murray et al. paper.

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

Connections between the latent variable model and the regression model

While the latent variable and regression models appear to have different necessary properties (homogeneity and interdependence), it is instructive to examine special cases of the two models that are equivalent (up to a linear transformation). Consider the special case of the exchangeable actor-partner model. The model has two β s that model the observed r_{xy} and $r_{xy'}$ correlations. Standard regression arguments show that this can be formalized as a matrix of coefficients A multiplying a vector of unknowns (the β s) leading to the vector of correlations r_{xy} and $r_{xy'}$ (Edwards, 1985). Similarly, the exchangeable latent variable model with two variables can represent the same two observed correlations so there is a matrix of coefficients B multiplying a vector of unknowns (r_i and r_d) leading to the vector of correlations r_{xy} and $r_{xy'}$. It can be shown that the vector of β s is linearly related to the vector of parameters from the latent variable. Thus, the special case implementations of these two models are identical up to a linear transformation. The two models diverge, however, in more complicated situations such as the addition of statistical interaction terms in the regression model or the freeing of equality constraints.

Moreover, it is possible to merge the two models into a more general model. Gonzalez and Griffin (1997) showed that for three or more variables one can compute separate matrices of individual-level correlations and dyad-level correlations. These matrices can then be entered into a standard regression package, and regression equations can be tested after appropriate adjustment to the statistical tests. These regressions are interpreted differently than the actor-partner regressions of the type depicted in figure 20.4. The actor-partner models are simple bivariate regressions, and are used to answer whether an actor's score on an outcome variable is predicted by that actor's score on a predictor variable and by his or her partner's score on the predictor variable. These models provide estimates and significance tests that are corrected for interdependence, but they do not specifically model the interdependence itself. The dyadic-level regressions, in contrast, can be bivariate or multiple regressions, but they explicitly model the interdependence within dyads and answer questions at a different level of analysis. Finally, the individual-level regressions may be bivariate or multiple regressions, and they answer whether the unique or unshared qualities of an individual on the outcome variable are determined by some combination of his or her unique qualities on the predictor variables. For more details, examples, and sample computer code see Gonzalez and Griffin (1997).

Summary and Conclusion

This chapter sketched the general pairwise model. This model provides a framework for dealing with issues of nonindependence as they arise in social psychological studies. Such a framework is useful for at least three reasons. First, it will supply the researcher with a tool to handle different types of problems. Our hope is that the technique will be used not only as a data analysis tool but also as a vehicle to translate psychological theory into testable models. For instance, we showed how some of the theoretical statements made by Kelley

and Thibaut could be translated into a regression model within the context of the pairwise approach leading to a direct way to test hypotheses in data.

Second, it will provide the empirical researcher with an intuitive understanding of why treating nonindependence correctly is important. This should not be undervalued. A new statistical technique that is not understood by the users, the empirical researchers in the "trenches," will not have much impact. Empirical researchers need to have both a clear understanding of why a new technique is needed (or is useful in their research), should have a relatively simple way of implementing the new technique, and should be familiar with how to interpret the results of the analyses. The advantage of the pairwise approach is that it is relatively easy to use (e.g., it uses parameter estimates that are familiar to the researcher, such as a Pearson correlation or a regression slope), it can illustrate why nonindependence in data requires special care (as illustrated above for the case of why the correlation between group means can be misleading), and it can provide a stepping stone to more complicated and more general techniques such as structural equations modeling and hierarchical linear modeling.

Third, it will provide the teacher of methodology and data analysis a way of showing how techniques that appear different on the surface are actually related. At present, students interested in dealing with nonindependent data must learn a battery of techniques such as SEM and HLM. Implementation of some tests presented here would require complicated SEM or HLM tricks (Kaplan & Elliott, 1997; Muthen, 1994). We hope that the simplicity of the pairwise model (and its generality) will be a welcome change in the classroom.

For these reasons, we see much value in the pairwise approach. We believe that such a simple yet general tool will be useful to researchers. The technique not only helps the analyst tackle thorny problems but also forces him or her to come to terms with the details of the data. The Introduction outlined a few theoretical questions that can be addressed with the techniques proposed here. However, more exciting opportunities may be the new theoretical questions that, we hope, will emerge once social psychological researchers begin dealing with different levels of analysis and tackling nonindependence.

We see the pairwise approach as offering one way to implement Allport's call to study the "master problem of social psychology. What *are* social phenomena if they are not the behaviors of individuals? Or, if social realities *are* entirely composed of individual actions, is there some way of describing and aggregating the latter, not before realized, that will hold the key to the statement of both realities simultaneously and without personification, tautology, or hyostatized agency?" (Allport, 1962, italics in original).

Notes

1. There are additional uses of the intraclass correlation. For instance, it appears in reliability theory and can be used where a measure of similarity between two scores is needed.
2. To simplify matters in this chapter, we have chosen to present large sample asymptotic significance tests. We present a null hypothesis testing approach rather than a confidence interval approach, but the latter will also be developed. Deriving analytic results for confidence intervals over correlations has not been an easy problem. Fortunately, there have been recent advances in the variance components literature for deriving confidence intervals that are applicable to the pairwise models (e.g., Donner & Eliasziw, 1988).

3. This restriction is well known in the structural equations modeling (SEM) literature. Note that the application of the SEM model in the case of exchangeable dyads is not straightforward because it is not clear how to compute the observed covariance matrix – one does not know which individual to put in column 1 and which individual to put in column 2 when computing the input covariance matrix. Implementing the exchangeable case in SEM models involves some “tricks” such as setting some equality constraints. However, in the distinguishable case the SEM implementation is relatively straightforward (Gonzalez & Griffin, 1999).

References

- Abelson, R. P. (1967). Mathematical models in social psychology. In L. Berkowitz (Ed.), *Advances in experimental social psychology* (Vol. 3, pp. 1–54). New York: Academic Press.
- Acitelli, L. K. (1993). You, me, and us: Perspectives on relationship awareness. In S. Duck (Ed.), *Understanding: relationship processes: Vol. 1. Individuals in relationships* (pp. 144–174). Newbury Park, CA: Sage.
- Allmendinger, J., & Hackman, R. (1996). Organizations in changing environments: The case of East German symphony orchestras. *Administrative Science Quarterly*, *41*, 337–369.
- Allport, F. H. (1924). The group fallacy in relation to social science. *Journal of Abnormal and Social Psychology*, *19*, 60–73.
- Allport, F. H. (1933). *Institutional behavior: Essays toward a re-interpretation of contemporary social organization*. Chapel Hill: University of North Carolina Press.
- Allport, F. H. (1962). A structuronomic conception of behavior: Individual and collective. *Journal of Abnormal and Social Psychology*, *64*, 3–30.
- Aron, A., Paris, M., & Aron, E. M. (1995). Falling in love: Prospective studies of self-concept change. *Journal of Personality and Social Psychology*, *69*, 1102–1112.
- Asch, S. E. (1952). *Social psychology*. New York: Prentice Hall.
- Back, K. W. (1950). The exertion of influence through social communication. In L. Festinger (Ed.), *Theory and experiment in social communication* (pp. 21–36). Ann Arbor, MI: Research Center for Group Dynamics.
- Bock, R. D. (1989). *Multilevel analysis of educational data*. San Diego, CA: Academic Press.
- Bollen, K. A. (1989). *Structural equations with latent variables*. New York: John Wiley.
- Bollen, K. A., & Hoyle, R. H. (1990). Perceived cohesion: A conceptual and empirical examination. *Social Forces*, *69*, 479–504.
- Bryk, A. S., & Raudenbush, S. W. (1992). *Hierarchical linear models: Applications and data analysis methods*. Newbury Park, CA: Sage.
- Byrne, D. (1997). An overview (and underview) of research and theory within the attraction paradigm. *Journal of Social & Personal Relationships*, *14*, 417–431.
- Campbell, D. T. (1958). Common fate, similarity, and other indices of the status of aggregates of persons as social entities. *Behavioral Science*, *3*, 14–25.
- Cartwright, D., & Zander, A. (1956). *Group dynamics: Research and theory* (2nd ed.). Evanston, IL: Row, Peterson.
- Castellan, N. J. (1973). Comments on the “lens model” equation and the analysis of multiple cue judgment tasks. *Psychometrika*, *38*, 87–100.
- Clark, H. H. (1996). *Using language*. Cambridge, England: Cambridge University Press.
- Coleman, J. S. (1964). *Introduction to mathematical sociology*. London: Free Press.
- Coleman, J. S. (1990). *Foundations of social theory*. Cambridge, MA: Harvard University Press.
- Cota, A. A., Evans, C. R., Dion, K. L., Kilik, L., & Longman, R. S. (1995). The structure of group cohesion. *Personality and Social Psychology Bulletin*, *21*, 572–580.
- Daubeny, C. (1850). *An introduction to the atomic theory* (2nd ed.). Oxford: Oxford University Press.
- Deal, J. E., Wampler, K. S., & Halverson, C. F. (1992). The importance of similarity in the marital

- relationship. *Family Process*, 31, 369-382.
- Doise, W. (1986). *Levels of explanation in social psychology*. New York: Cambridge University Press.
- Donner, A. (1986). A review of inference procedures of the intraclass correlation coefficient in the one-way random effects model. *International Statistical Review*, 54, 67-82.
- Donner, A., & Eliasziw, M. (1988). Confidence interval construction for parent-offspring correlations. *Biometrics*, 44, 727-737.
- Duncan, S., & Fiske, D. W. (1977). *Face-to-face interaction: Research, methods, and theory*. Hillsdale, NJ: Erlbaum.
- Durkheim, E. (1974). *Sociology and philosophy*. New York: Free Press.
- Edwards, A. L. (1985). *Multiple regression and the analysis of variance* (2nd ed.). New York: W. H. Freeman.
- Elston, R. C. (1975). On the correlation between correlations. *Biometrika*, 62, 133-140.
- Festinger, L., Gerard, H., Hymovitch, B., Kelley, H. H., & Raven, B. (1952). The influence process in the presence of extreme deviates. *Human Relations*, 5, 327-346.
- Festinger, L., Schachter, S., & Back, K. (1950). *Social pressures in informal groups: A study of human factors in housing*. Stanford, CA: Stanford University Press.
- Festinger, L., & Thibaut, J. (1950). Interpersonal communication in small groups. In L. Festinger (Ed.), *Theory and experiment in social communication* (pp. 37-50). Ann Arbor, MI: Research Center for Group Dynamics.
- Fisher, R. A. (1925). *Statistical methods for research workers*. Edinburgh, UK: Oliver & Boyd.
- Frey, K. P., & Smith, E. R. (1993). Beyond the actor's traits: Forming impressions of actors, targets, and relationships from social behaviors. *Journal of Personality and Social Psychology*, 65, 486-493.
- Funder, D. C. (1995). On the accuracy of personality judgment: A realistic approach. *Psychological Review*, 102, 652-670.
- Gigone, D., & Hastie, R. (1997). Proper analysis of the accuracy of group judgments. *Psychological Bulletin*, 121, 149-167.
- Goldstein, H. (1987). *Multilevel models in educational and social research*. New York: Oxford University Press.
- Goldstein, H., & McDonald, R. P. (1988). A general model for the analysis of multilevel data. *Psychometrika*, 53, 455-467.
- Gollob, H. F. (1991). Methods for estimating individual- and group-level correlations. *Journal of Personality and Social Psychology*, 60, 376-381.
- Gonzalez, R., & Griffin, D. (1997). On the statistics of interdependence: Treating dyadic data with respect. In S. Duck (Ed.), *Handbook of personal relationships* (2nd ed., pp. 271-302). New York: John Wiley.
- Gonzalez, R., & Griffin, D. (1999). *Analyses on group data*. University of Michigan and University of Sussex.
- Gonzalez, R., & Griffin, D. (1999). The correlational analysis of dyad-level data in the distinguishable case. *Personal Relationships*, 6, 449-469.
- Griffin, D., & Gonzalez, R. (1995). The correlational analysis of dyad-level data: Models for the exchangeable case. *Psychological Bulletin*, 118, 430-439.
- Griffin, D., & Gonzalez, R. (1998). *Regression models in dyadic research*. University of Sussex and University of Washington.
- Haggard, E. A. (1958). *Intraclass correlation and the analysis of variance*. New York: Dryden Press.
- Hamilton, D. L., & Sherman, S. J. (1996). Perceiving persons and groups. *Psychological Review*, 103, 336-355.
- Harary, F., Norman, R. Z., & Cartwright, D. (1965). *Structural models: An introduction to the theory of directed graphs*. New York: Wiley.
- Hauser, R. M. (1974). Contextual analysis revisited. *Sociological Methods and Research*, 2, 365-375.
- Hinde, R. A. (1979). *Towards understanding relationships*. London: Academic Press.
- Hinde, R. A. (1997). *Relationships: A dialectical perspective*. East Sussex, UK: Psychology Press.
- Hogg, M. A. (1993). Group cohesiveness: A critical review and some new directions. In W. Stroebe & M. Hewstone (Eds.), *European review of social psychology* (Vol. 4, pp. 85-111). Chichester: Wiley.

- Holmes, J. G., & Murray, S. L. (1996). Conflict in close relationships. In E. T. Higgins & A. W. Kruglanski (Eds.), *Social psychology: Handbook of basic principles* (pp. 622–654). Newbury Park, CA: Guilford Press.
- Homans, G. C. (1950). *The human group*. New York: Harpers.
- Ickes, B., & Gonzalez, R. (1994). Social cognition and social cognition: From the subjective to the intersubjective. *Small Group Research*, 25, 294–315.
- Kaplan, D., & Elliott P. R. (1997). A didactic example of multilevel structural equation modeling applicable to the study of organizations. *Structural Equation Modeling*, 4, 1–24.
- Karlin, S., Cameron, E. C., Williams, P. T. (1981). Sibling and parent–offspring correlation estimation with variable family size. *Proceedings of the National Academy of Science*, 78, 2664–2668.
- Kelley, H. H. (1979). *Personal relationships: Their structure and processes*. Hillsdale, NJ: Erlbaum.
- Kelley, H. H. (1984). The theoretical description of interdependence by means of transition lists. *Journal of Personality and Social Psychology*, 47, 956–82.
- Kelley, H. H., & Thibaut, J. W. (1978). *Interpersonal relations: A theory of interdependence*. New York: Wiley.
- Kenny, D. A. (1976). An empirical application of confirmatory factor analysis to the multitrait-multimethod matrix. *Journal of Experimental Social Psychology*, 12, 247–252.
- Kenny, D. A. (1995). Design issues in dyadic research. *Review of Personality and Social Psychology*, 11, 164–184.
- Kenny, D. A. (1996). Models of non-independence in dyadic research. *Journal of Social and Personal Relationships*, 13, 279–294.
- Kenny, D. A., & La Voie, L. (1984). The social relations model. In L. Berkowitz (Ed.), *Advances in experimental social psychology* (Vol. 18, pp. 141–182). Orlando, FL: Academic Press.
- Kenny, D. A., & La Vole, L. (1985). Separating individual and group effects. *Journal of Personality and Social Psychology*, 48, 339–348.
- Kim, U., Triandis, H. C., Kagitcibasi, C., Choi, S.-C., & Yoon, G. (1994). *Individualism and collectivism: Theory, method, and applications*. London: Sage.
- King, G. (1997). *A solution to the ecological inference problem*. Princeton, NJ: Princeton University Press.
- Klein, K. J., Dansereau, F., & Hall, R. J. (1994). Levels issues in theory development, data collection, and analysis. *Academy of Management Review*, 19, 195–229.
- Kraemer, H. C., & Jacklin, C. N. (1979). Statistical analysis of dyadic social behavior. *Psychological Bulletin*, 86, 217–224.
- Kreft, I., de Leeuw, J., & van der Leeden, R. (1994). Review of five multilevel analysis programs: Bmdp-5v, genmod, hlm, ml3 varcl. *American Statistician*, 48, 324–335.
- Kurdek, L. A. (1997a). Adjustment to relationship dissolution in gay, lesbian, and heterosexual partners. *Personal Relationships*, 4, 145–161.
- Kurdek, L. A. (1997b). Relation between neuroticism and dimensions of relationship commitment: Evidence from gay, lesbian, and heterosexual couples. *Journal of Family Psychology*, 11, 109–124.
- Larson, J. R. (1997). Modeling the entry of shared and unshared information into group discussion: A review and BASIC language computer program. *Small Group Research*, 28, 454–479.
- Latane, B., & Darley, J. M. (1969). Bystander “apathy.” *American Scientist*, 57, 244–268.
- Le Bon, G. (1903). *The crowd*. New York: Unwin.
- Lewin, K. (1935). Some social-psychological differences between the United States and Germany. *Character and Personality*, 4, 265.
- Lewin, K. (1940). The background of conflict in marriage. In M. Jung (Ed.), *Modern marriage* (pp. 52–69). New York: F. S. Crofts.
- Liberman, V., & Tversky, A. (1993). On the evaluation of probability judgments: Calibration, resolution, and monotonicity. *Psychological Bulletin*, 114, 162–173.
- Longford, N. T., & Murthen, B. O. (1992). Factor analysis for clustered observations. *Psychometrika*, 57, 581–597.
- Markham, S. E. (1988). Pay-for-performance dilemma revisited: Empirical example of the importance of group effects. *Journal of Applied Psychology*, 73, 172–180.
- Markus, H. R., Kitayama, S., & Heiman, R. J. (1996). Culture and “basic” psychological principles.

- In E. T. Higgins & A. W. Kruglanski (Eds.), *Social psychology: Handbook of basic principles* (pp. 857–913). Newbury Park, CA: Guilford Press.
- McArdle, J. J., & Hamagami, F. (1996). Multilevel models from a multiple group structural equation perspective. In G. A. Marcoulides & R. E. Schumacker (Eds.), *Advanced structural equation modeling: Issues and techniques* (pp. 89–124). Hillsdale, NJ: Erlbaum.
- McConnell, A. R., Sherman, S. J., & Hamilton, D. L. (1997). Target entitativity: Implications for information processing about individual and group targets. *Journal of Personality and Social Psychology*, 72, 750–762.
- McDougall, W. (1920). *The group mind*. London: Cambridge University Press.
- Mead, G. H. (1934). *Mind, self, and society*. Chicago: University of Chicago Press.
- Milgram, S., & Toch, H. (1969). Collective behavior: Crowds and social movements. In G. Lindzey & E. Aronson (Eds.), *Handbook of social psychology* (2nd ed., Vol. 4, pp. 507–610). Reading, MA: Addison-Wesley.
- Miller, D. T., & Prentice, D. A. (1996). The construction of social norms and standards. In E. T. Higgins & A. W. Kruglanski (Eds.), *Social psychology: Handbook of basic principles* (pp. 799–829). Newbury Park, CA: Guilford Press.
- Mullen, B., & Copper, C. (1994). The relation between group cohesiveness and performance: An integration. *Psychological Bulletin*, 115, 210–227.
- Murray, S. L., Holmes, J. G., & Griffin, D. W. (1996). The benefits of positive illusion: Idealization and the construction of satisfaction in close relationships. *Journal of Personality and Social Psychology*, 70, 79–98.
- Muthen, B. O. (1994). Multilevel covariance structure analysis. *Sociological Methods & Research*, 22, 376–398.
- Newcomb, T. M. (1961). *The acquaintance process*. New York: Holt, Rinehart, & Winston.
- Newcomb, T. M., Turner, R. H., & Converse, P. E. (1965). *Social psychology: The study of human interaction*. New York: Holt, Rinehart, & Winston.
- Pearson, K. (1901). Mathematical contributions to the theory of evolution ix. On the principle of homotypis and its relation to heredity, to the variability of the individual, and to that of the race. *Philosophical Transactions of the Royal Society of London, Series A*, 197, 285–379.
- Quine, W. (1960). *Word & object*. Cambridge MA: MIT Press.
- Resnick, L. B., Levine, J. M., & Teasley, S. D. (1991). *Perspectives on socially shared cognition*. Washington, DC: American Psychological Association.
- Robinson, W. S. (1950). Ecological correlations and the behavior of individuals. *American Sociological Review*, 15, 351–357.
- Rumelhart, D. E., & McClelland, J. L. (1986). Pdp models and general issues in cognitive science. In *Parallel distributed processing: Explorations in the microstructure of cognition: Vol. 1: Foundations* (pp. 110–149). Cambridge, MA: MIT Press.
- Rusbult, C. E., & Van Lange, P. A. (1996). Interdependence processes. In E. T. Higgins & A. W. Kruglanski (Eds.), *Social psychology: Handbook of basic principles* (pp. 564–596). Newbury Park, CA: Guilford Press.
- Schachter, S., Ellertson, N., McBride, D., & Gregory, D. (1951). An experimental study of cohesiveness and productivity. *Human Relations*, 4, 229–238.
- Schriesheim, C. A. (1995). Multivariate and moderated within- and between-entity analysis (waba) using hierarchical linear multiple regression. *Leadership Quarterly*, 6, 1–18.
- Schwartz, S. (1994). The fallacy of the ecological fallacy: The potential misuse of a concept and the consequences. *American Journal of Public Health*, 84, 819–824.
- Shaw, M. E. (1971). *Group dynamics: The psychology of small group behavior*. New York: McGraw-Hill.
- Sherif, M. (1936). *The psychology of norms*. New York: Harper & Row.
- Shrout, P. E., & Fleiss, J. L. (1979). Intraclass correlations: Uses in assessing rater reliability. *Psychological Bulletin*, 86, 420–428.
- Simon, H. A. (1957). *Models of man*. New York: Wiley.
- Stasser, G., Kerr, N., & Davis, J. (1980). Influence processes in decision-making groups: A modeling approach. In P. B. Paulus (Ed.), *Psychology of group influence* (pp. 431–477). Hillsdale, NJ: Erlbaum.

- Stasser, G., & Titus, W. (1985). Pooling of unshared information in group decision making: Biased information sampling during discussion. *Journal of Personality and Social Psychology*, *48*, 1467-1478.
- Stinson, L., & Ickes, W. (1992). Empathic accuracy in the interactions of male friends versus male strangers. *Journal of Personality and Social Psychology*, *62*, 787-797.
- Suppes P., & Atkinson, R. C. (1960). *Markov learning models for multiperson interactions*. Stanford, CA: Stanford University Press.
- Susser, M. (1994a). The logic in ecological: 1. the logic of analysis. *American Journal of Public Health*, *84*, 825-829.
- Susser, M. (1994b). The logic in ecological: 2. the logic of design. *American Journal of Public Health*, *84*, 830-835.
- Thibaut, J. W., & Kelley, H. H. (1959). *The social psychology of groups*. New York: Wiley.
- Thomas, E. A. C., & Malone, T. W. (1979). On the dynamics of two-person interactions. *Psychological Review*, *86*, 331-360.
- Thomas, E. A. C., & Martin, J. A. (1976). Analyses of parent-infant interaction. *Psychological Bulletin*, *83*, 141-156.
- Turner, R. H., & Killian, L. M. (1957). *Collective behavior*. Englewood Cliffs, NJ: Prentice Hall.
- Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications*. Cambridge, UK: Cambridge University Press.
- Williams, K. D. (1997). Social ostracism. In R. M. Kowalski (Ed.), *Aversive interpersonal behaviors* (pp. 133-170). New York: Plenum.
- Wilson, D. S., & Sober, E. (1994). Reintroducing group selection to the human behavioral sciences. *Behavioral and Brain Sciences*, *17*, 585-654.
- Zajonc, R. B. (1980). Feeling and thinking: Preferences need no inferences. *American Psychologist*, *35*, 151-175.