Dyadic Data Analysis

Andrew P. Knight

Washington University in St. Louis

Stephen A. Humphrey

Pennsylvania State University

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Abstract

Many foundational theories in the social sciences rely upon assumptions about dyadic interpersonal perceptions, behaviors, and relationships. This chapter provides a broad introduction to foundational concepts and techniques in analyzing dyadic data. The authors describe in detail one specific approach to dyadic data analysis—the social relations model—and provide software functions for conducting the analysis using multilevel modeling in R. The value of dyadic data analysis is illustrated through a discussion of prior publications that have used this approach. The authors also provide a step-by-step empirical example of how to use the social relations model with multilevel modeling in R, focused on dyadic trust in workgroups. The chapter concludes with a discussion of alternative approaches, beyond the social relations model, for analyzing dyadic data.

Dyadic Data Analysis

A manager and an employee meet to discuss a performance evaluation. A therapist greets a client and begins their weekly session. A recruiter conducts a series of one-on-one interviews with prospective employees. A worker shares a meal with a colleague with whom he hopes to partner on a new project. At the end of the day, the partner goes home and shares the interaction with her spouse over dinner. The spouse, in turn, recounts the meeting she had earlier that day with their son's teacher. As these examples illustrate, many human experiences transpire between two people—in a dyad.

Reflecting the ubiquity of dyadic experiences, many prominent theories of human behavior feature the dyad as a foundational unit of analysis. Exchange theories, for example, explain the flow of resources between, at the most basic level, two parties (Blau, 1964; Emerson, 1976; Homans, 1958). Conceptualizations of the process of social construction, such as through sensemaking and sensegiving, often diagnose the reciprocal dyadic interactions through which events are labeled and interpreted (Weick, 1995). Theories of interpersonal and romantic relationships offer explanations of the development and trajectory of connections between two people (e.g., Byrne, 1971; Finkel, Simpson, & Eastwick, 2017; Newcomb, 1961). Related, conceptualizations of interpersonal perception unpack the factors that underlie one person's view of another (Kenny, 1994). Within organizations, theories about roles and coordination rest upon dyadic connections between organizational subsystems (e.g., Katz & Kahn, 1978). And Weick's impactful theory of organizing treats the continuous reconstitution of organizations as composed of dyadic building blocks—double interacts between two people (Weick, 1979).

Although the dyad is the foundation of many prominent theories in the social sciences, the dyad has not historically been a focal level of analysis in empirical research (Krasikova &

LeBreton, 2012). In research on human behavior within organizations, for example, researchers have eschewed dyadic investigations due, in part, to a prevailing emphasis on individual (e.g., satisfaction, performance), group (e.g., cohesion, performance), and organizational (e.g., effectiveness) outcomes as the most meaningful phenomena to explain. The historical dearth of investigations using dyadic methods may also stem from the challenges of using the nuanced research methods needed to conduct dyadic research—both in data collection and data analysis. Research on diversity is an instructive example. Although many studies of diversity in organizations are grounded in social psychological theories of dyadic similarity-attraction (Williams & O'Reilly, 1998), researchers have most commonly examined aggregate diversity effects at the individual (e.g., Tsui, Egan, & O'Reilly, 1992) or group (e.g., van Knippenberg & Schippers, 2007) levels of analysis. As multilevel theorists have long admonished, misalignment of theory, method, and analysis can obscure or distort the substantive conclusions that researchers draw from empirical investigations (Klein, Dansereau, & Hall, 1994).

Spurred by these concerns, there has been burgeoning interest in recent years in dyadic data analysis. Scholars have used dyadic data analysis to study a wide range of phenomena, such as emotion (Eisenkraft & Elfenbein, 2010), deference (Joshi & Knight, 2015), helping behavior (Van der Vegt, Bunderson, & Oosterhof, 2006), rivalry (Kilduff, Elfenbein, & Staw, 2010), interpersonal harming (Lam, Van der Vegt, Walter, & Huang, 2011), the formation of work-related network ties (Casciaro & Lobo, 2008), and trust (Jones & Shah, 2016)—to name just a few topics recently studied. This burgeoning interest stems first from a growing recognition that there are substantively interesting criterion variables at the dyad level and, further, that understanding dyadic processes can unpack the interpersonal mechanisms that might precede the emergence of higher-level individual, group, and organizational phenomena (e.g., Gooty &

Yammarino, 2011; Krasikova & LeBreton, 2012; Liden, Anand, & Vidyarthi, 2016; Tse & Ashkanasy, 2015). Second, the growing use of dyadic data analysis reflects organizational researchers' increasing familiarity with and access to the methodological and statistical tools needed to conduct a dyadic investigation (e.g., Gonzalez & Griffin, 2012; Kenny, Kashy, & Cook, 2006; Kenny & Kashy, 2011; Krasikova & LeBreton, 2012).

The purpose of this chapter is to provide researchers with an entry point to dyadic data analysis. Recognizing the diversity of methods used across different literatures, which are grounded in different substantive research traditions, our objective is not to provide a comprehensive review of the vast range of methods that are available. Readers interested in a more comprehensive treatment should consult Kenny and colleagues' (2006) accessible and informative book on the topic. Instead, our goal in this chapter is to expose researchers to core concepts and a basic theoretical framework that can guide a research effort targeting the dyad level. To help researchers apply these methods to their own questions, we describe several exemplar publications that use dyadic data analysis. To illustrate the nuances of dyadic data analysis, we describe in detail one specific model—the social relations model—and present a step-by-step empirical example to delineate the basic steps of a dyadic analysis. As part of this illustrative application, we provide new software code for estimating the social relations model using multilevel modeling in R and describe how to interpret the output of the analysis.

We first describe the scope of the chapter, which focuses on a tradition of dyadic data analysis with roots in social psychology. Next, we define and explain a broad framework underlying a dyadic analysis. We then review several exemplar papers, highlighting the unique insights that can be gained from this approach. In a deep dive into a specific dyadic approach, we then discuss issues of statistical estimation, software, and the interpretation of results. We conclude by addressing alternative techniques and areas on the frontiers of dyadic data analysis.

Foundations of Modeling Dyadic Phenomena

In the social sciences, there are two main analytical traditions that focus on dyadic phenomena. The first, which is perhaps best known to researchers who examine phenomena at a more macro level, is social network analysis (Borgatti, Mehra, Brass, & Labianca, 2009; Wasserman & Faust, 1994). With deep roots in sociology, and to a lesser extent social psychology, researchers have used social network analysis to shed light on a broad range of topics—both at the micro level (e.g., creativity, leadership, power and influence) and at the macro level (e.g., syndication, strategic alliances) (Brass, Galaskiewicz, Greve, & Tsai, 2004; Burt, Kilduff, & Tasselli, 2013). The dyad—the connection (e.g., relationship, communication frequency) between two entities (e.g., people, firms)—is the basic building block in social network analysis. But the dyad is not generally the core focus within social network analysis. Reflecting its roots in sociology, the focus of most social network research is social structure—either understanding how different patterns of ties emerge or on how different patterns of ties provide constraints or opportunities (e.g., production of social capital). Although there are branches of social network analysis that feature dyadic ties more prominently (e.g., Snijders, van de Bunt, & Steglich, 2010), the dyadic tie is typically used as an input to some aggregation function in network analysis (e.g., centrality, density, network closure).

The second tradition—which we feature in this chapter—is the modeling of interpersonal perceptions and relationships developed by Kenny and his colleagues (Kenny & Albright, 1987; Kenny et al., 2006; Kenny & La Voie, 1984; Kenny & Zaccaro, 1983; Kenny, 1994; Malloy & Kenny, 1986; Warner, Kenny, & Stoto, 1979). This tradition is especially prevalent in research examining phenomena at a more micro level, such as in the study of families and the development of romantic relationships (e.g., Finkel & Eastwick, 2008). Kenny's paradigm for dyadic data analysis offers significant potential for researchers whose work rests upon dyadic theoretical mechanisms. With its roots in social psychology, this tradition developed initially as an ANOVA-based approach, focused on identifying, estimating, and explaining different sources of variance in individuals' interactions with others (e.g., Kenny, 1994). In the decades since its initial development, however, the paradigm has matured and now affords researchers tremendous flexibility, offering a range of models that can be estimated with structural equation modeling (e.g., Cook, 1994; Olsen & Kenny, 2006), multilevel modeling (e.g., Kenny & Kashy, 2011; Snijders & Kenny, 1999), and Bayesian modeling (e.g., Lüdtke, Robitzsch, Kenny, & Trautwein, 2013). The approach has also become practically accessible to researchers across all major statistical platforms (e.g., R, SAS, SPSS, Stata).

We focus in this chapter specifically on this second research tradition. We do so for three reasons. First, a heavy focus of social network analysis is modeling social structure, rather than dyadic interactions and behavior. Second, other chapters in this handbook familiarize readers with the core principles and ideas of social network analysis. Third, Kenny and his colleagues' framework for conceptualizing and modeling interpersonal behavior allows scholars to test and refine theories that a network approach is less well-equipped to answer. To provide researchers with an introduction to a relatively newer and less familiar approach, we bound our focus to dyadic data analysis focused on interpersonal perception and relationships.

Conceptualization of Sources of Variance in Interpersonal Perception and Behavior

As an introduction to dyadic data analysis, we first describe an overarching way of conceptualizing sources of variance in interpersonal perception and behavior, using a running example to explain these sources. Imagine two groups of 5 people (Group 1: Alex, Brianna, Carl, Diane, and Emily; Group 2: Frank, Gary, Heidi, Ingrid, James) who interact with one another in a brainstorming exercise. At the end of the exercise, the group members rate how much they trust each other. This design, which is common in dyadic research, is called a round robin design—each member of the group rates every other member of the group on some attribute or provides a rating of his or her relationship with each other member. Although a full round robin design is not essential for conducting a dyadic study—and, indeed, Kenny et al. (2006) describe several other research designs—a round robin design offers the most flexibility and potential for estimating the drivers of dyadic interpersonal perceptions, relationships, or behaviors.

Conceptually, there are three primary levels of analysis in this framework: the group level, the individual level, and the dyad level (Snijders & Kenny, 1999). The group level reflects contextual effects that lead the members of one group to interact with or perceive one another in a way that, on average, differs from the members of another group. For example, consider a scenario in which Group 1 brainstorms face-to-face and Group 2 brainstorms virtually. The face-to-face interactions might lead the members of Group 1 to report trusting one another more, on average, than the members of Group 2 report trusting one another.

The individual level reflects the consistent ways that people interact with or perceive one another. Note that this consistency is across partners in a given situation, not necessarily across time or across situations. In a dyadic framework, there are two kinds of individual-level tendencies, referred to as the actor (or perceiver) effect and the partner (or target) effect. The actor effect reflects how people tend to view or behave with others, in general; it is “the tendency for a person to exhibit a consistent level of response across all interaction partners” (Kenny et al., 2006, p. 192). For example, Alex may tend to be very trusting, reporting high levels of trust with each other member of his group. Diane, on the other hand, may not be so trusting—her ratings of her teammates may be uniformly low. This difference between Alex and Diane is captured by variance in the actor effect. The partner effect in a dyadic framework describes how individuals tend to be viewed or rated by others, in general; that is, “the degree to which multiple partners respond in a similar way to a particular individual” (Kenny, Mohr, & Levesque, 2001, p. 129). In this example, all members of Group 1 may report relatively high trust with Emily, but relatively low trust with Diane. Whereas Emily is viewed as very trustworthy by her teammates, Diane is viewed as very untrustworthy. This difference is captured by variance in the partner effect.

Finally, the dyad level (or, the relational level) reflects idiosyncratic ways that a given actor views or behaves with a given partner. The dyad effect “is the unique way in which a person behaves with a particular partner” (Kenny et al., 2001, p. 130); that is, it is one person’s rating of another after accounting for the actor’s general tendency in viewing others and the partner’s general tendency in being viewed by others. The dyad effect is a form of residual that remains after controlling for group level, individual level actor, and individual level partner effects. For example, Alex may especially trust Carl, and vice versa, because Alex and Carl are both vocal and passionate fans of a given sports team.

As we have described it so far, dyadic data analysis may seem identical to the typical multilevel model with which organizational researchers are highly familiar. However, the prototypical multilevel model in the social sciences reflects a “Russian dolls” model of nesting, in which individuals are perfectly nested within groups and groups are perfectly nested within organizations (e.g., Klein et al., 1994). What makes a dyadic analysis with round robin data unique is that dyadic ratings are cross-nested (Snijders & Kenny, 1999); actors and partners are nested within one another. Rather than viewing this as a nuisance factor, dyadic models leverage cross-nesting to capture nuances of interpersonal perceptions and relationships. Cross-nesting enables examining, for example, how symmetric an interpersonal process is.

Kenny and colleagues' framework describes two kinds of symmetry—dyadic reciprocity and generalized reciprocity. Dyadic reciprocity reflects the degree to which a given actor's perception is linked to a given partner's perception, controlling for each person's individual tendencies. Generalized reciprocity, in contrast, reflects the degree to which actor effects (i.e., people's stable tendencies in viewing others) are linked to partner effects (i.e., people's stable tendencies in being viewed by others). The difference between dyadic and generalized reciprocity is subtle, but important. Applied to our running example, dyadic reciprocity addresses the question of whether if Alex especially trusts Carl, does Carl also especially trust Alex? Generalized reciprocity, in contrast, addresses the question of whether group members who tend to report trusting most others also tend to be trusted by most others. Generalized reciprocity is the covariance between individual actor and partner effects.

The group, individual, and dyad levels of analysis described above underlie a myriad of specific models for dyadic data analysis (for detail, see Gonzalez & Griffin, 2012; Kenny et al., 2006). Which specific model a researcher adopts should be driven by the overarching research question, the associated research design, and the availability of data. Some research designs preclude estimating some of the effects described above. For example, estimating an actor (perceiver) effect requires that each person rates (i.e., perceives or evaluates) multiple other partners (targets); estimating a partner (target) effect requires that each person is rated by multiple other actors (perceivers); and, estimating a dyad or relational effect requires that each person rates and is rated by others (i.e., participants serve as both actors and partners). As noted above, the round robin design in which each person rates each other person in the group provides the most flexibility examining dyadic phenomena. Because of its comprehensiveness and flexibility, we focus our empirical illustration in this chapter on this design.

Exemplar Applications of Dyadic Data Analysis

To highlight the potential value of using dyadic data analysis, we describe in detail three recent exemplar publications that used the social relations model. These examples provide a sample of the kinds of questions that dyadic analysis can help answer, as well illustrate the unique insights that can stem from a dyadic analysis.

Eisenkraft and Elfenbein (2010) provided a unique application of dyadic data analysis for studying the origins of affective experiences in organizations. Building from theories of individual differences, they postulated that there were systematic and idiosyncratic differences in how people make *others* feel—what they referred to as “affective presence.” That is, some people are hypothesized to elicit positive feelings in their partners during interpersonal interactions, while other people are hypothesized to elicit negative feelings in their interaction partners. In contrast to most research on individual differences, which focuses on how an individual’s traits *influence his or her own behavior*, Eisenkraft and Elfenbein’s (2010) research examined how an individual’s traits *influence the attitudes or behaviors of others*. Note that affective presence is, to use the language introduced above, a partner effect—it is the way that a person’s characteristics systematically influence the responses of others. Eisenkraft and Elfenbein (2010) studied affective presence using a round robin research design, in which 239 MBA students who were organized into 48 teams rated their positive and negative affect during interactions with each of their fellow teammates. Results derived from a social relations analysis revealed that individuals’ feelings during interpersonal interactions were shaped by their own trait affectivity, but also by the affective presence of their partners. Eisenkraft and Elfenbein

(2010) found that affective presence was as powerful in explaining a person's feelings as was the person's own trait affectivity. Their findings underscore the value of a dyadic approach in theory development, research design, and data analysis for explicating how both people's stable individual differences—the actor's trait affectivity and the partner's affective presence—influence the emotional experiences that unfold during interpersonal interactions.

Erez et al. (2015) provided a second, and related, exemplar application of dyadic data analysis. The authors used a dyadic lens to consider how individual differences influence actors' appraisals of their interaction partners' performance, as well as actors' behavior towards their partners. Erez et al. (2015) postulated that introverted people are especially sensitive to the interpersonal characteristics of others when forming perceptions of them, relying heavily on others' interpersonal personality traits like agreeableness and extraversion to form their judgments. Note that Erez et al.'s (2015) arguments focused inherently on a *dyadic* or relational effect—that one actor's perception of another *depends on* the attributes of both the actor and the partner. The way that a partner's characteristics (i.e., agreeableness, extraversion) influence an actor's perceptions depends on the actor's own characteristics (i.e., introversion). Said differently, the relationship between a partner's personality and an actor's perception of and behavior towards that partner is moderated by the actor's personality. Erez et al. (2015) used two studies—one survey-based and the second experimental—to examine their conceptual model. In the survey-based study, 207 graduate students were organized into teams of four to five members and within each team participants provided round robin ratings of one another. Social relations analyses and multilevel modeling supported the idea that an actor's perception of a partner is a function of the interaction between the actor's personality and the partner's personality. Introverted individuals' perceptions were more strongly influenced (negatively) by a partner's extraversion and agreeableness. Erez et al.'s (2015) findings illustrate the value, both theoretical and empirical, of a dyadic perspective for examining interpersonal perception.

A third exemplar application of dyadic data analysis is Joshi and Knight's (2015) study of dyadic deference in multidisciplinary research groups. Using a dyadic perspective, the authors built and tested a theoretical model to explain the dyadic drivers, above and beyond any individual drivers, of interpersonal deference—the act of yielding to the preferences or perspectives of another. The authors used the social relations model with round robin survey data from 619 members of 55 multidisciplinary research groups to examine the degree to which deference is a function not just of one person's attributes, but of the interaction of the attributes (e.g., gender, education) of the person receiving deference and of the person conferring deference. Joshi and Knight's (2015) analysis showed that, in addition to any individual level drivers of deference (i.e., actor and partner effects), the degree of alignment between two interaction partners' attributes (e.g., similarity) shapes deference. Furthermore, the authors' findings highlighted how a dyadic approach can yield unique insights into interpersonal processes. The results of the social relations analysis—and, specifically, the reciprocity correlations—showed that perceiving competence is a fundamentally different interpersonal process than perceiving social closeness or affinity with another. Perceiving competence is an asymmetric process at the individual level ($r = -0.20$)—those who are viewed as highly competent tend to view their teammates as being lower in competence. Perceiving social affinity, on the other hand, is a symmetric process at the individual level ($r = 0.39$)—those who are viewed as being friends tend to also view their teammates as friends. At the dyad-level, however, both of these processes are symmetric—dyadic reciprocity correlations were positive for both perceptions of competence ($r = 0.14$) and feelings of social affinity ($r=0.56$). These insights into the symmetry and asymmetry of interpersonal dynamics are unique strengths of a dyadic approach; studying status at the individual level would obscure these important differences in social perceptions.

As these examples illustrate, dyadic data analysis can provide new insights into enduring areas of inquiry in the social sciences. Dyadic data analysis offers researchers at least three unique benefits. First, and with respect to *theory*, dyadic data analysis affords the opportunity to align the level of methods and analysis with the theory that underlies a prediction, thus avoiding fallacies of inference (Krasikova & LeBreton, 2012). Of course, this benefit is only realized if the theory underlying a prediction is indeed about a dyadic phenomenon. Second, and with respect to *statistical analysis*, dyadic data analysis offers the ability to account for the multiple sources of non-independence and the cross-nested nature of interpersonal interactions. Failing to account for these nuances when analyzing dyadic data can result in biased parameter estimates and flawed conclusions. Third, and with respect to *understanding*, dyadic data analysis can offer insights into a phenomenon that are unavailable if a researcher focuses instead on an individual or group level of analysis. For example, and as shown by both Eisenkraft and Elfenbein (2010) and Erez et al. (2015), a dyadic approach facilitates examining specifically which element (actor, partner, dyad) of an interpersonal interaction is driving variance in perceptions or behaviors. Dyadic data analysis can help answer the question of whether an interpersonal phenomenon is something that is elicited by a person, something that is in the eye of the beholder, or something that is dependent on the interaction of two people. A dyadic approach can also, as shown by Joshi and Knight (2015), provide unique insights into the symmetry of interpersonal processes that are not available from other approaches. For example, do those who give advice to others also tend to receive advice from others? If one worker gives advice to her colleague, does that specific colleague reciprocate and also give advice? Answering such questions necessitates a dyadic approach, which separates the individual (actor and partner) and relational effects, and also models reciprocity. These unique elements help refine old theories and enable the development of new insights into interpersonal dynamics in organizations.

An Empirical Illustration of the Social Relations Model

To further illustrate the value of dyadic data analysis for organizational research, and to provide a step-by-step guide for doing such an analysis, we examine the concept of trust—the willingness of one person to be vulnerable to another (Rousseau, Sitkin, Burt, & Camerer, 1998)—within work teams. Trust is multi-dimensional, comprising both cognitive and affective components (McAllister, 1995). The cognitive dimension of trust in work teams reflects one person's belief that a team member can contribute to the work of the group. The affective dimension reflects one person's belief that another team member genuinely cares for him or her. Importantly, scholars commonly conceptualize trust as a relational phenomenon that is shaped by individual characteristics of a trustor (i.e., actor or perceiver) and a trustee (i.e., partner or target), as well as aspects of the relationship between the two (i.e., dyadic relationship) (cf. Mayer, Davis, & Schoorman, 1995; Schoorman, Mayer, & Davis, 2007). The relational nature of trust invites the use of dyadic data analysis (Jones & Shah, 2016).

Our illustration uses survey data from 432 students organized into 108 four-person teams that were instructed to complete a creative task. Due to missing data on some of the predictor variables included in this illustrative analysis, the sample used below comprised 108 groups, 414 unique individuals, and 1190 directed dyads (i.e., actor ratings of a given partner)[1]. The teams were asked to, in a 60-minute work period, develop and execute a creative idea for a poster to

[1] As the purpose of this chapter is not to test and evaluate formal theory, but rather to provide an illustration of how one goes about using the SRM, we did not attempt to impute missing data (for guidance on imputing missing data, see Grund, Lüdtke, and Robitzsch, this volume).

recruit volunteers to participate in a campus blood drive. Before beginning this interdependent task, participants first completed a survey that assessed individual characteristics and team members' familiarity with one another. After completing the team task and delivering their blood drive poster, participants completed a second survey that assessed elements of team dynamics and team members' perceptions of one another.

For this example, we examined the degree to which trust between team members is a function of two characteristics—gender (-1 = Female, 1 = Male) and self-reported social skills. These characteristics were assessed on the survey that participants completed prior to working on the poster with their teammates. Social skills—reflecting participants' ability to take others' perspective, read others' intentions, and adjust their behavior—was measured using a 7-item scale ($\alpha = 0.81$) (Ferris, Witt, & Hochwarter, 2001). A sample item is "I find it easy to put myself in the position of others."

The criterion variables that we examined were team members' cognitive and affective trust of their teammates. In the survey administered after the group task, participants responded to items from McAllister (1995) assessing their perceptions of their teammates. Data were collected using a round robin design, with each person rating each other member of the team. Three items measured the cognitive dimension of trust (e.g., "I can rely on this person not to make my job more difficult by careless work", $\alpha = 0.75$) and three items measured the affective dimension of trust (e.g., "If I share my problems with this person, I know [s]he would respond constructively and caringly", $\alpha = 0.87$).

Analytical Approach

We illustrate how to conduct a social relations analysis using random coefficient modeling (variously called hierarchical linear modeling and, more generally, multilevel modeling)—a type of analysis that is already familiar to many social science researchers. Although Kenny and his colleagues initially developed the SRM as an ANOVA-based model, Snijders and Kenny (1999) showed how the parameters of the SRM can be estimated using multilevel modeling. The unit of observation for criterion variables in the SRM is the directed dyadic relationship, which describes the perception or relationship from one person, the actor (i), to another person, the partner (j). An actor's perception of a given partner can result from characteristics of the group the two are in (i.e., the group effect), individual-level actor characteristics (i.e., the actor effect), individual-level partner characteristics (i.e., the partner effect), and, dyad-level characteristics (i.e., the relational or dyad effect, which is conditional on the unique pairing of a given actor with a given partner). Variance in directed dyadic ratings by actors of their partners can thus stem from differences across groups (i.e., group variance), differences across individual actors (i.e., actor variance), differences across individual partners (i.e., partner variance), and differences across dyads (i.e., relational or dyad variance). The SRM is therefore a multilevel model, in which directed dyadic outcomes are nested within individuals, which are nested within groups (Kenny et al., 2006; Snijders & Kenny, 1999). However, as noted above, the SRM estimates the cross-nested nature of the dyadic perceptions or relationships by specifying the covariance between dyad members' relational effects and the covariance between actor effects and partner effects.

A multilevel modeling approach to fitting the SRM has several advantages compared to the ANOVA-based estimation methods initially developed by Kenny. Snijders and Kenny (1999, p. 476) noted three strengths, in particular, of the multilevel modeling approach: "The multilevel formulation of the SRM allows straightforwardly for the inclusion of covariates, for missing data on the dependent variable (provided that the data are missing by design or at random), and the estimation of specialized models (e.g., equal actor and partner variance)." A multilevel modeling approach also easily handles unequal group sizes (Kenny, 1996). These strengths, combined with researchers' growing familiarity with multilevel modeling, make it an attractive option for estimating the SRM. Kenny et al. (2006) provided the code used to run the SRM as a multilevel model using various software packages (e.g., MLWIN, SAS) in an online supplement. In this chapter, we introduce a new option for researchers seeking to estimate the SRM using multilevel modeling—the lme function in the nlme package (Pinheiro, Bates, DebRoy, Sarkar, & Team, 2016) in the software environment R (R Core Team, 2015). Below we describe our approach and in the Appendix provide the code needed to estimate the SRM using multilevel modeling in R.

Data Preparation

As a first step, a researcher must prepare a dataset at the dyad level with a few key identifiers. Each observation in the dataset (i.e., each row) contains one group member's rating of another group member. This structure captures the fact that the dataset comprises directed dyadic ratings—there is one row for A's rating of B and a separate row for B's rating of A. Note that this mandates having a distinct criterion rating from each member of the dyad; it is not appropriate to assign a single criterion value to both observations. Table 1 provides a subset of the dataset used in this illustration, showing one way to prepare data for a dyadic analysis. Several variables in the dataset indicate the nested and interdependent nature of the observations. Unique identifiers indicate the team (group_id), rater (act_id), ratee (part_id), and dyad (dyad_id) to which a given observation belongs. Further, the dataset includes two sets of dummy variables—a1 to a4 and p1 to p4—that are needed to estimate the SRM using multilevel modeling and the clever approach described by Snijders and Kenny (1999) for circumventing the limitations regarding cross-nesting in many multilevel modeling software packages. These dummy variables range from 1 to *k*, where *k* is the size of the largest group in the dataset; in this empirical example, the largest group has four members. One set of the dummies identifies the rater or actor (i.e., “a”) and the second set identifies the ratee or partner (i.e., “p”) for a given directed dyadic observation.

In addition to these identifiers, Table 1 also illustrates how dyadic datasets may include covariates across multiple levels of analysis. Table 1 only contains a subset of the covariates used in the illustration; however, what is shown reflects the general structure of how covariates can be included in an analysis. At the team level, for example, the dataset contains the mean rating of team members’ social skills (ss_x). At the individual level, there are values for the social skills of the trustor (act_ss) and of the trustee (part_ss). At the dyad level, there is a variable indicating the absolute value of the difference between the trustor and the trustee’s social skills (absdif_ss). Also at the dyad level, there is the directed dyadic rating of the cognitive dimension of how much one person trusts the other (trust_cog). This—the directed dyad level—is the lowest level of analysis in a round robin design. All other values are, in some way, repeated across rows, because the actor in one row is the partner in a different row. The identifier variables described above instruct the software on how to handle this interdependence in accordance with the social relations model.

Null Models: Variance Decomposition of Cognitive and Affective Trust

The next step in a social relations analysis is to conduct a variance decomposition of the focal directed dyadic ratings, which estimates how much a given rating is attributable to characteristics of groups, actors, partners, and relationships. This variance decomposition is analogous to the first step of any other multilevel analysis, in which a researcher first examines intraclass correlations or changes in model fit indices to determine whether there is meaningful variation in intercepts or slopes at different levels of analysis. The variance decomposition for a social relations analysis entails fitting a null model—that is, a model without fixed effect covariates—to the data. This null model is presented below:

$$Y_{ijk} = \mu + G_k + A_{ik} + P_{jk} + E_{ijk} \qquad (1),$$

where Y_{ijk} is actor *i's* trust of partner *j* in group *k*, μ is an overall intercept term, G_k is the random group effect for group *k*, A_{ik} is the random actor effect for actor *i*, P_{jk} is the random partner effect for partner *j*, and E_{ijk} is the random relational effect that reflects the unique way that actor *i* rated partner *j*. To estimate the SRM, it is necessary to specify the structure of the variance-covariance matrix for these random effects. Note that the relational component in Equation 1 reflects a combination of both the true relational effect and random error (i.e., residual). Unless there are multiple measures of the focal criterion variable, these effects are confounded (i.e., it is not possible to separate the true relational effect from the residual, or error; Kenny, 1994).

Per our prior discussion, the model estimates the variance of the group effects (σ^2_G), the individual actor effects (σ^2_A), the individual partner effects (σ^2_P), and the relational effects (σ^2_E). As above, without multiple measures of the focal criterion variable, it is not possible to separate relational variance from residual, or error, variance. The covariances among all random effect terms except for two are fixed to zero. The two that are estimated reflect the model's assumption of two forms of reciprocity. The model estimates the covariance between actor effects and partner effects, which is the generalized reciprocity term (σ_{AP}). And the model estimates the covariance between the relational effects for the members of a given dyad (i.e., E_{ijk} and E_{jik}), which is the dyadic reciprocity term ($\sigma_{Eijk,Ejik}$). The results of the null model thus provide the parameter estimates needed to parse the variance in a given directed dyadic rating.

Figure 1 provides annotated code and output for the null model for cognitive trust. Additional code, including expanded commentary, is available in the Appendix and online (http://apknight.org/pdsrm-example.R). Note that the raw output of R's lme function contains standard deviations and correlations, rather than variances and covariances, for the random effects. Standard error estimates are not provided by lme for these random effects parameters because these are only asymptotically valid and, accordingly, should only be used with large sample sizes (see Singer, 1998, p. 351). Even without standard errors and tests of whether these parameters significantly differ from zero, however, the variance partitioning enables examining the relative contribution that group, actor, partner, and dyad characteristics make to trust ratings.

Table 2 shows the conversion of the raw output from lme into variance-covariance parameter estimates and, then, into variance component percentages and reciprocity correlations. To convert the standard deviations into variance parameters, square the standard deviation parameter. To convert the correlations into covariance parameters, multiply the correlation estimate by the product of the standard deviations of its elements. Computing variance component percentages requires two additional steps. First, sum the variance parameter estimates for group, actor, partner, and dyad—this provides the sum total variance (Snijders & Kenny, 1999). Then, divide each of these values by the sum total to compute the portion of total variance accounted for by group, actor, partner, and dyad, respectively. The helper function srm.pct, included in the pdSRM code linked above, can be used to easily perform these transformations and covert the raw output from lme into variance percentages and reciprocity correlations.

Given that these values represent the portion of variance in a directed dyadic rating attributable to each source, one could use traditional approaches for interpreting them as effect sizes (see LeBreton & Senter, 2008). As Table 2 shows, for both cognitive trust (59%) and affective trust (58%) a substantial portion of the variance in directed dyadic ratings is attributable to the trustor (i.e., actor effect). The variance partitioning indicates that some individuals tend to be relatively more trusting of others, in general, whereas other individuals tend to be relatively less trusting of others, in general. In contrast, the partner effect contributes relatively little to perceptions of cognitive (2%) and affective (2%) trust. The results of the null model suggest that the phenomenon of trust—at least early on in the life of a relationship (Jones & Shah, 2016)—is heavily in the eye of the beholder, not the beholden.

In addition to decomposing the variance into group, actor, partner, and relational components, the results of the null model indicate the degree to which ratings are symmetric, or reciprocal. As described above, generalized reciprocity is a form of reciprocity at the individual level, measuring the degree to which the individual tendencies of actors align with the individual tendencies of partners. In this example, generalized reciprocity describes how much a person who tends to trust others is, himself or herself, similarly trusted by others. Table 2 provides the generalized reciprocity correlation, which reflects the association between the actor effect and the partner effect. For cognitive trust this value is -0.31, which indicates that those who tend to trust others' abilities tend to be trusted slightly less by their teammates. As Table 2 shows, the generalized reciprocity correlation for affective trust is very small, but positive: 0.03. Changing to the dyad level, Table 2 also shows the estimate of dyadic reciprocity—both as a correlation and as a covariance parameter. Note that in the SRM, the variance of the dyad members is fixed to be equivalent through the specification of a compound symmetric structure. Accordingly, for the covariance between E_{ijk} and E_{jik}, the components have equal variance. The dyadic reciprocity correlation is 0.14 for cognitive trust and 0.25 for affective trust. These values indicate that, within a dyad, if an actor trusts a partner, that specific partner is likely to also trust the actor.

The results illustrate the value of considering reciprocity for understanding interpersonal relationships and perception in work teams. As other research using dyadic data analysis has shown (e.g., Joshi & Knight, 2015), the basic properties of interpersonal processes reflecting competence may be strikingly different from those reflecting warmth. For the example of trust, we observe that reciprocity at the individual level (i.e., generalized reciprocity) is negative for the cognitive dimension, but positive for the affective dimension. Perceiving competence seems to be an asymmetric interpersonal process, such that those who are viewed by their teammates as highly competent tend to view their teammates as lower in competence. In contrast, perceiving warmth seems to be a symmetric interpersonal process—those who are viewed as caring tend to view others also as caring. Once individual tendencies are controlled, however, ratings of trust are symmetric for both the cognitive and affective dimensions; that is, dyadic reciprocity is positive for both. Within a given dyad, people tend to reciprocate their beliefs about trust.

Prediction Models: Examination of Covariates at Multiple Levels of Analysis

Although the variance decomposition and reciprocity correlations are interesting and shed light on the nature of an interpersonal process, many researchers may wish to test hypotheses about covariates—that is, about why scores on outcome variables (e.g., trust, relationship satisfaction, work-family conflict) vary across teams, actors, partners, and dyads. In the next step of our illustration, we include two common types of covariates—one categorical and one continuous—at multiple levels of analysis to show how to estimate and interpret the results of analyses with predictor variables. In predicting cognitive and affective trust, we examine the role of social skills and gender, organizing our discussion of these covariates by level of analysis.

The prediction models for both cognitive and affective trust may be specified using the following equation:

$$Y_{ijk} = \mu + G_k + A_{ik} + P_{jk} + E_{ijk} + \beta_{TSS}\text{TeamSocialSkills}_k + \beta_{TGD}\text{TeamPctMale}_k + \beta_{ActSS}\text{SocialSkills}_{ik} + \beta_{ActMale}\text{Male}_{ik} + \beta_{PartSS}\text{SocialSkills}_{jk} + \beta_{PartMale}\text{Male}_{jk} + \beta_{DydMale}(\text{Male}_{ik} \times \text{Male}_{jk}) + \beta_{DydSS}(|\text{SocialSkills}_{ik} - \text{SocialSkills}_{jk}|) \quad (2)$$

where, again, Y_{ijk} is actor *i's* trust of partner *j* in group *k* and μ is an overall intercept term. In contrast to Equation 1, however, the overall intercept and the group (G_k), actor (A_{ik}), partner (P_{jk}), and relational (E_{ijk}) effects in Equation 2 are now conditional upon the included fixed effect covariates. Each of these covariates is explained in greater detail below.

When using multilevel modeling to estimate the SRM—and, especially, when testing hypotheses about covariates—it is common to present the results in the format illustrated by Table 3, in addition to the variance decomposition results provided in Table 2. Note that Models 1 and 3 of Table 3 are the results of the null models described above for cognitive and affective trust, respectively. Reflecting the fact that these models lack covariates, there are no fixed effect coefficients in Models 1 and 3, other than the intercept. For reporting in Table 3, the standard deviations and correlations for the random effects included in the raw output from lme have been transformed into variances and covariances. Given that the raw output of different multilevel modeling functions (e.g., R's lme, SAS's PROC MIXED) contain different kinds of estimates, researchers should specify what values they report (e.g., variance, standard deviation).[2]

[2] It is useful to note other differences in the output from lme compared to, for example, the output from SAS PROC MIXED. In PROC MIXED, the two terms for the dyadic component—the residual and the dyadic covariance—are independent components, such that the total dyadic variance is the sum of the two. In the output from lme, the residual term reflects the sum of the unique dyadic variance and the dyadic covariance. So, the residual term output by lme is equal to the sum of the two SAS components.

Models 2 and 4 of Table 3 include covariates predicting cognitive and affective trust, respectively. In entering these covariates into our analyses, we first grand mean centered any continuous variables, which is important given that the intercept terms in these multilevel models are substantively interesting (Hofmann & Gavin, 1998). In lme's raw output, the results for fixed effect covariates are listed directly beneath the header for "Fixed Effects." In the null model results depicted in Figure 1, there is only the Intercept term listed here; for the prediction models, there would be additional covariates, listed one per line beneath the Intercept term.

Starting at the highest level of analysis, we observed in the null model results discussed above that groups in this sample vary meaningfully in how much members tend to trust one another. For both affective and cognitive trust, the members of some groups trust one another more than do the members of other groups. To examine whether social skills and gender can help explain this variance, we created two group-level variables that represent group composition with respect to gender and social skills. For gender, we computed the percentage of group members who are male (TeamPctMale_k) and for social skills we computed the average (mean) of group members' social skills ($\text{TeamSocialSkills}_k$). As Table 3 shows, neither of these team-level covariates helps to explain why trust is higher in some groups than others. Gender composition has a non-significant relationship with cognitive (β_{TGD} = -0.28, n.s.) and affective (β_{TGD} = -0.09, n.s.) trust, as does average social skills (cognitive trust: β_{TSS} = -0.13, n.s.; affective trust: β_{TSS} = -0.06, n.s.). Note that these parameter estimates are conditional upon the inclusion of other effects in the model. That is, the percentage of men in a team does not provide statistically significant incremental prediction above and beyond actor, partner, and relational effects.

Next, at the individual level of analysis there are two sets of covariates to consider—characteristics of the actor and characteristics of the partner. Models 2 and 4 of Table 2 include both the actor's gender and social skills, as well as the partner's gender and social skills as covariates of trust. With respect to actor characteristics, actor social skills is significantly positively related to cognitive trust ($\beta_{ActSS} = 0.18$, $p < 0.01$) and affective trust ($\beta_{ActSS} = 0.19$, $p < 0.01$), holding constant the other effects in the model. This positive coefficient indicates that those who are higher in social skills tend to be more trusting of others, in general, than those who are lower in social skills. Across their partners, actors higher in social skills report higher cognitive and affective trust than do actors lower in social skills. Second, with respect to partner characteristics, both gender and partner social skills help explain who tends to be trusted by team members. The results in Table 3 show that men are trusted relatively less than are women for cognitive ($\beta_{PartMale} = -0.05$, $p < 0.05$) and affective ($\beta_{PartMale} = -0.08$, $p < 0.01$) trust. Additionally, partner social skills has a positive relationship with trust: team members who are higher in social skills are trusted more by their teammates than are team members lower in social skills (cognitive: $\beta_{PartSS} = 0.06$, $p < 0.05$; affective: $\beta_{PartSS} = 0.05$, $p < 0.10$).

Finally, at the dyad level of analysis, Models 2 and 4 present two different ways of examining dyadic effects. With respect to gender, the interaction term between actor gender and partner gender sheds light on specifically who tends to trust whom in teams (cognitive: $\beta_{DydMale} = 0.05$, $p < 0.05$; $\beta_{DydMale} = 0.09$, $p < 0.01$). As shown in Figure 2, the gender effect for cognitive and affective trust is driven by women tending to report more trust of other women than of men; the effect is particularly strong for the affective dimension of trust. Note that an alternative approach for examining the role of gender would be to include a variable indicating whether dyad members are either the same or different genders. This approach could be appropriate for testing hypotheses motivated by a similarity-attraction or social identity mechanism, but offers a less nuanced view of dyadic effects (as it would show a muted effect of similarity – that is, the average of the female-female and male-male relationships – rather than the unique effect of the female-female relationships). We illustrate this type of approach with the continuous variable social skills. In this case, we computed the absolute value of the difference between an actor's and a partner's social skills (i.e., $|\text{SocialSkills}_{ik} - \text{SocialSkills}_{jk}|$). The coefficients for this variable in Table 2, which are both non-significant (cognitive: $\beta_{\text{DydSS}} = -0.01$, n.s; affective: $\beta_{\text{DydSS}} = -0.03$, n.s.), reflect the degree to which separation between an actor and a partner on this attribute relates to trust between the two, accounting for their individual tendencies to trust and be trusted.

In addition to the statistical significance of fixed effect covariates, researchers often wish to communicate how important the covariates are for explaining the group, actor, partner, and relational effects. Scholars have suggested a number of different approaches for calculating the variance explained by predictors at different levels of analysis in multilevel models (e.g., Hox, 2002; Singer, 1998; Snijders & Bosker, 1999). These scholars also note, however, that there are potential problems with estimates of variance explained that are derived from comparing the size of the variance parameter estimates across models with and without covariates. One possible approach for circumventing these challenges, which might be particularly appropriate given the complexity of the SRM, is a Bayesian framework for multilevel modeling. Gelman and Pardoe (2006) provide detailed information about how to implement such an approach.

How Valuable Is the Complexity of Dyadic Data Analysis?

To illustrate the unique benefits of dyadic data analysis, we reanalyzed the data described above using an approach focused on the individual level of analysis. Specifically, we approached the dataset with a focus on why some individuals might be trusted more than others (i.e., on perceptions of individual trustworthiness). This focus on why some are trusted more than others targets one of the sources of variance that we described above—namely, the partner effect that reflects individual partners' tendencies to elicit relatively homogeneous reactions from actors. As a first step in taking this individual-level approach, we examined whether teammates tended to agree with one another in their ratings of a given person and whether teammates' average ratings of a person varied (i.e., whether there is consensus in views of trustworthiness). To do so, we computed two versions of the intraclass correlation and the $r_{wg(j)}$ metric (Bliese, 2000). These calculations showed significant non-independence in team members' ratings of a focal person on their team for cognitive trust [ICC(1) = 0.17, $p < 0.01$] and for affective trust [ICC(1) = 0.15, $p < 0.01$]. Reflecting the small size of the groups in this dataset, however, the mean ratings of a given individual were low in reliability for both cognitive [ICC(2) = 0.37] and affective [ICC(2) = 0.35] trust. Group members did tend to agree with one another in their ratings of trust in a focal team member, as shown in measures of interrater agreement for cognitive (Average $r_{wg(j)} = 0.81$) and affective (Average $r_{wg(j)} = 0.77$) trust.

Given these values, we proceeded to aggregate team members' ratings of one another, computing the mean of team members' ratings of trust with a given person, for each person on the team. We then fit a set of multilevel models for cognitive and affective trust that focused on the individual level of analysis; we also included a random intercept for team to account for potential team-level non-independence. The results of these models, presented in Table 4, show few significant effects of gender or social skills on perceptions of trustworthiness at either the team-level or the individual-level. In contrast to the dyadic analysis, which depicted gender and social skills relating to trust in nuanced ways, the individual-level analysis showed only that men are less likely than women to be trusted on the affective dimension ($\beta = -0.08$, $p < 0.01$).

It is important to note that the insights drawn from this individual-level analysis are fundamentally different from those derived from the dyadic analysis. In part this reflects the fact that the kinds of questions that researchers have the flexibility to ask at the dyad level differ from those that a researcher targeting the individual level might ask. The dyadic analyses unpacked the main effect of gender found in the individual-level analysis and revealed that men received lower trust ratings because women tended to rate other women more highly in trust. By separating the variance in an interpersonal perception or relationship into the constituent parts of the interacting individuals, a dyadic approach offers the flexibility to test effects at multiple levels of analysis. The individual-level analysis that we report here focuses only on one portion of the pattern of variance—the partner—examined by the dyadic analysis. As the dyadic variance decomposition revealed, the partner component is actually the least impactful driver of trust in early relationships. Actor tendencies and relational effects have a far greater impact on ratings of trust. This ability to tease apart effects is constrained in an aggregate analysis. Whether this is a limitation, though, depends on a researcher's question and the theoretical perspectives that inform the investigation. As with any form of multilevel research, theory must come first.

Alternative Approaches for Analyzing Dyadic Data

We have illustrated above—both through a discussion of published research and an empirical illustration—one type of dyadic data analysis that is useful for understanding the nature and drivers of interpersonal perception and relationships. This chapter has, however, just scratched the surface and researchers have several other alternatives for analyzing dyadic data. Some of these alternatives reflect software differences that would provide the same substantive results and insights as those that we reported. Other alternatives, however, reflect different statistical approaches that are grounded in different assumptions about the drivers of dyadic phenomena. Using these alternatives would yield results that would likely mirror the results above in some ways, but could also differ in some ways.

Before describing these alternatives, we first underscore a key assumption underlying the social psychological approach that we have illustrated above, which is that dyadic interactions are independent. That is, the model presumes that the variance in an interpersonal perception or relationship is due to the group, the actor, the partner, and the dyad—not to other combinations of interactions, such as triadic effects or some other structure of connections among individuals. In some research contexts, however, this assumption may not be tenable—at least on the surface. For example, two employees who interact with a shared boss also probably interact with each another. Any conversations and interactions about their boss open the door to effects that are not modeled by the SRM, such as the possibility that one employee's relationship with the boss influences her perception of her coworker. Kenny and colleagues (2006) noted that they have found little evidence that triadic effects bias the insights from the SRM. However, it is important for researchers using the SRM—or, really, any of the models in this same family—to consider whether variance in a given interpersonal perception or behavior could be due to effects other than the group, the actor, the partner, and the dyad.

Software Alternatives

We illustrated how to estimate the SRM using multilevel modeling, which offers flexibility, easily addresses missing data, and accommodates unbalanced group sizes (Snijders & Kenny, 1999). As mentioned above, Kenny et al. (2006) provided code for estimating the SRM using a range of software platforms, including SAS, SPSS, and MLwiN. In this chapter, we showed a new method for estimating the SRM in the free and open-source software environment R using the lme function of the multilevel modeling package nlme. One alternative to using lme to estimate the SRM using R is the R2MLwiN package (Zhang, Parker, Charlton, Leckie, & Browne, 2016) and the code provided by Snijders and Kenny (1999) for MLwiN (i.e., Snijders &

Kenny, 1999). This approach, however, would require a license for MLwiN, which will be called by R. Stata users could take a similar approach, using the runmlwin command in Stata (Leckie & Charlton, 2012) to call MLwiN; this would also require an MLwiN license.

Beyond using multilevel modeling, there are other alternatives for researchers interested in conducting dyadic data analysis in R. If a researcher wishes to use ANOVA or SEM to conduct dyadic data analysis, there are several options available within R. The TripleR package (Schönbrodt, Back, & Schmukle, 2015) enables estimating the SRM using an ANOVA-based approach. The fSRM package (Schönbrodt, Stas, & Loeys, 2016) provides tools for fitting the SRM with roles using a SEM-based approach. Additionally, Kenny and colleagues have developed a web-based suite of R applications for conducting several different kinds of dyadic data analyses (Kenny, 2016). With options in R proliferating and many pre-existing options in other software environments, there is no shortage of options for conducting dyadic data analysis, making the technique increasingly accessible for organizational researchers.

Alternative Statistical Models

Although we do not intend this chapter to provide a comprehensive accounting of techniques for dyadic data analysis, we highlight here two alternative models that may be particularly useful for researchers who have collected dichotomous and/or longitudinal data on interpersonal perceptions or relationships. Because the SRM and its derivatives grew out of an ANOVA-based framework, they are less attractive options for analyzing such data. Instead, models that grew out of the social networks tradition could offer more flexibility and the potential to model structural effects alongside dyadic effects.

First, for data that are dichotomous and at a single point in time, the *p*2 model is an option that, conceptually, aligns well with the SRM (Van Duijn, Snijders, & Zijlstra, 2004;

Zijlstra, Van Duijn, & Snijders, 2006). Like the SRM, *p*2 partitions a directed dyadic, binary outcome into group-level, individual-level, and dyad-level components. However, reflecting roots in a social networks tradition, the model is a probabilistic one, in which the drivers of a relationship are examined as influencing the likelihood that it matches one of four possibilities (i.e., 0,0; 1,0; 0,1; 1,1). The model is estimated using a Bayesian Markov Chain Monte Carlo algorithm and is implemented in freely-available software.

Second, researchers have only recently begun to tackle dynamics using the SRM (i.e., Jones & Shah, 2016; Nestler, Geukes, Hutteman, & Back, 2016). For a more flexible approach to modeling dyadic data that are longitudinal, and for research questions regarding how relationships change over time, researchers might consider dynamic stochastic actor-based modeling (Snijders et al., 2010). These models use Bayesian Markov Chain Monte Carlo algorithms to fit a range of flexible models and test hypotheses regarding the interplay of actor states and interpersonal relationships over time. The RSiena package in R can be used to fit these models (Ripley, Boitmanis, & Snijders, 2013).

Conclusion

Many core theories in the social sciences rely on assumptions about dyadic perceptions, interactions, or relationships (Krasikova & LeBreton, 2012). Yet dyadic dynamics have often been overlooked in social science research, with focusing instead on individual-level, group-level, and organizational-level processes and outcomes. In this chapter we described approaches to data analysis that are uniquely focused on the dyad, offering researchers the ability to test theories of interpersonal dynamics at the appropriate level (or levels) of analysis.

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Table 1
Sample portion of dataset used in empirical illustration

group_id	act_id	part_id	dyad_id	a1	a2	a3	a4	p1	p2	p3	p4	ss_x	act_ss	part_ss	absdif_ss
1	1	2	1	1	0	0	0	0	1	0	0	4.18	4.00	4.40	0.40
1	1	3	2	1	0	0	0	0	0	1	0	4.18	4.00	3.50	0.50
1	1	4	3	1	0	0	0	0	0	0	1	4.18	4.00	4.80	0.80
1	2	1	1	0	1	0	0	1	0	0	0	4.18	4.40	4.00	0.40
1	2	3	4	0	1	0	0	0	0	1	0	4.18	4.40	3.50	0.90
1	2	4	5	0	1	0	0	0	0	0	1	4.18	4.40	4.80	0.40
1	3	1	2	0	0	1	0	1	0	0	0	4.18	3.50	4.00	0.50
1	3	2	4	0	0	1	0	0	1	0	0	4.18	3.50	4.40	0.90
1	3	4	6	0	0	1	0	0	0	0	1	4.18	3.50	4.80	1.30
1	4	1	3	0	0	0	1	1	0	0	0	4.18	4.80	4.00	0.80
1	4	2	5	0	0	0	1	0	1	0	0	4.18	4.80	4.40	0.40
1	4	3	6	0	0	0	1	0	0	1	0	4.18	4.80	3.50	1.30
2	5	6	7	1	0	0	0	0	1	0	0	2.83	3.50	3.10	0.40
2	5	7	8	1	0	0	0	0	0	1	0	2.83	3.50	2.10	1.40
2	5	8	9	1	0	0	0	0	0	0	1	2.83	3.50	2.60	0.90
2	6	5	7	0	1	0	0	1	0	0	0	2.83	3.10	3.50	0.40
2	6	7	10	0	1	0	0	0	0	1	0	2.83	3.10	2.10	1.00
2	6	8	11	0	1	0	0	0	0	0	1	2.83	3.10	2.60	0.50
2	7	5	8	0	0	1	0	1	0	0	0	2.83	2.10	3.50	1.40
2	7	6	10	0	0	1	0	0	1	0	0	2.83	2.10	3.10	1.00
2	7	8	12	0	0	1	0	0	0	0	1	2.83	2.10	2.60	0.50
2	8	5	9	0	0	0	1	1	0	0	0	2.83	2.60	3.50	0.90
2	8	6	11	0	0	0	1	0	1	0	0	2.83	2.60	3.10	0.50
2	8	7	12	0	0	0	1	0	0	1	0	2.83	2.60	2.10	0.50

Table 2
Results of Variance Decomposition Analysis for Cognitive Trust and Affective Trust

	Cognitive Trust			Affective Trust		
	Output from lme (standard deviation)	Variance Parameter	Variance Percentage	Output from lme (standard deviation)	Variance Parameter	Variance Percentage
Team-level (σ^2_G)	0.46	0.21	15.35	0.48	0.23	14.24
Individual-level, Actor (σ^2_A)	0.90	0.81	59.41	0.98	0.96	58.41
Individual-level, Partner (σ^2_P)	0.15	0.02	1.57	0.18	0.03	1.94
Dyad-level (σ^2_E)	0.57	0.32	23.67	0.64	0.42	25.41
	Output from lme (correlation)	Covariance estimate	Reciprocity Correlation	Output from lme (correlation)	Covariance estimate	Reciprocity Correlation
Generalized reciprocity ($\sigma_{A,P}$)	-0.31	-0.04	-0.31	0.03	0.01	0.03
Dyadic reciprocity ($\sigma_{Eijk,Ejik}$)	0.14	0.04	0.14	0.25	0.11	0.25

Note. N = 1190 directed dyadic ratings from 414 individuals nested in 108 groups.

Table 3
Results of dyadic data analysis using the social relations model

	Cognitive Trust				Affective Trust			
	Model 1		Model 2		Model 3		Model 4	
	Est.	SE	Est.	SE	Est.	SE	Est.	SE
Fixed Effects								
Intercept	5.52	0.06	5.54	0.07	5.31	0.07	5.32	0.07
Team percent male			-0.28	0.28			-0.09	0.31
Team social skills			-0.13	0.16			-0.06	0.18
Actor gender			-0.06	0.06			0.00	0.06
Actor social skills			0.18	0.06^{**}			0.19	0.07^{**}
Partner gender			-0.05	0.02^{*}			-0.08	0.03^{**}
Partner social skills			0.06	0.02^{*}			0.05	0.03^{+}
Actor gender × Partner gender			0.05	0.02^{*}			0.09	0.03^{**}
Absolute Difference in Social Skills			-0.01	0.03			-0.03	0.04
Random Effects								
Team	0.21		0.20		0.23		0.24	
Actor	0.81		0.79		0.96		0.94	
Partner	0.02		0.02		0.03		0.03	
Dyad	0.32		0.32		0.42		0.40	
Generalized reciprocity	-0.04		-0.04		0.01		0.01	
Dyadic reciprocity	0.04		0.04		0.11		0.09	
Model Fit								
Log Likelihood	-1503.98		-1507.61		-1634.26		-1636.02	
AIC	3021.95		3045.21		3282.52		3302.03	

Note. Fixed Effect entries are unstandardized coefficients (Est.) and standard errors (SE). Random Effect entries are variance and covariance parameter estimates. N = 1190 directed dyadic ratings from 414 individuals nested in 108 groups.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, two-tailed

Table 4
Results of individual-level analysis using traditional multilevel modeling

	Cognitive Trust				Affective Trust			
	Model 1		Model 2		Model 3		Model 4	
	B	SE	B	SE	B	SE	B	SE
Fixed Effects								
Intercept	5.52	0.06	5.53	0.06	5.31	0.07	5.33	0.07
Team percent male			-0.42	0.25			-0.01	0.29
Team social skills			0.12	0.15			0.16	0.17
Gender			-0.03	0.03			-0.08	0.03**
Social skills			-0.001	0.03			-0.01	0.04
Random Effects								
Team	0.37		0.36		0.48		0.48	
Residual	0.26		0.26		0.31		0.31	
Model Fit								
Deviance	819.30		814.20		896.20		889.80	
AIC	829.00		845.00		905.70		919.60	

Note. N = 414 individuals nested in 108 groups. Random effects are variance estimates.
$^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, two-tailed

Figure 1
Plots of interaction between actor gender and partner gender predicting trust

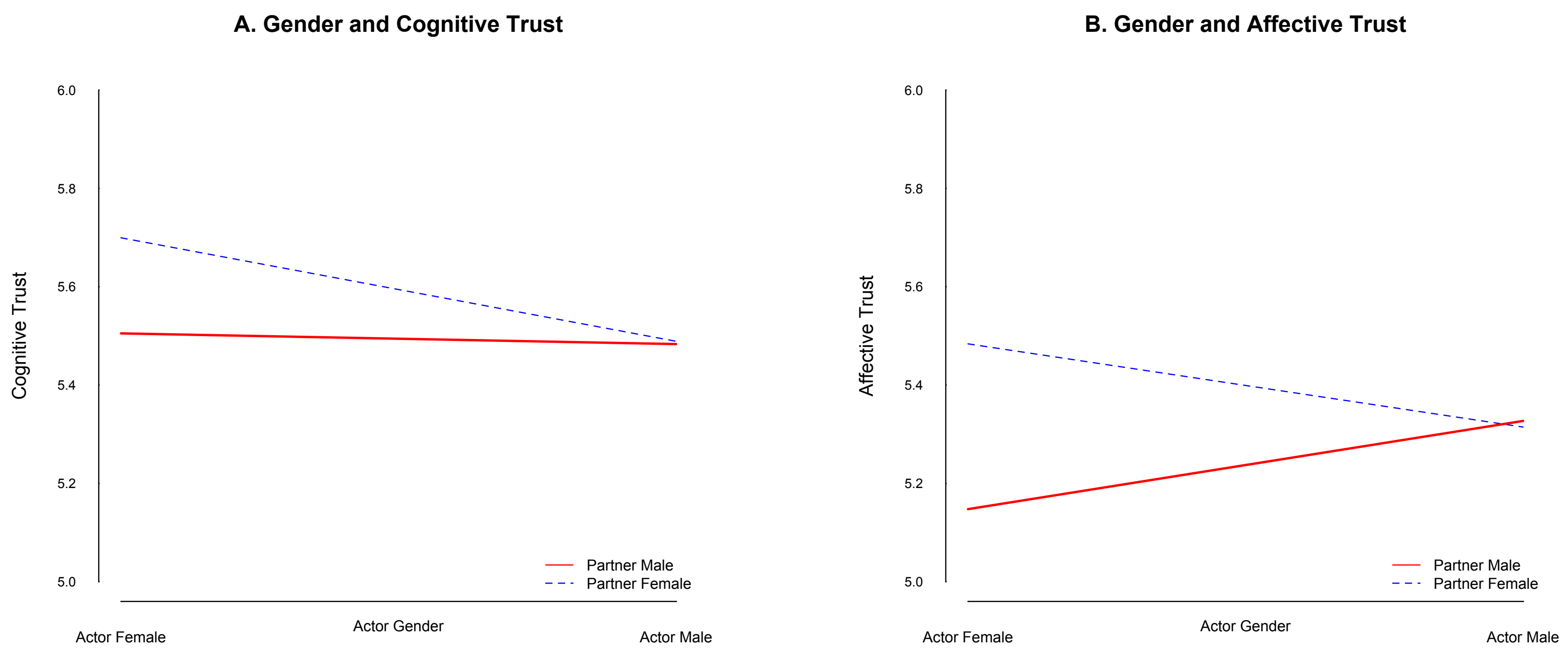

Figure 2

Explanation of code and output for estimating the social relations model using the lme function in the nlme package in R

```
aff.0 <- lme(trust_aff ~
     1,
       random = list(
           team_id = pdBlocked(list(
             pdIdent(~1),
             pdSRM(~-1 + a1 + a2 + a3  + a4
             + p1 + p2 + p3 + p4)))),
       correlation=corCompSymm(form=~1 | team_id/dyad_id),
     data=d.sub, na.action=na.omit)
summary(aff.0)
srm.pct(aff.0)
```

Criterion variable

Overall Intercept

Group Effect

Actor Effect

Partner Effect

Dyadic Reciprocity

Obtain fitted model results and variance decomposition (not shown)

Note. This code uses the dummy variable approach described by Snijders and Kenny (1999). In this approach, there are a sequence of dummy variables for actor and for partner. The list of components in the random statement, and in particular pdSRM, specifies a variance-covariance matrix structure that presumes this use of dummy variables to estimate the variance of group, actor, partner, and dyad effects (residual), as well as the covariance between the actor and partner effects. The within dyad covariance is then specified by the correlation statement. Users of pdSRM should become familiar with the procedure described in detail in Snijders and Kenny (1999).

```
Linear mixed-effects model fit by REML
 Data: d.sub
      AIC      BIC    logLik
  3282.517 3318.083 -1634.259

Random effects:
 Composite Structure: Blocked

 Block 1: (Intercept)
 Formula: ~1 | team_id
         (Intercept)
StdDev:   0.4828982

 Block 2: a1, a2, a3, a4, p1, p2, p3, p4
 Formula: ~-1 + a1 + a2 + a3 + a4 + p1 + p2 + p3 + p4 - 1 | team_id
 Structure: Social Relations Model
         StdDev    Corr
a1       0.9779942
a2       0.9779942 0.00
a3       0.9779942 0.00 0.00
a4       0.9779942 0.00 0.00 0.00
p1       0.1783378 0.03 0.00 0.00 0.00
p2       0.1783378 0.00 0.03 0.00 0.00 0.00
p3       0.1783378 0.00 0.00 0.03 0.00 0.00 0.00
p4       0.1783378 0.00 0.00 0.00 0.03 0.00 0.00 0.00
Residual 0.6449938

Correlation Structure: Compound symmetry
 Formula: ~1 | team_id/dyad_id
 Parameter estimate(s):
      Rho
0.2536856
Fixed effects: trust_aff ~ 1
               Value Std.Error   DF  t-value p-value
(Intercept) 5.305883 0.0710364 1082 74.69245       0

Standardized Within-Group Residuals:
        Min          Q1         Med          Q3         Max
-5.63890153 -0.22651250  0.04718172  0.25314018  4.34135565

Number of Observations: 1190
Number of Groups: 108
```

Model fit indices

SD of Group Effect

SD of Actor Effect

Generalized Reciprocity Correlation

SD of Partner Effect

SD of Relational Effect

Dyadic Reciprocity Correlation

Overall Intercept

Appendix

The code below was used to produce the results included in the chapter for cognitive trust. There are two models below—a null model and a prediction model. An expanded version of this code, with detailed annotations and comments that explain what each of the lines of code mean is available at http://apknight.org/pdsrm-example.R.

Before running the models below, you must input a set of specialized functions. To do so, run the following command, which loads a the structure for the social relations model

```
source("http://apknight.org/pdSRM.R")
```

This is a null social relations model, which provides the parameters needed to conduct a variance decomposition

```
cog.0 <-
lme(trust_cog ~
      1,
      random = list(
            team_id = pdBlocked(list(
                  pdIdent(~1),
                  pdSRM(~-1
                        + a1 + a2 + a3  + a4
                        + p1 + p2 + p3 + p4)))),
      correlation=corCompSymm(form=~1 | team_id/dyad_id),
      data=d.sub, na.action=na.omit)

summary(cog.0)
```

The results of this `summary` statement are

```
Linear mixed-effects model fit by REML
 Data: d.sub
       AIC      BIC    logLik
  3021.952 3057.518 -1503.976

Random effects:
 Composite Structure: Blocked

 Block 1: (Intercept)
```

```
 Formula: ~1 | team_id
        (Intercept)
StdDev:   0.4564505

 Block 2: a1, a2, a3, a4, p1, p2, p3, p4
 Formula: ~-1 + a1 + a2 + a3 + a4 + p1 + p2 + p3 + p4 | team_id
 Structure: Social Relations Model
         StdDev    Corr
a1       0.8978951
a2       0.8978951  0.000
a3       0.8978951  0.000  0.000
a4       0.8978951  0.000  0.000  0.000
p1       0.1459404 -0.311  0.000  0.000  0.000
p2       0.1459404  0.000 -0.311  0.000  0.000  0.000
p3       0.1459404  0.000  0.000 -0.311  0.000  0.000  0.000
p4       0.1459404  0.000  0.000  0.000 -0.311  0.000  0.000  0.000
Residual 0.5668108

Correlation Structure: Compound symmetry
 Formula: ~1 | team_id/dyad_id
 Parameter estimate(s):
      Rho
0.1379389
Fixed effects: trust_cog ~ 1
               Value  Std.Error   DF  t-value p-value
(Intercept) 5.520423 0.06377217 1082 86.56477       0

Standardized Within-Group Residuals:
       Min         Q1        Med         Q3        Max
-6.6440216 -0.2198626  0.0502427  0.2611959  4.4251627

Number of Observations: 1190
Number of Groups: 108
```

END `summary` STATEMENT RESULTS

```
srm.pct(aff.0)
```

The results of this `srm.pct` statement are

```
                        variances.and.covariances percents.and.correlations
Group                                       0.208                    15.352
Actor                                       0.806                    59.406
Partner                                     0.021                     1.569
Dyad                                        0.321                    23.673
Generalized Reciprocity                    -0.041                    -0.311
Dyadic Reciprocity                          0.044                     0.138
```

END srm.pct STATEMENT RESULTS

This is a model that includes fixed effects parameters to predict the group, actor, partner, and dyadic variance

```
cog.1 <- lme(trust_cog ~
                  gender_pct_grd + social_skills_x_grd
                  + act_gender + act_social_skills_grd
                  + part_gender + part_social_skills_grd
                  + act_gender*part_gender + absdif_social_skills_grd
                  ,
                  random = list(
                        team_id = pdBlocked(list(
                              pdIdent(~1),
                              pdSRM(~-1 + a1 + a2 + a3  + a4
                              + p1 + p2 + p3 + p4)))),
                  correlation=corCompSymm(form=~1 | team_id/dyad_id),
            data=d, na.action=na.omit)

summary(cog.1)
```

The results of this `summary` statement are

```
Linear mixed-effects model fit by REML
 Data: d.sub
       AIC      BIC    logLik
  3045.212 3121.324 -1507.606

Random effects:
 Composite Structure: Blocked
```

```
 Block 1: (Intercept)
 Formula: ~1 | team_id
        (Intercept)
StdDev:   0.4525179

 Block 2: a1, a2, a3, a4, p1, p2, p3, p4
 Formula: ~-1 + a1 + a2 + a3 + a4 + p1 + p2 + p3 + p4 | team_id
 Structure: Social Relations Model
         StdDev    Corr
a1       0.8887494
a2       0.8887494  0.000
a3       0.8887494  0.000  0.000
a4       0.8887494  0.000  0.000  0.000
p1       0.1462831 -0.355  0.000  0.000  0.000
p2       0.1462831  0.000 -0.355  0.000  0.000  0.000
p3       0.1462831  0.000  0.000 -0.355  0.000  0.000  0.000
p4       0.1462831  0.000  0.000  0.000 -0.355  0.000  0.000  0.000
Residual 0.5628685

Correlation Structure: Compound symmetry
 Formula: ~1 | team_id/dyad_id
 Parameter estimate(s):
      Rho
0.1257927
Fixed effects: trust_cog ~ 1 + gender_pct_grd + social_skills_x_grd + act_gender +
act_social_skills_grd + part_gender + part_social_skills_grd +      act_gender * part_gender +
absdif_social_skills_grd
                             Value  Std.Error   DF  t-value p-value
(Intercept)               5.544265 0.06513712 1076 85.11683  0.0000
gender_pct_grd           -0.276140 0.27638097  105 -0.99913  0.3200
social_skills_x_grd      -0.128293 0.15933052  105 -0.80520  0.4225
act_gender               -0.058049 0.05810358 1076 -0.99906  0.3180
act_social_skills_grd     0.184720 0.06129098 1076  3.01382  0.0026
part_gender              -0.050029 0.02410284 1076 -2.07565  0.0382
part_social_skills_grd    0.057971 0.02489518 1076  2.32860  0.0201
absdif_social_skills_grd -0.010907 0.03031094 1076 -0.35984  0.7190
act_gender:part_gender    0.047186 0.02265628 1076  2.08271  0.0375
 Correlation:
                         (Intr) gndr__ scl___ act_gn act___ prt_gn prt___ abs___
gender_pct_grd            0.118
social_skills_x_grd       0.006 -0.016
```

```
act_gender               -0.239 -0.422  0.006
act_social_skills_grd     0.000  0.015 -0.399 -0.009
part_gender              -0.103 -0.180  0.004  0.051 -0.002
part_social_skills_grd    0.000  0.008 -0.173 -0.002  0.031 -0.015
absdif_social_skills_grd -0.003 -0.016  0.012  0.008 -0.008  0.026 -0.033
act_gender:part_gender    0.002 -0.032  0.004 -0.076  0.004 -0.186  0.010 -0.009

Standardized Within-Group Residuals:
        Min          Q1         Med          Q3         Max
-6.61434986 -0.23963132  0.03880915  0.28392874  4.32217245

Number of Observations: 1190
Number of Groups: 108
```