Short Methodological Report

SRM_R: A Web-Based Shiny App for Social Relations Analyses

Organizational Research Methods
2024, Vol. 27(1) 114–139

DOI: 10.1177/10944281221134104
journals.sagepub.com/home/orm
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Abstract

Many topics in organizational research involve examining the interpersonal perceptions and behaviors of group members. The resulting data can be analyzed using the social relations model (SRM). This model enables researchers to address several important questions regarding relational phenomena. In the model, variance can be partitioned into group, actor, partner, and relationship; reciprocity can be assessed in terms of individuals and dyads; and predictors at each of these levels can be analyzed. However, analyzing data using the currently available SRM software can be challenging and can deter organizational researchers from using the model. In this article, we provide a "go-to" introduction to SRM analyses and propose SRM_R (https://davidakenny.shinyapps.io/SRM_R/), an accessible and user-friendly, web-based application for SRM analyses. The basic steps of conducting SRM analyses in the app are illustrated with a sample dataset of 47 teams, 228 members, and 884 dyadic observations, using the participants' ratings of the advice-seeking behavior of their fellow employees.

Keywords

social relations model, social relations designs, directed dyadic data, shiny

The development of theories about interpersonal dynamics has fostered the emerging trend of studying workplace phenomena that occur between two people—at the level of the relationship or dyad. Following the assumption that "it is very unlikely that a person will behave in an identical manner toward everyone" (Venkataramani & Dalal, 2007, p. 952), a growing body of research (e.g., Lee & Duffy, 2019; Xu et al., 2020) has advanced to investigate how employees interact with or judge coworkers in different ways. *Social relations designs* have increasingly been applied in

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organizational research to examine these phenomena, in which each person interacts with or rates more than one person, as these designs provide a more fine-grained analysis of phenomena across dyads.

Data collected from social relations designs are often referred to as *directed dyadic data* (DDD). In a DDD set, the unit of measurement is a rating or behavior directed from one person (e.g., an *actor* or a *perceiver*) toward another (i.e., a *partner* or a *target*). Organizational researchers have typically analyzed DDD using the social relations model (SRM; Kenny & La Voie, 1984). This model has been applied in at least 36 articles[1] published in top-tier management journals. The SRM is a statistical model which considers each directed dyadic measurement to be equal to the sum of four components: group, actor, partner, and relationship. Several types of questions regarding relational phenomena can be effectively addressed through SRM parameters. As a flexible model, researchers and methodologists have developed and described numerous statistical methods for estimating SRM parameters, including an original ANOVA approach, maximum likelihood methods, and Bayesian approaches. Table 1 provides an overview of these methods and their use in management research.

Perhaps because of this proliferation of statistical approaches for estimating the SRM, researchers unfamiliar with the model have found it increasingly challenging to use. Each statistical approach has its own terminology and assumptions. Thus, although numerous powerful and extensible statistics approaches have been developed, significant barriers to entry and a steep learning curve when conducting social relations analyses remain. Current estimation procedures and software require a thorough understanding of statistical details and error-handling skills before conclusions can be reached from SRM. This impedes scientific discovery because most organizational researchers are not professional data scientists (Kenny, 2019). As Knight and Humphrey (2019) pointed out, “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” (p. 423).

Thus, this paper aims to provide organizational researchers with a “go-to” conceptual and methodological introduction to the SRM. Our principal objective is to make the SRM accessible to a broad range of researchers whose theories involve dyadic phenomena but who do not know fully how to empirically examine them. We present the model’s concept and then introduce and illustrate a web-based application that makes SRM easy to use and interpret. This free, user-friendly online app, SRM_R (https://davidakenny.shinyapps.io/SRM_R/),[2] provides a nontechnical means of analyzing the DDD resulting from a range of social relations designs. Although SRM can be estimated using several methods, SRM_R uses multilevel modeling estimation (Snijders & Kenny, 1999), which is the most commonly used method in the management literature (see Table 1).

The SRM_R app provides various benefits to management researchers. First, SRM_R is freely accessible online and requires neither statistical software nor detailed background knowledge of statistical techniques to use all of its features. Second, SRM_R automatically performs much of the complicated setup of dyadic datasets—data manipulation and organization steps that can be a barrier for those with limited programming skills. Third, SRM_R provides users with text that summarizes and interprets the statistical analyses. Finally, it produces a new dataset with all of the necessary transformed variables and the R code to run additional analyses outside of the SRM_R environment. Thus, researchers do not need to be methodological experts to use the SRM_R app—they can focus on the nontrivial challenges of developing theory regarding dyadic processes, while the software takes care of the complex data analysis routines.

Social Relations Model: A Conceptual Overview and Types of Questions to Be Addressed

A DDD set regarding the actions or responses of a given actor toward a given partner can be described using the SRM (Kenny & La Voie, 1984). To illustrate this, we assume that member i interacts with member j within the group k, and the SRM equation expresses i’s dyadic relationship (Y_{ijk})

Table 1. A Review of the Estimation Methods in SRM.

Estimation methods	Key references	Details	Methods used in top-tier management journals[a]	
Analysis of variance (ANOVA) approach	Kenny and La Voie (1984); Warner et al. (1979)	ANOVA: Estimating the SRM variances and correlations using the expected mean squares and cross-products of the random effects. Note: When researchers add covariates to the model, they must use a two-step approach (by first deriving the SRM effect scores from dyadic outcomes, then regressing these effect scores on the covariates). Software: SOREMO (FORTRAN), BLOCKO (FORTRAN), TripleR (R package)	13	36.11%
Maximum likelihood methods	Snijders and Kenny (1999)	Multilevel modeling: Creating a set of dummy variables for each individual actor and partner within the group and imposing constraints on the variance–covariance matrix of the random slopes for these dummies. Software: MLwiN, SAS (PROC MIXED program), pdSRM.R/RoundRobinR (R package), SRM_R (Shiny)	18	50.00%
	Nestler (2016, 2018) (also see Jones & Shah, 2016; Maloney et al., 2019, for similar approaches)	Likelihood estimation of SRM: The variance-covariance matrix of the SRM is derived by embedding the SRM into a (linear) mixed-model framework, and then the SRM parameters are estimated using an ML or REML estimator. Software: R	2	5.56%
	Jendryczko (2022); Kenny (2016); Olsen and Kenny (2006)	Structural equation model: Arranging the DDD set in wide format (i.e., each row depicts a different group *k* and every column contains the dyadic relationship between a specific member *i* and a specific member *j*) and including a set of latent actor and partner factors loading onto each person (observed) within a group. Correlations and equality constraints are added based on the SRM specification. Software: Amos, Mplus, lavaan (R package), OpenMx (R package)	0	0.00%

(continued)

Table 1. (continued)

Estimation methods	Key references	Details	Methods used in top-tier management journals[a]	
	Mehta (2018)	N-level structural equation model: A modeling framework that introduces methodological constructs such as "virtual levels" and "role models" that formulate a four-level SEM. Software: xxM (R package)	0	0.00%
	Nestler et al. (2020, 2021)	Social relations structural equation model: The mean structure and the covariance structure of the multivariate round-robin data vector is derived based on SRM, and then the SR-SEM parameters are estimated using the ML estimator. Software: SRM (R package)	0	0.00%
Bayesian approach	Jorgensen et al. (2018); Ludtke et al. (2013)	Bayesian approach: Considering SRM as a cross-classified multilevel regression model and estimating the SRM parameters based on Bayesian methods using Markov chain Monte Carlo techniques. Software: WinBUGS, rstan (R package)	2	5.56%

[a]See note 1 regarding the 36 papers published in the reviewed top-tier management journals.
The total is less than 100% as one paper (Truong et al., 2020) cannot be classified into one of these methods. The authors estimated DDD collected through a block design using a three-level mixed-effects linear regression (participants were nested within dyads and dyads were nested within sessions) regardless of individual-level (i.e., actor and partner) effects.

with j in group k as the sum of four components:

$$Y_{ijk} = G_k + A_{ik} + P_{jk} + R_{ijk}.$$

The first component (G_k: the group effect) reflects the tendency of members in group k to provide dyadic ratings regarding others' actions or responses. The second component (A_{ik}: the actor effect) reflects member i's general tendency to direct actions or provide responses to others in group k. The third component (P_{jk}: the partner effect) reflects member j's general tendency to be the target of an action or response from others in group k. The final component (R_{ijk}: the relationship effect) reflects member i's unique tendency to direct actions or responses toward member j in group k. Based on these specific SRM effects, model parameters can be estimated to address various research questions. Table 2 summarizes the types of research questions, the questions from the illustrative example (presented in the next section), and key applications in organizational research associated with the model parameters estimated in SRM.

Addressing Questions of Variance. According to the SRM formula, the variance of a directed dyadic relationship (Y_{ijk}) is partitioned into four different levels: group, actor, partner, and relationship,

Table 2. Summary of Types of Research Questions and Their Corresponding Applications.

Model parameters	Types of research questions	Key applications in organizational research	The focal question from the illustrative example (advice seeking)
Variances: group, actor, partner, and relationship variance. The SRM decomposes a directed dyadic rating into four main variance components: the group, the actor, the partner, and the relationship. The proportion of each SRM variance (group, actor, partner, and relationship) represents the relative importance of the corresponding characteristic component.	Question of variance: To what extent is an employee's perception of or behavior toward a particular coworker attributable to characteristics of the group, actor, partner, or relationship?	In their negotiation study, Elfenbein et al. (2018) compared the overall importance of dyadic interaction effects with the overall importance of individual differences in negotiation performance. In a trust study, Jones and Shah (2016) examined the dominant locus of trust (trustor, trustee, or dyad) and how it changes over time.	What is the source (or locus) of advice seeking—the group, the individual (actor and partner), or the relationship?
Covariances: generalized and dyadic reciprocity. The SRM models two forms of reciprocity at the individual and at the relational level. At the individual level, *generalized reciprocity* reflects the general extent to which actors' ratings of their partners are linked to partners' ratings of the same actors. This provides a correlation between the actor and the partner components in the SRM.	Question of reciprocity: To what extent are dyadic interactions reciprocal in nature?	Joshi and Knight (2015) examined the degree of reciprocity in deference, perceptions of task contributions, and social affinity before testing their hypothesis.	General reciprocity—To what extent do prolific advice-seekers attract high levels of advice-seeking from others? Dyadic reciprocity—Do team members give each other the same or opposite levels of advice-seeking behavior?

(continued)

Table 2. (continued)

Model parameters	Types of research questions	Key applications in organizational research	The focal question from the illustrative example (advice seeking)
At the relational level, *dyadic reciprocity* reflects how much one specific actor's rating of a given partner is linked to the partner's rating of the actor.			
Covariate estimates (regression coefficients). The SRM allows the inclusion of predictive or explanatory variables of the dyadic dependent variable.	Question of explanation: How are the predictors related to relationship outcomes?	Joshi (2014) examined how men and women in science and engineering teams evaluate their coworkers' expertise by considering attributes of the dyad members such as gender and education level.	Whether advice seeking between group members is a function of the two characteristics of gender and proactive personality (i.e., participants' disposition toward taking action to influence their environment; Crant, 2000; Seibert et al., 1999).

with actors and partners crossed with one another and with individuals further nested within groups. The variances of these four components are the central SRM parameters that can address *Questions of Variance*, that is, the extent to which an employee's perceptions of or behavior toward a particular coworker is attributable to characteristics of the group, actor, partner, or relationship. For example, Elfenbein et al. (2018) conducted a negotiation study and examined the relative overall importance of unique pairings between negotiators and their counterparties (i.e., relationship effects) and of individual differences in negotiation outcomes (i.e., actor effects). They found that when considering economic negotiation outcomes, relationship effects explained more variation in performance than actor effects, which suggests that organizations should attempt to identify the best "pairing" of negotiators and counterparties at the bargaining table rather than being solely concerned about who the best individual negotiator is. As another example, Jones and Shah (2016) examined the relative importance of trustor, trustee, and relational components in shaping perceptions of various dimensions of trustworthiness over time. They concluded that perceptions of ability were mainly driven by the trustee component (i.e., the partner component) and perceptions of benevolence mainly by the trustor component (i.e., the actor component), whereas perceptions of integrity were evenly balanced between the two. They also found that the relative importance of these components changed over time. In the initial stages of relationships, the trustor component was most important; however, the trustee component grew in importance over time.

Addressing Questions of Reciprocity. SRM also allows for two possible types of correlations: generalized and dyadic reciprocity. Generalized reciprocity indicates the degree to which a member's actions or responses as an actor may be associated with others' actions or responses to that member as a partner, or the correlation of A_{ik} with P_{ik}. Dyadic reciprocity indicates the degree to which a member's specific actions or responses to another member can be associated with the other's specific actions or responses to the first within a dyadic relationship, or the correlation of R_{ijk} with R_{jik}. These two correlation parameters reveal symmetric or asymmetric patterns of interpersonal phenomena, thus addressing *Questions of Reciprocity*, that is, to what extent dyadic interactions are reciprocal in nature and at what levels of analysis. For example, Joshi and Knight (2015) examined both generalized and dyadic reciprocity correlations in their investigation of the nature of interpersonal deference. They found a negative generalized reciprocity correlation for deference ($r = -.23$), indicating that people who receive deference do not generally defer to others. However, their finding of a positive dyadic reciprocity correlation ($r = .10$) indicated that within a given dyad, an actor who uniquely confers deference on a specific partner is more likely to receive deference from that partner.

Addressing Questions of Explanation. The conventional SRM can be extended to include covariates that can explain variance in the directed dyadic outcome variable (Snijders & Kenny, 1999). Including fixed covariates as predictors, the SRM equation becomes:

$$Y_{ijk} = G_k + A_{ik} + P_{jk} + R_{ijk} + b_1X_1 + \ldots + b_nX_n$$

where the new terms are the predictors of X_1 through X_n. These covariates can be measured at group, actor, partner, or relationship levels. The effect estimates of the covariates address the third type of research question, which we refer to as *Questions of Explanation*, that is, how the predictors are associated with relationship outcomes. For example, to investigate how members of science and engineering teams evaluate their coworkers' expertise, Joshi (2014) examined the effects of covariate estimates of the dyad members' attributes, such as their gender and education level, on actors' evaluations of targets' expertise.

To conclude, the SRM is useful when addressing three types of questions in dyadic research (those concerning variance, reciprocity, and explanation). The focus of the SRM on directed dyadic

Table 3. Social Relations Designs in a Group of Six Members.

Round-robin design

Actor	Partner 1	2	3	4	5	6
1		Y_{12}	Y_{13}	Y_{14}	Y_{15}	Y_{16}
2	Y_{21}		Y_{23}	Y_{24}	Y_{25}	Y_{26}
3	Y_{31}	Y_{32}		Y_{34}	Y_{35}	Y_{36}
4	Y_{41}	Y_{42}	Y_{43}		Y_{45}	Y_{46}
5	Y_{51}	Y_{52}	Y_{53}	Y_{54}		Y_{56}
6	Y_{61}	Y_{62}	Y_{63}	Y_{64}	Y_{65}	

Usage:
Use a round-robin design when the dyadic variables of interest are interactive and two-sided in nature and if there are few limitations or concerns about burdening the research participants.

Application:
A round-robin design is perfectly suited to collecting DDD for examining the bidirectionality of interpersonal perceptions and behaviors in small teams, such as helping (Tse et al., 2013; Van der Vegt et al., 2006), harming (Lam et al., 2011; Tse et al., 2018; Xu et al., 2020), deference (Joshi & Knight, 2015), social learning (Lee & Duffy, 2019), and trust (Jones & Shah, 2016).

Block design

Actor	Partner 1	2	3	4	5	6
1				Y_{14}	Y_{15}	Y_{16}
2				Y_{24}	Y_{25}	Y_{26}
3				Y_{34}	Y_{35}	Y_{36}
4	Y_{41}	Y_{42}	Y_{43}			
5	Y_{51}	Y_{52}	Y_{53}			
6	Y_{61}	Y_{62}	Y_{63}			

Usage:
Use a block design when a full round-robin will overburden the participants in terms of time or attention, or when members are distinguishable into two groups where members in one group only provide ratings for members in the other, not for those in the same group.

Application:
For example, in their networking study, Truong et al. (2020) applied a block design and randomly divided participants into two equal subgroups of networkers, with one subgroup remaining seated (i.e., sitters) and the other rotating (i.e., movers). Each participant engaged in a 3-min conversation with every member of the other group (i.e., each sitter talked to every mover and vice versa). Each participant then had a 3-min conversation with each member of the other group (i.e., each sitter talked to each mover, and vice versa).

Half block design

Actor	Partner 4	5	6
1	Y_{14}	Y_{15}	Y_{16}
2	Y_{24}	Y_{25}	Y_{26}
3	Y_{34}	Y_{35}	Y_{36}

Usage:
Use a half block design when the dyadic variables of interest are not bidirectional (i.e., whoever provides ratings will not be rated).

Application:
A half block design is suitable for collecting non-bidirectional DDD, such as in ratings studies where participants provide ratings for presented stimuli (e.g., photos, videotapes), or recruitment studies in which hiring managers appraise job applicants.

Note. Y_{12} = member *1*'s actions or responses toward member *2*.

outcomes and the variance in these outcomes differentiates it from traditional social network analysis (SNA) used to study interpersonal relationships. Whereas the SRM focuses on modeling interpersonal interactions between two individuals, SNA focuses on identifying and characterizing individuals' social network structures that are defined by patterns, or compilations, of multiple interlocking dyads, as well as research questions about individual-level antecedents and outcomes of social network structures.[3]

Descriptions of Social Relations Designs

Social relations designs involve collecting DDD that provide a detailed view of dyadic processes, which can then be analyzed through SRM. In this section, we describe three common social relations designs supported by the free web-based app SRM_R: the round-robin design, the block design, and the half block design (Kenny & La Voie, 1984). These enable researchers to collect data from individuals interacting with or rating more than one other person. The research requirements and the study context determine the appropriate design. We provide a summary of these designs and their applications in Table 3 using a simplified illustration of a single group, although most SRM studies consider multiple groups.

Round-Robin Design

The most common social relations design in the management literature is the round-robin design (Kenny & La Voie, 1984). In a round-robin study, every possible dyad that can be formed from a group of individuals is measured, and each dyad provides two scores, one for each member as the actor. Each individual can be both an actor and a partner, making the design reciprocal. Thus, a round-robin design has $N \times (N-1)$ observations, where N is the number of people in a given group. The data matrix shown in Table 3, for example, includes the 30 dyadic measurements, Y_{ij}, that would result from a round-robin group of six members (one through six).

Each entry in the matrix is a dyadic measurement Y_{ij} from an actor i to a partner j. The first row of the matrix in Table 3 gives member 1's dyadic ratings Y_{1j} to all other members and the first column gives the dyadic ratings Y_{i1} of member 1 to all other members. Note that the data are directional; for example, Y_{12} is different from Y_{21}. The SRM does not require self-rated scores, so there are no entries along the main diagonal of the data matrix.

The round-robin design captures the interactive, two-sided nature of social interaction and can be implemented in organizational settings through various approaches. Researchers can distribute a survey to every member of a group to obtain their perceptions of every other member, or they can observe the interactions of groups of individuals and record who initiates a specific action toward whom (Dabbs & Ruback, 1987). Another alternative is to conduct round-robin experiments by arranging one-on-one interactions between every pair of individuals in a group (Elfenbein et al., 2018). Although it is desirable to have a complete matrix, as in Table 3, it may be very difficult to obtain every possible value, particularly through field surveys, as some employees may be absent, on vacation, taking sick leave, or otherwise unable or unwilling to participate in such research.

Block Design

In a *block design*, a group is divided into two subgroups, and members in one interact with those in the other. The block design is, like the round-robin design, reciprocal. Consider a group that includes six members (one through six), in which members 1–3 interact with members 4–6. This block design will yield two sets of observations, as illustrated by the upper-right and lower-left sections of Table 3.

Note that the two subgroups must be arbitrary or have no effect. This is referred to as a *symmetric block design*. Compared to a full round-robin design, this effectively requires less time or attention from participants, as it reduces the number of other individuals each actor needs to rate or interact with—in this example from five for the round-robin to three for the block design. If the two groups are distinguishable in some way, for example by gender in a study on speed dating, the block design is *asymmetric*. Cronin (1994) used an asymmetric block design to study interactions between buyers and sellers. Each seller met multiple buyers and each buyer met multiple sellers. The asymmetric block design is more appropriate for buyer-seller research than the round-robin design because "there is no reason to have sellers meet with other sellers, or buyers meet with other buyers" (Cronin, 1994, p. 72).

Half Block Design

The *half block design* is one half of the block design, such that members 1–3 rate members 4–6, but not vice versa. This is a non-reciprocal design because each individual is either an actor or a partner for a given measurement. Table 3 presents an example of a half block design. This design is primarily used to collect DDD for behaviors and perceptions that are not bidirectional, that is, whoever provides ratings will not be rated. The half block design is commonly applied in rating studies (e.g., Biesanz, 2010) in which the targets are presented with inanimate or nonreactive stimuli (e.g., photos and videotape): the participant rates the stimuli but the stimuli do not rate the participant. The half block design can be potentially useful when examining various workplace phenomena such as recruitment and selection, in which managers judge job applicants who do not judge them back. However, this design's main limitation is that it does not capture the interactive nature of social relationships and so is unable to measure and test reciprocity.

Conducting SRM Analyses: An Introduction to SRM_R

We have provided an overview of SRM, identified the types of questions it can address, and described various social relations designs. In the following, we discuss how SRM_R can effectively be used for SRM analyses.

SRM_R is written in shiny (Chang et al., 2015), a web application framework for R by RStudio. Although R is the engine for SRM_R, users do not have to install it (or any other software) on their local machines, nor do they need to specify any R-code. All computations within SRM_R are executed in the cloud, accessed by the user through a web browser, and the complex data transformations and programming specifications (i.e., multilevel modeling (MLM] equation code, dummy variable creation, and equality constraints) are automatically performed behind the scenes. After execution, users receive a summary description of the results and an accompanying interpretation through their web browser. The program is designed to reduce barriers for organizational researchers who wish to use appropriate statistical models to study relational phenomena. Users can conduct dyadic analyses using a guided point-and-click interface through their web browser rather than writing their own programming code.

SRM_R can currently perform SRM analyses for round-robin, symmetric block, and half block designs. For reciprocal DDD (i.e., round-robin and symmetric block designs), SRM_R uses the mixed effects modeling package *nlme* (Pinheiro et al., 2017) and a custom class (Knight & Humphrey, 2019) to estimate SRM variances and correlations. Dummy variables are created for each actor and partner, following the approach of Snijders and Kenny (1999). For a non-reciprocal DDD (i.e., the half block design), it applies a simple linear mixed model estimated using the *lme4* package for R (Bates et al., 2015). In addition, SRM_R allows for the inclusion of fixed variables in the MLM equation and relies on the default method within the lmer function of lme4 when

Table 4. An Illustration of the DDD of Group 1.

GID	AID	*PID*	*Y*	*GX1*	*GX2*	*AX1*	*AX2*	*PX1*	*PX2*	*RX1*	*RX2*
1	11	12	5	0.6	5.7	1	6.7	−1	4.4	−1	2.3
1	11	13	5	0.6	5.7	1	6.7	−1	5.9	−1	0.8
1	11	14	5	0.6	5.7	1	6.7	1	4.8	1	1.9
1	11	15	5	0.6	5.7	1	6.7	1	6.7	1	0
1	12	11	4.5	0.6	5.7	−1	4.4	1	6.7	−1	2.3
1	12	13	4	0.6	5.7	−1	4.4	−1	5.9	1	1.5
1	12	14	4.5	0.6	5.7	−1	4.4	1	4.8	−1	0.4
1	12	15	3	0.6	5.7	−1	4.4	1	6.7	−1	2.3
1	13	11	3.5	0.6	5.7	−1	5.9	1	6.7	−1	0.8
1	13	12	4	0.6	5.7	−1	5.9	−1	4.4	1	1.5
1	13	14	5	0.6	5.7	−1	5.9	1	4.8	−1	1.1
1	13	15	5	0.6	5.7	−1	5.9	1	6.7	−1	0.8
1	14	11	4	0.6	5.7	1	4.8	1	6.7	1	1.9
1	14	12	4	0.6	5.7	1	4.8	−1	4.4	−1	0.4
1	14	13	2	0.6	5.7	1	4.8	−1	5.9	−1	1.1

Note. GID = Group identifier. AID = Actor identifier. PID = Partner identifier. Y = Actor's advice seeking from partner. GX1 = Percentage of female members in groups. GX2 = Group average of members' levels of proactive personality. AX1 = Actor's gender (1 = female, −1 = male). AX2 = Actor's proactive personality. PX1 = Partner's gender (1 = female, −1 = male). PX2 = Partner's proactive personality. RX1 = Same versus different gender (Actor's gender × partner's gender). RX2 = Similarity of actor's and partner's proactive personalities (|Actor's proactive personality − Partner's proactive personality|).

estimating degrees of freedom. For group-level predictors, degrees of freedom are the number of groups minus the number of predictors plus one. For other predictors, they are the total number of non-missing data values minus the total number of predictors plus one. Finally, SRM_R provides extensive explanatory text to help interpret the results of and draw conclusions from the SRM analyses, as many researchers will be unfamiliar with SRM.

An Illustrative Example and Dataset Preparation

We investigated interpersonal advice-seeking in our example. This has been considered as a relational phenomenon that can be shaped by the individual characteristics of the advice seeker (i.e., actor) and the advice provider (i.e., partner), and the relationship between the two (Lee & Duffy, 2019; Morrison & Vancouver, 2000). We focused our analysis on questions of variance, reciprocity, and explanation, as mentioned earlier and summarized in Table 2.

Sample. We collected DDD on advice-seeking behavior from members of project groups in a large state-owned Chinese telecommunications company. Our sample comprised 228 individuals nested within 47 groups of four or five members giving a total of 884 direct dyadic observations. The project groups were mainly aimed at helping clients develop new telecommunication technologies and offering customized business solutions to their customers.

Measures. All of the items used in our research were back-translated into Mandarin Chinese by bilingual experts, following best practices (Brislin, 1980). We measured an actor's advice-seeking from each of the other members (i.e., partners) in their work group using a round-robin design, with each member rating each other member of the group on a two-item scale adapted from previous research (Alexiev et al., 2010; McDonald & Westphal, 2003). The items were "I seek opinions from (partner name) when I have problems or face difficulty at work" and "I solicit advice from (partner name) about work" ($\alpha = 0.80$). Approximately, 1 week before obtaining the round-robin measurements of advice-seeking behavior, we administered a self-report survey to identify differences between the participants, including gender (1 = female, −1 = male) and proactive personality, measured using the 10-item scale developed by Seibert et al. (1999). A sample item is "I am constantly on the lookout for new ways to improve my life" ($\alpha = 0.74$). No values were missing in our study.

Data. DDD must be organized in a long format when preparing a dataset for SRM_R, so that each row is one directed dyadic observation, that is, one group member's rating of another member. Table 4 displays one group from the larger illustrative DDD set. The four columns required in this DDD for SRM_R are the group identifier, the actor identifier, the partner identifier, and a column for the outcome variable (i.e., an actor's advice-seeking from a partner). Actor and partner identifiers need not be unique across groups; that is, they can be from 1 to n, where n is the group size in all of the groups. These identifier variables instruct SRM_R on how to handle interdependence in the data. In our demo DDD set, the four columns are called "GID," "AID," "PID," and "Y," but any names can be assigned to these columns.

Table 4 also shows the general structure of how covariates (group level predictors: GX1, GX2; actor level predictors: AX1, AX2; partner level predictors: PX1, PX2; and relationship level predictors: RX1, RX2) can be included in a DDD set. Any desired covariates in the DDD set must be merged before SRM_R is used. Note that the lowest level of analysis in the DDD set is the directed dyadic rating. Thus, values located at any level higher than this, including symmetric relational variables (e.g., RX1, RX2, and above), are repeated. Very often, DDD sets have missing data. For example, a team member may not be at work on the day of the survey, so their data will be missing. The MLM estimation in the SRM_R proceeds without the values of the missing data rather than imputing them,[4] and any case with missing covariates would be dropped from the analysis.

Demonstration of SRM_R: A Step-by-Step Guide

We provide a step-by-step guide on how SRM_R can help researchers address theoretically important research questions through our analyses of advice-seeking behavior. SRM_R is based on an R shiny framework and can be accessed directly at https://davidakenny.shinyapps.io/SRM_R/. We encourage readers to access the app, download the sample data, and run it to follow the example themselves.

Step 1: Uploading/Selecting Data on SRM_R and Defining the Variables

Before the actual SRM analyses, the input DDD set organized in a long format must first be uploaded. On the opening SRM_R screen, users click the green tab labeled "Select Data." The program accepts files in either SPSS (.sav) or comma-separated variable (.csv) format. After selecting the format, the users then search for and select the file on their device. An "upload complete" message is shown when the dataset is uploaded successfully. We include the DDD set used in our example in the SRM_R app so that researchers can reproduce our analyses and experiment with the software using known results. Users should choose "Round-Robin Example" in the scrolling list of "Input Data File Type" on the "Select Data" tab to access the illustrative DDD set.

The next step is to denote the reciprocal nature of the selected dataset and specify the group, actor, partner, and outcome identifier variables by clicking on the green "Variables, Design, & Terms" tab. By default, SRM_R presumes that the design is reciprocal (i.e., a round-robin or block design), so if the nonreciprocal half block design is required, the user should uncheck the "Data Reciprocal" box. The user must then find the numeric variables that denote group, actor, and partner, along with the outcome variable, in the dataset. In our example, we chose "GID," "AID," "PID," and "Y" from the list of variable names. The outcome for the text and tables can also be named, and ours is called "Advice Seeking."

Text Tables Computer Output

Table 1: Descriptive Statistics

Variable	Mean	SD	Minimum	Maximum
Outcome	3.647	1.455	1.000	7.000

Table 2: SRM Results: Predictor Variables' Effects

Variable	Effect	Lower	95 CI	Upper	df	p
Intercept	3.653	3.493	to	3.813	837	<.001

Table 3: SRM Results: Random Effects

Term	Type	Absolute	Relative or Correlation	chi square	p
Group	Variance	0.000	.000	0.001	.980
Actor		0.957	.447	206.729	<.001
Partner		0.193	.090	19.078	<.001
Relationship		0.990	.463		
Generalized	Covariance	0.024	.057	0.190	.663
Dyadic		0.214	.216	11.367	<.001

Figure 1. View of tables tab showing social relations analysis results of advice-seeking (null model).

Step 2: Testing Questions of Variance and Reciprocity

To answer our first two research questions, the variance in a dyadic measurement must be partitioned. For our example, this entails estimating the extent to which the rating of advice-seeking is attributable to the characteristics of groups, actors (i.e., advice-seekers), partners (i.e., advice providers), and relationships. We thus estimated a null model—the SRM without fixed-effect predictors—in SRM_R.[5] Following Step 1, we provided the mandatory information in the green "Select Data" and "Variables, Design, and Terms" tabs. The results appear on the right-hand side of the screen after "Estimate the SRM Now!" is clicked.

A table of the random effects is provided via the *Tables* tab in SRM_R (see Figure 1). Researchers can examine the relative variance in each random effect component when considering the proposed questions of variance, i.e., to determine whether advice-seeking is a function of the group, the actor, the partner, or the relationship. The results in Figure 1 show that nearly half of the variance (46.3%) in advice-seeking occurred at the relationship level. We note that this relationship component comprises both relationship and error variance, so we should be cautious about concluding that all of the variance is due to meaningful relational characteristics. Individual-level characteristics can also help explain variance in advice-seeking (actor variance = 44.7%, partner variance = 9%, both $p < .001$), as noted in other studies. However, group variance was found to essentially equal zero and was not statistically different from zero ($\chi^2 = 0.001$, $p = .980$, n.s.), indicating that the group context is unlikely to explain any of the variance in advice-seeking behavior.

Figure 1 also gives the generalized and the dyadic correlations, which indicate the degree of reciprocity in advice-seeking and can be used to address our questions of reciprocity. We observed a

Table 2: SRM Results: Predictor Variables' Effects

Variable	Effect	Lower	95 CI	Upper	df	p
Intercept	3.439	3.221	to	3.656	831	<.001
Percentage of female members in groups	-0.593	-1.422	to	0.235	44	.156
Group average of members' levels of proactive personality	0.497	-0.362	to	1.357	44	.250
Actor's gender	0.126	-0.136	to	0.389	831	.344
Actor's proactive personality	0.312	0.026	to	0.599	831	.033
Partner's gender	0.173	0.010	to	0.336	831	.038
Partner's proactive personality	-0.140	-0.317	to	0.038	831	.123
Same vs. different gender	0.144	0.013	to	0.275	831	.032
Similarity of actor's and partner's proactive personalities	-0.060	-0.259	to	0.140	831	.558

Table 3: SRM Results: Random Effects

Term	Type	Absolute	Relative or Correlation	chi square	p
Group	Variance	0.002	.001	0.045	.832
Actor		0.943	.449	200.611	<.001
Partner		0.178	.085	16.220	<.001
Relationship		0.977	.466		
Generalized	Covariance	0.036	.089	0.453	.501
Dyadic		0.201	.206	10.182	.001

Figure 2. View of tables tab showing social relations analysis results of advice-seeking with fixed effect predictors.

non-significant generalized correlation for advice-seeking ($r = .057$, $p = .663$, n.s.), and thus we found no evidence that advice-seekers tend to attract advice-seeking from others. The dyadic correlation of advice-seeking, however, was significant and positive ($r = .216$, $p < .001$), indicating that there was reciprocal advice-seeking behavior within a given pair of team members. We reproduce the text provided in the *Text* tab in Appendix B, which summarizes in plain language the SRM results regarding the random effects.

Step 3: Testing Questions of Explanation

After partitioning the variance and reciprocity correlations, we explored the impact of gender and proactive personality on advice-seeking behavior (questions of explanation) in the next step by including fixed effect predictors in the model. We followed Knight and Humphrey's (2019) approach when preparing the dataset and included two group-level variables (GX1: percentage of female members in groups; GX2: group average of members' levels of proactive personality), two actor-level variables (AX1: actor's gender; AX2: actor's proactive personality), two partner-level variables (PX1: partner's gender; PX2: partner's proactive personality), and two relationship-level variables (RX1: Same versus different gender; RX2: Similarity of actor's and partner's proactive personalities). Users can go to the *Predictor Variables* tab after estimating the null model and enter these predictors into the model. Within the same tab, we checked *Center Predictor Variables* and grand-mean centered the continuous variables (GX1, GX2, AX2, PX2, and RX2) to better interpret the intercept.[6] By again clicking "Estimate the SRM Now!" the results appear on the right-hand side of the screen.

At the group level, as Figure 2 shows, neither of the predictors can explain why advice-seeking behavior is more common in some groups than others. The percentage of female members in groups has a non-significant relationship with advice-seeking behavior ($b = -0.593$, $p = .156$, n.s.), as does the group average of members' levels of proactive personality ($b = 0.497$, $p = .250$, n.s.). This lack of significant predictors at the group level is consistent with the lack of meaningful group-level variance reported earlier.

At the individual level, we considered the gender and proactive personality characteristics of both actor and partner. Actors' proactive personality was significantly and positively related to advice-seeking behavior ($b = 0.312$, $p = .033$), indicating that in general, those with higher levels of proactivity tend to seek more advice than those with lower levels. Actors' gender, however, had a nonsignificant relationship with advice-seeking behavior ($b = 0.126$, $p = .344$, n.s.).

In terms of partner characteristics, gender helped to identify those more likely to be asked for advice. As Figure 2 shows, women are more often the target of others' advice-seeking behavior than men ($b = 0.173$, $p = .038$). A partner's proactive personality was found to have a non-significant relationship with advice-seeking ($b = -0.140$, $p = .123$, n.s.).

Finally, the interaction term between actor gender and partner gender at the relationship level revealed the levels of advice-seeking in same- versus different-gendered pairs. The results in Figure 2 indicate a positive interaction effect, suggesting that more advice-seeking occurred in pairs of the same gender than of different genders ($b = 0.144$, $p = .032$). Similarity of actor's and partner's proactive personalities had a non-significant relationship with advice-seeking behavior ($b = -0.060$, $p = .558$, n.s.).

Discussion

Although the benefits of social relations designs have been recognized, few analyses at the dyadic level using appropriate statistical tools have been conducted (Krasikova & LeBreton, 2012). Such analyses can also be extremely difficult and error-prone if researchers are not familiar with SRM. We address these concerns by introducing the SRM_R app and demonstrating how it can be used to analyze DDD. Although the introduction of SRM_R can reduce the barriers that currently inhibit management researchers from exploring important relationship phenomena within groups, many other factors must be considered when conducting SRM research. Thus, to conclude, we provide some practical recommendations regarding measures, data collection, sample requirements, analysis, and reporting related to SRM, as summarized in Table 5.

Implications for Organizational Research: Removing Barriers to Dyadic Research

Although the process of estimating the parameters of a statistical model may be of interest to methodologists, organizational researchers are more concerned with answering specific questions. However, in terms of dyadic studies, many organizational researchers do not know how to analyze the DDD sets they collect and consider the complicated steps in social relations analyses as a necessary evil required to satisfy editors, reviewers, and coauthors. The SRM should ideally

Table 5. Recommendations for Conducting SRM Analyses.

Issues	Recommendations
Measures	
Challenges in balancing the burden placed on participants (due to repeated measures) while retaining the validity of measures	- Trim items and report rationale, procedures, and selection criteria. Presenting the full items used in SRM studies is recommended. - A novel approach to eliminating items involves embedding multiple items in the scale description and asking participants to respond to a single item regarding the description. For example, in assessing employee trust in coworkers, Ferrin et al. (2006) embedded the trustworthiness scale of Mayer and Davis (1999) in the scale description and asked participants to respond to a single item: To what extent do you perceive that each person is dependable? For example, do you perceive that the person sticks to his/her word, and makes sure his/her actions and behaviors are consistent? Use the following scale to indicate the extent to which you agree that the person is dependable: disagree strongly, disagree, neither agree nor disagree, agree, agree strongly (scale of 1–5). (p. 876)
Relevance of modifying or adapting individual-to dyadic-level scales	- Scales across levels of analysis may not always be psychometrically isomorphic. Therefore, even if researchers carefully select the highest factor loading items from the individual-level scale to reflect construct of interest, they must adapt it to a dyadic-level scale that is relevant to social interactions. For example, in the study by de Jong et al. (2007), the task-focused citizenship item "Takes on extra responsibilities in order to help coworkers when things get demanding at work" was slightly modified to "X takes on extra responsibilities in order to help me when things get demanding at work." (p. 1629)
Data collection	
Choice of design and interaction structure	- The needs and study context should determine which social relations design to choose (see Table 3). - In many cases, either design can be applied in examining dyadic phenomena. For example, in laboratory studies, researchers may decide to have participants interact one-on-one (round-robin design) or in groups (block design). Unless the response burden is excessive, a round-robin design is generally used, as it captures the full interactive nature of social interactions. If reciprocity is not an issue, a half block design can be selected.
Streamlining workflow for survey preparation and administration by using an online survey platform	- The participants in SRM studies are often required to fill out survey questions for other members of their team. Researchers, therefore, need to prepare a unique roster (i.e., the target's name followed by stem questions) for each participant before beginning the study. A large-scale study will make it difficult for the researcher to manually ensure that the roster is correctly prepared for each participant and that the corresponding questionnaires are delivered accurately, particularly when using paper-and-pencil surveys. Researchers can consider streamlining the data collection process by using an online survey platform specifically designed to collect DDD.

(continued)

Table 5. (continued)

Issues	Recommendations
	- Several online survey platforms in the market allow for rosters to be included in surveys. Qualtrics, for example, allows researchers to manage custom relationships (i.e., peers) in its Participants Tools (360) and to add targets' names to the questions by including display logic. Other platforms (e.g., LimeSurvey or SurveyMonkey) can also achieve this function by setting the embedded values (target names for each participant) from a contact list. - Huajue (www.huajuetech.com) is a mobile survey platform designed for OBHR researchers to conduct surveys with complex research designs (e.g., round-robin). By first defining employees' team affiliations (who belongs to a certain team), researchers can generate corresponding rosters for each participant with just a few clicks and administer surveys efficiently using the push-out function embedded in Huajue (i.e., participants receive and fill in the surveys on their mobile phones). Note that participants are required to have their mobile device associated with the Huajue platform via WeChat (a Chinese mobile application that integrates SMS, social networking, online commerce, and payment functions), and so the Huajue platform is currently only available to researchers who conduct field SRM studies in China. Future releases may address this issue by removing the reliance on WeChat.
Motivating participants in SRM studies	- Filling out SRM questionnaires can be a burden (as repeated measures must be completed) and threatening (in terms of social desirability, as participants may be required to report the social relationships they actually experience), so participants are often reluctant to cooperate with researchers on the site. To motivate participants, researchers can consider providing them with gifts or financial incentives as a token of appreciation and take measures to ensure that their responses are confidential.
Sample requirements	
Group size and statistical power	- For round-robin designs, the minimum group size is three, and if all groups have only three members, SRM_R sets the group variance to zero. For the half block design, groups must have at least two actors and two partners. - Use the guidance of Lashley and Kenny (1998) to determine the power for the number of groups, the number of actors and partners per group, and the *a priori* variances and reciprocities. Note that Lashley and Kenny used ANOVA methods, but this is likely to give reasonable estimates of power for MLM analyses. The literature should also be consulted to determine the sample sizes in other studies.
Analysis and reporting	
Centering predictors and using effect scores in SRM	- The SRM has four levels: group, actor, partner, and relationship. Enders and Tofighi (2007) provided general advice on centering predictor variables in multilevel regression models. The following recommendations

(continued)

Table 5. (continued)

Issues	Recommendations
	should be further investigated in future research, and researchers should be aware of the effects of different centering options on the results that they obtain in their analyses. - The analysis of predictor variables measured at the group level is straightforward. Consider a group-level variable of group size. As this predictor variable is at the highest level, it does not need to be centered, and only group-level variance in the dyadic outcome is explained. Nonetheless, it is advisable to grand-mean center to ensure that the intercept is the predicted value for a member of the average-sized group. - Predictor variables measured at individual levels (actor and partner) are analogous to level-one fixed variables using the Enders and Tofighi strategy. First, to account for group-level variance in dyadic outcome, researchers can include in the model the group-level covariates obtained by aggregating the variables measured at the individual level (Chan, 1998). Further, to account for individual-level variance in dyadic outcomes, researchers need to first subtract any group effects in variables measured at the individual level by group-mean centering. - The analysis of predictor variables measured at the relationship level is complicated by four random effects. Explaining group-level variance in the dyadic outcome is straightforward, as researchers can directly include in the model the group-level covariates obtained by aggregating variables measured at the relationship level. However, a typical centering approach (i.e., group-mean centering or person-mean centering) may not be sufficient to separate the effects of actor, partner, and relationship in variables measured at the relationship level. Thus, to account for actor, partner, or relationship variance in the dyadic outcomes, researchers need to compute the SRM effect scores of variables measured at the relationship level using TripleR's *RR* function (the SRM effects can be retrieved from the *RR* object using *$effects* and *$effectsRel*) based on the formula given by Warner et al. (1979) on p. 1747.
Reporting checklist	- Report the following: (1) the number of groups in a sample; (2) minimum, maximum, and average number of people in the groups; (3) the level of missing data; (4) descriptive statistics of all outcome variables and covariates; (5) the statistical method used (estimator, approach, and software); (6) the absolute and relative variances; (7) dyadic and generalized reciprocities. - If there are covariates, report (8) their effects on the dyadic outcomes; (9) residual variance at each level (to assess the statistical power of the fixed effects added to the model); (10) measures indicating the goodness of fit for a model (e.g., AIC or BIC).

enable researchers to better understand relationship phenomena, not present them with data manipulation challenges and technical obstacles.

Thus, the SRM_R app was developed to bridge the gap between methodologists and organizational researchers when conducting social relations analyses. The SRM_R is part of the larger DyadR[7] project, which is a cluster of web programs aimed at helping researchers conduct and understand dyadic data analyses. The main purpose of DyadR, and thus of SRM_R, is to automate complex dyadic data analyses and to present the results in a straightforward and accessible manner. With SRM_R, researchers can easily perform social relations analyses by simply clicking on the required information (e.g., names of variables or types of analyses) without having to master all of the complicated processes involved. Thus, organizational researchers can sidestep the complex data manipulation and programming in SRM and focus their attention on the theoretical substance of their investigations.

However, SRM_R potentially has the disadvantage of discouraging researchers from examining the statistical background of SRM. Although we acknowledge that this may be a risk, the ease of using SRM_R can remove the barriers for those setting out to investigate relationship phenomena. It can thus provide a beginner's guide for researchers on the underlying mechanics of dyadic data analyses. Those interested can access the R syntax behind SRM_R and useful information from Snijders and Kenny (1999) in the "Computer Output" section. We hope to promote a more effective understanding of SRM and its application in organizational settings through the introduction of SRM_R.

Limitations and Future Developments for SRM_R

Although SRM_R greatly simplifies any DDD analysis, it has some limitations. First, it inherits the shortcomings of the multilevel modeling approach developed by Snijders and Kenny (1999), as the analyses executed by SRM_R are limited to criterion variables that are univariate and normally distributed. Advanced users can consider other software options, as presented in Table 1 (e.g., TripleR and xxM for bivariate SRM analyses), or alternative statistical models (e.g., the p2 model of van Duijn et al. (2004) for dichotomous outcome data). In addition, although the initial release of SRM_R provides many analytical options and can handle most types of SRM analyses, users are limited by the predefined sets of variance and covariance structure within the program that cannot be changed. Thus, SRM_R cannot currently handle DDD sets collected from a block round-robin design (e.g., Peters et al., 2004) or an asymmetric block design, and it does not allow for random slope to be added into the model or longitudinal analyses with random effects to be implemented. Users who wish to conduct more complicated analyses can, however, download the R syntax in the "Computer Output" section in addition to their configured dataset and perform these analyses locally.

Conclusion

The SRM has become an important tool for testing hypotheses in organizational research and is particularly appropriate when studying groups or teams. However, performing a social relations analysis using the currently available options is complex and time-consuming for researchers who are new to dyadic analyses or who are not proficient in computer programming. In this article, we show how the SRM_R app can be used to both analyze DDD and interpret the results. Thus, our study can provide guidance to beginners, thus encouraging the more frequent use of SRM when examining organizational phenomena that occur at the dyadic level.

Appendix

A. Sample Tables from the SRM_R Output of the Example.

Tables of SRM Results Reproduced for the Null Model

SRM Results: Predictor Variables' Effects

Variable	Effect	Lower	95 CI	Upper	df	p
Intercept	3.653	3.493	to	3.813	837	<.001

SRM Results: Random Effects

Term	Type	Absolute	Relative or correlation	Chi-square	p
Group	Variance	0.000	.000	0.001	.980
Actor		0.957	.447	206.729	<.001
Partner		0.193	.090	19.078	<.001
Relationship		0.990	.463		
Generalized	Covariance	0.024	.057	0.190	.663
Dyadic		0.214	.216	11.367	<.001

Tables of SRM Results Reproduced for the Predictive Model

SRM Results: Predictor Variables' Effects

Variable	Effect	Lower	95 CI	Upper	df	p
Intercept	3.439	3.221	to	3.656	831	<.001
Percentage of female members in groups	−0.593	−1.422	to	0.235	44	.156
Group average of members' levels of proactive personality	0.497	−0.362	to	1.357	44	.250
Actor's gender	0.126	−0.136	to	0.389	831	.344
Actor's proactive personality	0.312	0.026	to	0.599	831	.033
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Partner's proactive personality	−0.140	−0.317	to	0.038	831	.123
Same versus different gender	0.144	0.013	to	0.275	831	.032
Similarity of actor's and partner's proactive personalities	−0.060	−0.259	to	0.140	831	.558

SRM Results: Random Effects

Term	Type	Absolute	Relative or correlation	Chi-square	p
Group	Variance	0.002	.001	0.045	.832
Actor		0.943	.449	200.611	<.001
Partner		0.178	.085	16.220	<.001
Relationship		0.977	.466		
Generalized	Covariance	0.036	.089	0.453	.501
Dyadic		0.201	.206	10.182	.001

B. Sample Text Output of the Example

Text Reproduced for the Null Model

Model
SRM_R conducts a Social Relations analysis of directed dyadic data. The data were collected by ManNok Wong and are discussed in Wong, M-N, Kenny, D. A., Knight, A. (2022) SRM_R: A web-based shiny app for Social Relations Analyses. The design is reciprocal in that actors are also partners and vice versa. There are 884 observations from 228 individuals who are members of 47 groups with groups that vary in size from 4 to 5 members. The outcome variable is Advice Seeking and its name in the datafile is Y. For all the analyses, alpha is set at .050. The analyses employ the method developed by Andrew Knight of Washington University to estimate SRM variances and covariances using R's nlme package. The estimation method used is restricted maximum likelihood (REML), and the optimizer used is optim. The descriptive statistics for the outcome variable are contained in Table 1. All chi square tests are deviance difference tests.

Fixed Effects: Tests of Intercept and Predictors
The estimate of the intercept is 3.653, which is the predicted value for Advice Seeking. There are no predictor variables in the model. The degrees of freedom used for the test of the intercept are 837.

Random Effects: SRM Variances and Correlations
Next considered are the random effects of the SRM whose results are summarized in Table 3. The absolute group variance equals 0.000 with a relative variance of .000 and is not statistically significantly different from zero (chi-square(1) = 0.00, $p = .980$). The absolute actor variance equals 0.957 with a relative variance of .447 and is statistically significantly different from zero (chi-square(1) = 206.73, $p < .001$). The absolute partner variance equals 0.193 with a relative variance of .090 and is statistically significantly different from zero (chi-square(1) = 19.08, p < .001). The test of equal actor and partner variances is statistically significantly different from zero (chi-square(1) = 42.94, $p < .001$). The actor variance is significantly larger than the partner variance. The absolute relationship variance equals 0.990 with a relative variance of .463. (Note that the relationship effect in this analysis is confounded with error because there is only a single replication. Moreover, because the relationship variance with a single replication must be non-zero, there is no significance test.) Turing to the correlations, the covariance between actor and partner effects or generalized reciprocity equals 0.024 with the correlation being .057 and is not statistically significantly different from zero (chi-square(1) = 0.19, $p = .663$). The dyadic covariance between two relationship effects from the same dyad or dyadic reciprocity equals 0.214 with the correlation being .216 and is statistically significantly different from zero (chi-square(1) = 11.37, p < .001). These results are contained in Table 3. The results suggest that a simpler model in which the Group variance and generalized reciprocity are set to zero might be good fitting model. In fact, the chi square test comparing this simpler model to the more complex is not statistically significant(chi-square(2) = 0.19, $p = .910$), which indicates that the simpler model does indeed yield a good fitting model.

Text Reproduced for the Predictive Model

Model
SRM_R conducts a Social Relations analysis of directed dyadic data. The data were collected by ManNok Wong and are discussed in Wong, M-N, Kenny, D. A., Knight, A. (2022) SRM_R: A web-based shiny app for Social Relations Analyses. The design is reciprocal in that actors are also partners and vice versa. There are 884 observations from 228 individuals who are members of 47 groups with groups that vary in size from 4 to 5 members. The outcome variable is Advice Seeking and its name in the datafile is Y. There are 8 predictor variables in the analysis and they are Percentage of female members in groups, Group average of members' levels

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(continued)

Text Reproduced for the Predictive Model
of proactive personality, Actor's gender, Actor's proactive personality, Partner's gender, Partner's proactive personality, Same vs. different gender, and Similarity of actor's and partner's proactive personalities and their names in datafile are GX1, GX2, AX1, AX2, PX1, PX2, RX1, and RX2. The predictor variables at the group level are Percentage of female members in groups and Group average of members' levels of proactive personality. The predictor variables at the actor level are Actor's gender and Actor's proactive personality. The predictor variables at the partner level are Partner's gender and Partner's proactive personality. User chosen variables were grand-mean centered. Those variables centered are GX1, GX2, AX2, PX2, and RX2. For all the analyses, alpha is set at .050. The analyses employ the method developed by Andrew Knight of Washington University to estimate SRM variances and covariances using R's nlme package. The estimation method used is restricted maximum likelihood (REML), and the optimizer used is optim. The descriptive statistics for the outcome variable and the predictor variables are contained in Table 1. All chi square tests are deviance difference tests. **Fixed Effects: Tests of Intercept and Predictors** The estimate of the intercept is 3.439, which is the predicted value for Advice Seeking, with all of the predictor variables equal to zero. The degrees of freedom used for tests of the 2 predictor variables at the group level are 44 and are 831 for the intercept and the other fixed variables. The effect of Percentage of female members in groups is −0.593 with a p value of .156. The effect of Group average of members' levels of proactive personality is 0.497 with a p value of .250. The effect of Actor's gender is 0.126 with a *p* value of .344. The effect of Actor's proactive personality is 0.312 with a p value of .033. The effect of Partner's gender is 0.173 with a p value of .038. The effect of Partner's proactive personality is −0.140 with a p value of .123. The effect of Same vs. different gender is 0.144 with a p value of .032. The effect of Similarity of actor's and partner's proactive personalities is −0.060 with a p value of .558. See Table 2 for the results for the predictor variables. The chi square test that the effects of the 8 predictor variables are zero is statistically significant (chi-square(8) = 24.07, $p = .002$), which indicates that the inclusion of the predictor variables does improve the fit of the model. **Random Effects: SRM Variances and Correlations** Next considered are the random effects of the SRM whose results are summarized in Table 3. The absolute group variance equals 0.002 with a relative variance of .001 and is not statistically significantly different from zero (chi-square(1) = 0.05, $p = .832$). The absolute actor variance equals 0.943 with a relative variance of .449 and is statistically significantly different from zero (chi-square(1) = 200.61, $p < .001$). The absolute partner variance equals 0.178 with a relative variance of .085 and is statistically significantly different from zero (chi-square(1) = 16.22, $p < .001$). The test of equal actor and partner variances is statistically significantly different from zero (chi-square(1) = 44.71, $p < .001$). The actor variance is significantly larger than the partner variance. The absolute relationship variance equals 0.977 with a relative variance of .466. (Note that the relationship effect in this analysis is confounded with error because there is only a single replication. Moreover, because the relationship variance with a single replication must be non-zero, there is no significance test.) Turing to the correlations, the covariance between actor and partner effects or generalized reciprocity equals 0.036 with the correlation being .089 and is not statistically significantly different from zero (chi-square(1) = 0.45, $p = .501$). The dyadic covariance between two relationship effects from the same dyad or dyadic reciprocity equals 0.201 with the correlation being .206 and is statistically significantly different from zero (chi-square(1) = 10.18, $p = .001$). These results are contained in Table 3. The results suggest that a simpler model in which the Group variance and generalized reciprocity are set to zero might be good fitting model. In fact, the chi square test comparing this simpler model to the more complex is not statistically significant(chi-square(2) = 0.40, $p = .820$), which indicates that the simpler model does indeed yield a good fitting model.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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Notes

1. Of the SRM studies published between January 1991 and May 2022, 36 explicitly stated the use of SRM in their main studies. These include 10 papers in the *Journal of Applied Psychology*, 6 in *Academy of Management Journal*, 5 in *Organization Science*, 3 in *Organizational Behavior and Human Decision Processes*, 2 in each of *Administrative Science Quarterly*, *Journal of Management Studies*, *Journal of Organizational Behavior*, and *Personnel Psychology*, and 1 in each of *Human Relations*, *Human Resource Management*, *Journal of Business Ethics*, and *Journal of Management*.
2. The underlying R functions used in the SRM_R (Kenny & Wong, 2016) are available as an R package. This package, called roundRobinR, is currently available as a developmental release (https://github.com/andrewpknight/roundRobinR) prior to a stable release through the Comprehensive R Archive Network (CRAN).
3. Interested readers may refer to Chapter 11 of Kenny et al.'s (2006) book for a more detailed discussion of the similarities and differences between the SRM and SNA.
4. Other approaches to estimating the SRM can offer more flexible treatments of missing data (e.g., Jorgensen et al., 2018; Schönbrodt et al., 2012), and interested readers can learn more by reviewing the key references presented in Table 1.
5. The null model can be viewed as mis-specified if covariates are required and if excluding them can lead to wrong conclusions about variance components. However, including a covariate can potentially remove "too much" variance of a component if it is merely another measure of the criterion variable. SRM_R is reactive, as it enables users to change the analysis based on previous results, so we suggest that researchers can take a sequential approach and initially examine the null model to establish whether they should include covariates. Such a sequential approach has often been taken in management studies (e.g., Joshi & Knight, 2015).
6. Centering is also important in MLM for the interpretation of effects (Enders & Tofighi, 2007). The SRM has at least four levels, so centering becomes even more complicated. Appropriately centering fixed covariates within the SRM has rarely been discussed in the literature except in the work of Banchefsky et al. (2016). In Table 5, we offer recommendations for various centering options that scholars can use in their SRM research.
7. Readers can access all programs under DyadR by visiting http://davidakenny.net/DyadR/DyadRweb.htm.

References

Alexiev, A. S., Jansen, J. J. P., Van den Bosch, F. A. J., & Volberda, H. W. (2010). Top management team advice seeking and exploratory innovation: The moderating role of TMT heterogeneity. *Journal of Management Studies*, *47*(7), 1343-1364. https://doi.org/10.1111/j.1467-6486.2010.00919.x

Banchefsky, S., Westfall, J., Park, B., & Judd, C. M. (2016). But you don't look like a scientist!: Women scientists with feminine appearance are deemed less likely to be scientists. *Sex Roles*, *75*(3), 95-109. https://doi.org/10.1007/s11199-016-0586-1

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1), 1-48. https://doi.org/10.18637/jss.v067.i01

Biesanz, J. C. (2010). The social accuracy model of interpersonal perception: Assessing individual differences in perceptive and expressive accuracy. *Multivariate Behavioral Research*, *45*(5), 853-885. https://doi.org/10.1080/00273171.2010.519262

Brislin, R. W. (1980). Translation and content analysis of oral and written materials. In H. C. Triandis, & J. W. Berry (Eds.), *Handbook of cross-cultural psychology* (Vol. 2, pp. 349-444). Allyn & Bacon.

Chan, D. (1998). Functional relations among constructs in the same content domain at different levels of analysis: A typology of composition models. *Journal of Applied Psychology*, *83*(2), 234-246. https://doi.org/10.1037/0021-9010.83.2.234

Chang, W., Cheng, J., Allaire, J. J., Xie, Y., & Jonathan, M. (2015). Shiny: Web application framework for R. Retrieved from https://cran.r-project.org/package = shiny.

Crant, J. M. (2000). Proactive behavior in organizations. *Journal of Management*, *26*(3), 435-462. https://doi.org/10.1177/014920630002600304

Cronin, J. J. (1994). Analysis of the buyer-seller dyad: The social relations model. *Journal of Personal Selling & Sales Management*, *14*(3), 69-77. https://doi.org/10.1080/08853134.1994.10753994

Dabbs, J. M., & Ruback, R. B. (1987). Dimensions of group process: Amount and structure of vocal interaction. In L. Berkowitz (Ed.), *Advances in experimental social psychology* (Vol. 20, pp. 123-169). Academic Press.

de Jong, S. B., Van der Vegt, G. S., & Molleman, E. (2007). The relationships among asymmetry in task dependence, perceived helping behavior, and trust. *Journal of Applied Psychology*, *92*(6), 1625-1637. https://doi.org/10.1037/0021-9010.92.6.1625

Elfenbein, H. A., Eisenkraft, N., Curhan, J. R., & DiLalla, L. F. (2018). On the relative importance of individual-level characteristics and dyadic interaction effects in negotiations: Variance partitioning evidence from a twins study. *Journal of Applied Psychology*, *103*(1), 88-96. https://doi.org/10.1037/apl0000255

Enders, C. K., & Tofighi, D. (2007). Centering predictor variables in cross-sectional multilevel models: A new look at an old issue. *Psychological Methods*, *12*(2), 121-138. https://doi.org/10.1037/1082-989X.12.2.121

Ferrin, D. L., Dirks, K. T., & Shah, P. P. (2006). Direct and indirect effects of third-party relationships on interpersonal trust. *Journal of Applied Psychology*, *91*(4), 870-883. https://doi.org/10.1037/0021-9010.91.4.870

Jendryczko, D. (2022). Multiple group structural equation modeling of the social relations model. *Structural Equation Modeling: A Multidisciplinary Journal*, *29*(5), 791-799. https://doi.org/10.1080/10705511.2022.2032715

Jones, S. L., & Shah, P. P. (2016). Diagnosing the locus of trust: A temporal perspective for trustor, trustee, and dyadic influences on perceived trustworthiness. *Journal of Applied Psychology*, *101*(3), 392-414. https://doi.org/10.1037/apl0000041

Jorgensen, T. D., Forney, K. J., Hall, J. A., & Giles, S. M. (2018). Using modern methods for missing data analysis with the social relations model: A bridge to social network analysis. *Social Networks*, *54*, 26-40. https://doi.org/10.1016/j.socnet.2017.11.002

Joshi, A. (2014). By whom and when is women's expertise recognized? The interactive effects of gender and education in science and engineering teams. *Administrative Science Quarterly*, *59*(2), 202-239. https://doi.org/10.1177/0001839214528331

Joshi, A., & Knight, A. P. (2015). Who defers to whom and why? Dual pathways linking demographic differences and dyadic deference to team effectiveness. *Academy of Management Journal*, *58*(1), 59-84. https://doi.org/10.5465/amj.2013.0718

Kenny, D. A. (2016). Estimation of the SRM using specialized software. Retrieved from http://davidakenny.net/doc/srmsoftware.pdf.

Kenny, D. A. (2019). *Interpersonal perception: The foundation of social relationships*. Guilford Publications.

Kenny, D. A., Kashy, D. A., & Cook, W. L. (2006). *Dyadic data analysis*. Guilford Publications.

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). Academic Press.

Kenny, D. A. & Wong, M.-N. (2016). SRM_R: An interactive tool for estimating the Social Relations Model from directed dyadic data with round-robin-like designs [Computer software]. Available from https://davidakenny.shinyapps.io/SRM_R/

Knight, A. P., & Humphrey, S. E. (2019). Dyadic data analysis. In S. E. Humphrey, & J. M. LeBreton (Eds.), *The handbook of multilevel theory, measurement, and analysis* (pp. 423-447). American Psychological Association.

Krasikova, D. V., & LeBreton, J. M. (2012). Just the two of us: Misalignment of theory and methods in examining dyadic phenomena. *Journal of Applied Psychology*, *97*(4), 739-757. https://doi.org/10.1037/a0027962

Lam, C. K., Van der Vegt, G. S., Walter, F., & Huang, X. (2011). Harming high performers: A social comparison perspective on interpersonal harming in work teams. *Journal of Applied Psychology*, *96*(3), 588-601. https://doi.org/10.1037/a0021882

Lashley, B. R., & Kenny, D. A. (1998). Power estimation in social relations analyses. *Psychological Methods*, *3*(3), 328-338. https://doi.org/10.1037/1082-989X.3.3.328

Lee, K., & Duffy, M. K. (2019). A functional model of workplace envy and job performance: When do employees capitalize on envy by learning from envied targets? *Academy of Management Journal*, *62*(4), 1085-1110. https://doi.org/10.5465/amj.2016.1202

Ludtke, O., Robitzsch, A., Kenny, D. A., & Trautwein, U. (2013). A general and flexible approach to estimating the social relations model using Bayesian methods. *Psychological Methods*, *18*(1), 101-119. https://doi.org/10.1037/a0029252

Maloney, M. M., Shah, P. P., Zellmer-Bruhn, M., & Jones, S. L. (2019). The lasting benefits of teams: Tie vitality after teams disband. *Organization Science*, *30*(2), 260-279. https://doi.org/10.1287/orsc.2018.1254

Mayer, R. C., & Davis, J. H. (1999). The effect of the performance appraisal system on trust for management: A field quasi-experiment. *Journal of Applied Psychology*, *84*(1), 123-136. https://doi.org/10.1037/0021-9010.84.1.123

McDonald, M. L., & Westphal, J. D. (2003). Getting by with the advice of their friends: CEOs' advice networks and firms' strategic responses to poor performance. *Administrative Science Quarterly*, *48*(1), 1-32. https://doi.org/10.2307/3556617

Mehta, P. D. (2018). Virtual levels and role models: N-level structural equations model of reciprocal ratings data. *Multivariate Behavioral Research*, *53*(3), 315-334. https://doi.org/10.1080/00273171.2018.1443787

Morrison, E. W., & Vancouver, J. B. (2000). Within-person analysis of information seeking: The effects of perceived costs and benefits. *Journal of Management*, *26*(1), 119-137. https://doi.org/10.1177/014920630002600101

Nestler, S. (2016). Restricted maximum likelihood estimation for parameters of the social relations model. *Psychometrika*, *81*(4), 1098-1117. https://doi.org/10.1007/s11336-015-9474-9

Nestler, S. (2018). Likelihood estimation of the multivariate social relations model. *Journal of Educational and Behavioral Statistics*, *43*(4), 387-406. https://doi.org/10.3102/1076998617741106

Nestler, S., Lüdtke, O., & Robitzsch, A. (2020). Maximum likelihood estimation of a social relations structural equation model. *Psychometrika*, *85*(4), 870-889. https://doi.org/10.1007/s11336-020-09728-z

Nestler, S., Lüdtke, O., & Robitzsch, A. (2021). Analyzing longitudinal social relations model data using the social relations structural equation model. *Journal of Educational and Behavioral Statistics*, *47*(2), 231-260. https://doi.org/10.3102/10769986211056541

Olsen, J. A., & Kenny, D. A. (2006). Structural equation modeling with interchangeable dyads. *Psychological Methods*, *11*(2), 127-141. https://doi.org/10.1037/1082-989X.11.2.127

Peters, S., Kinsey, P., & Malloy, T. E. (2004). Gender and leadership perceptions among African Americans. *Basic and Applied Social Psychology*, *26*(1), 93-101. https://doi.org/10.1207/s15324834basp2601_8

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., Heisterkamp, S., Van Willigen, B., & Maintainer, R. (2017). Package 'nlme'. Retrieved from https://cran.r-project.org/web/packages/nlme/nlme.pdf.

Schönbrodt, F. D., Back, M. D., & Schmukle, S. C. (2012). TripleR: An R package for social relations analyses based on round-robin designs. *Behavior Research Methods*, *44*(2), 455-470. https://doi.org/10.3758/s13428-011-0150-4

Seibert, S. E., Crant, J. M., & Kraimer, M. L. (1999). Proactive personality and career success. *Journal of Applied Psychology*, *84*(3), 416-427. https://doi.org/10.1037/0021-9010.84.3.416

Snijders, T. A. B., & Kenny, D. A. (1999). The social relations model for family data: A multilevel approach. *Personal Relationships*, *6*(4), 471-486. https://doi.org/10.1111/j.1475-6811.1999.tb00204.x

Truong, M., Fast, N. J., & Kim, J. (2020). It's not what you say, it's how you say it: Conversational flow as a predictor of networking success. *Organizational Behavior and Human Decision Processes*, *158*, 1-10. https://doi.org/10.1016/j.obhdp.2020.02.004

Tse, H. H. M., Lam, C. K., Gu, J., & Lin, X. S. (2018). Examining the interpersonal process and consequence of leader-member exchange comparison: The role of procedural justice climate. *Journal of Organizational Behavior*, *39*(8), 922-940. https://doi.org/10.1002/job.2268

Tse, H. H. M., Lam, C. K., Lawrence, S. A., & Huang, X. (2013). When my supervisor dislikes you more than me: The effect of dissimilarity in leader-member exchange on coworkers' interpersonal emotion and perceived help. *Journal of Applied Psychology*, *98*(6), 974-988. https://doi.org/10.1037/a0033862

Van der Vegt, G. S., Bunderson, J. S., & Oosterhof, A. (2006). Expertness diversity and interpersonal helping in teams: Why those who need the most help end up getting the least. *Academy of Management Journal*, *49*(5), 877-893. https://doi.org/10.5465/amj.2006.22798169

van Duijn, M. A. J., Snijders, T. A. B., & Zijlstra, B. J. H. (2004). P2: A random effects model with covariates for directed graphs. *Statistica Neerlandica*, *58*(2), 234-254. https://doi.org/10.1046/j.0039-0402.2003.00258.x

Venkataramani, V., & Dalal, R. S. (2007). Who helps and harms whom? Relational antecedents of interpersonal helping and harming in organizations. *Journal of Applied Psychology*, *92*(4), 952-966. https://doi.org/10.1037/0021-9010.92.4.952

Warner, R. M., Kenny, D. A., & Stoto, M. (1979). A new round robin analysis of variance for social interaction data. *Journal of Personality and Social Psychology*, *37*(10), 1742-1757. https://doi.org/10.1037/0022-3514.37.10.1742

Xu, E., Huang, X., Jia, R. W., Xu, J. E., Liu, W., Graham, L., & Snape, E. (2020). The "evil pleasure": Abusive supervision and third-party observers' malicious reactions toward victims. *Organization Science*, *31*(5), 1115-1137. https://doi.org/10.1287/orsc.2019.1349

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