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

Man-Nok Wong[1], David A. Kenny[2], Andrew P. Knight[3]

[1] School of Business, Sun Yat-sen University

[2] Department of Psychological Sciences, University of Connecticut

[3] Olin Business School, Washington University in St. Louis

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Correspondence concerning this paper should be addressed to Man-Nok Wong, School of Business, Sun Yat-sen University, No.135 Xingang Xi Road, Haizhu District, Guangzhou, 510275, China. Email: wongmn@mail.sysu.edu.cn

Man-Nok Wong https://orcid.org/0000-0001-6828-7827

Abstract

Organizational researchers are interested in many topics that require examining the perceptions and behavior of group members. The resulting data from these designs can be analyzed using the Social Relations Model (SRM). This model allows researchers to address several important research questions regarding relational phenomena. In particular, the variance can be partitioned into group, actor, partner, and relationship; reciprocity can be assessed for individuals and dyads, and different predictors at each of these levels can be analyzed. Unfortunately, analyzing data with existing software can be challenging, which deters organizational researchers from employing the method. The purpose of this paper is to introduce organizational researchers to a free, user-friendly online app—SRM_R (https://davidakenny.shinyapps.io/SRM_R/), which greatly reduces the barrier for analyzing data regarding relational phenomenon. The app is illustrated using a dataset of 47 teams, 228 members, and 884 dyadic observations, who provide ratings of their advice seeking from fellow employees.

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

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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). For instance, along with the notion 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 relational differences in how an employee interacts with or judges a specific coworker. In addition, many concepts traditionally regarded as individual constructs, such as workplace incivility (low-intensity deviant behavior with ambiguous intent to harm that violates workplace norms for mutual respect; Andersson & Pearson, 1999), have been shown to exhibit considerable variation across relationship partners that interests organizational scholars (e.g., who is uncivil toward or experiences incivility from whom? Taylor et al., 2021). Further, in team and organization research, scholars (Joshi, 2014; Joshi & Knight, 2015; Shah et al., 2021; Van der Vegt et al., 2006) have been exploring the reciprocal patterns of social interactions, working to unpack the interpersonal processes that underlie intra-team dynamics (e.g., interpersonal cooperation and conflict). To address these research questions, organizational researchers have increasingly recognized the need to apply *social relations designs*—designs in which each person interacts with or rates more than one person—that provide more fine-grained observations 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 dyadic relationship, one of which is the *actor* or the person who directs an action or who provides dyadic ratings and the other is the *partner* or the person who is the target of an action or who is being rated. The terms "actor" and "partner" are generic, and different terms would be more appropriate in other contexts. For instance, *perceiver* and *target* would be used in the context of interpersonal perception; *giver* and *recipient* would be used in the context of exchange relationships. Typically, organizational researchers model DDD using the Social Relations Model (SRM; Kenny & La Voie, 1984), which considers each dyadic measurement to be equal to the sum of four components: group, actor, partner, and relationship. Separating a dyadic relationship into components can help researchers understand the interdependence of observations, resulting in more precise and valid statistical inferences (Kenny et al., 2006).

For decades, researchers applying the SRM have steadily advanced its implementation through novel estimation procedures and statistical software. Through the 1990s, Kenny developed two FORTRAN programs—SOREMO and BLOCKO—that relied on an ANOVA approach to SRM analyses. Although still functional, these programs are difficult to install and execute on today's computers, and the resulting outputs are challenging to interpret for many users. Twenty years later, Schmukle et al. (2010) advanced the ANOVA-based software solution by implementing an open source R package called TripleR (see also Schönbrodt et al., 2012). Parallel to the ANOVA-based paradigm, the development of statistical techniques has enabled researchers to estimate SRM with other estimation procedures, such as multilevel modeling (MLM: Snijders & Kenny, 1999) and structural equations modeling (SEM: Olsen & Kenny, 2006). Kenny (2016) provided the code for these alternatives in an online supplement, illustrating how to run SRM using specialized software such as SAS, SPSS, MLwiN and Mplus.

Notwithstanding the steady growth in usage of powerful and extensible statistics packages, significant barriers to entry and a steep learning curve for using these packages remain. Indeed, the estimation procedures and software today require a thorough understanding of statistical details and error-handling skills before reaching a conclusion from SRM. Together, these barriers impede scientific discovery because most organizational researchers are not professional data scientists. We believe that a tool that makes SRM easier to conduct and provides the user with text to understand the statistical analyses would be particularly valuable to organizational researchers. As such, the purpose of this paper is to introduce to organizational researchers a free, user-friendly online app—SRM_R (https://davidakenny.shinyapps.io/SRM_R/). The focal contribution of the paper is the accessible and user-friendly web application. However, the underlying R functions used in the web application are available as an R package. This package, called roundRobinR is currently available as a developmental release via github at https://github.com/andrewpknight/roundRobinR, but will soon be available through the Comprehensive R Archive Network (CRAN). This app facilitates a relatively simple and straightforward analysis of DDD using the social relations model.

The main value of SRM_R is that it provides a non-technical means for organizational researchers to analyze the DDD resulting from a range of social relations designs. There are several advantages of using SRM_R to analyze DDD. First, SRM_R is freely accessible online and requires neither statistical software nor a detailed background knowledge of the statistical techniques to use all of its features. Second, and in addition to the SRM analyses, 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 computer programming skills. Third, SRM_R provides the user with text that summarizes and interprets the statistical analyses. Fourth, SRM_R provides the user a new dataset with all of the necessary transformed variables and the R code to run additional analyses, outside of the context of SRM_R. In all, because researchers do not need to be SRM experts to use SRM_R, this app enables management scholars to focus their expertise on the non-trivial challenges of developing theory regarding dyadic processes; the software takes care of the complicated data analysis routines.

In the rest of the paper, we begin by providing an overview of SRM. We then describe different social relations designs. We next introduce SRM_R and provide a detailed description of its user interface, functionality, and a step-by-step guide on the use of SRM_R to conduct SRM analyses. Throughout this paper, we provide an empirical example to demonstrate the features of SRM_R so that readers can understand the logic of the methods and use the tool to perform SRM analysis on their own DDD. Finally, we discuss how SRM_R removes barriers for dyadic research, its limitations, and future developments for SRM_R.

Social Relations Model: An Overview

The DDD set regarding actions or responses of a given actor toward or about a given partner can be described using the Social Relations Model (SRM; Kenny & La Voie, 1984). To illustrate the model, we assume that member i interacts with member j within the group k, and the SRM equation expresses i's dyadic relationship (Y_{ijk}) 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 G_k in providing overall dyadic rating regarding their actions or responses of each other. The second component (A_{ik}: the actor effect) reflects member i's general tendency to direct actions or provide responses toward 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 separated effects, SRM partitions the variance of dyadic relationship (Y_{ijk}) into four different levels: group, actor, partner, and relationship, with actors and partners crossed with one another and with individuals further nested within groups.

SRM also allows for two possible forms of correlations: the *generalized reciprocity* and the *dyadic reciprocity*. The *generalized reciprocity* indicates the degree to which a member's actions or responses as an actor might be associated with others' actions or responses to that member as a partner; or, the correlation of A_{ik} with B_{ik}. The *dyadic reciprocity* indicates the degree to which one member's special actions or responses to a second member might be associated with the second member's special actions or responses to the first within a dyadic relationship; or, the correlation of R_{ijk} with R_{jik}. These two correlations in DDD uncover reciprocal or symmetric (or asymmetric) patterns of interpersonal phenomena. For example, to investigate the nature of interpersonal deference, Joshi and Knight (2015) examined both generalized reciprocity and dyadic reciprocity correlations. They found a negative generalized reciprocity correlation for deference (r = -.23), indicating that people who receive deference in general tend not to defer to others. However, they also found a positive dyadic reciprocity correlation (r = .10), indicating that within a given dyad, if an actor uniquely confers deference on a specific partner, this actor is more likely to receive deference from that partner.

Further, extending this conventional model, predictors can be included to account for variances in the dyadic outcome variable (Snijders & Kenny, 1999). The SRM equation can be expanded to include fixed covariates as predictors:

$$Y_{ijk} = G_k + A_{ik} + P_{jk} + R_{ijk} + \beta_1 X_1 + \ldots + \beta_n X_n$$

where the new terms are the predictors of X_1 through X_n. These predictors can be measured at the group, actor, partner, or relationship levels. For instance, Joshi and Knight (2015) reported independent effects of demographic attributes of the dyad members—such as gender and ethnicity—on dyadic deference.

Descriptions of Social Relations Designs

To collect DDD that affords a clear and detailed view of dyadic process, with the resulting data analyzed by means of SRM, researchers need to employ social relations designs. In this section, we describe three common social relations designs—namely, the round-robin design, the block design and the half-block design (Kenny & La Voie, 1984). These designs enable researchers to collect data with each person interacting with or rating more than one other person. Although most SRM studies have multiple groups, to simplify our illustration, only a single group for each of the following designs is presented.

Round-Robin Design

The most common social relations design in management literature is the round-robin design (Kenny & La Voie, 1984). In a round-robin study, measurements are made on every possible dyad that can be formed from a group of individuals; each dyad provides two scores, one for each member. This design is reciprocal because for a given measurement each person serves as both an actor and a partner. Accordingly, a round robin design yields $N \times (N - 1)$ observations, where N is the number of people in a given group. As an example, consider the data matrix shown in Table 1, which includes the 30 dyadic measurements, Y_{ij}, that would result from a round-robin group of six members (1, 2, 3, 4, 5, 6).

------- Insert Table 1 about here -------

Each entry in the matrix is the dyadic measurement Y_{ij} from an actor to a partner. For instance, in the round robin presented in Table 1, member 1's dyadic ratings Y_{1j} to all other members are noted into the first row of matrix; the dyadic ratings Y_{i1} of member 1 by all other members are noted into the first column of matrix. Note that the data in Table 1 are directional; so, for example, Y_{12} is different from Y_{21}. Because the SRM does not require self-rated scores, there are no entries along the diagonal of the data matrix. A round robin design is perfectly suited to collect DDD for bi-directionality of interpersonal perceptions and behaviors, 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), voice (Liu et al., 2015), deference (Joshi & Knight, 2015), social learning (Lee & Duffy, 2019), emotions (Lam et al., 2016), trust (Jones & Shah, 2016), and conflict (Shah et al., 2021)—to name just a few.

The round-robin design captures the interactive, two-sided nature of social interaction. There are several options to implement a round-robin design in organizational settings. Researchers can distribute a survey to every member of a group to yield perceptions of every other member in that group. Researchers can also observe the interactions of groups of individuals and record who initiated a specific action on whom (Dabbs & Ruback, 1987). Another alternative would be conducting 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 illustrated in Table 1, it may be very difficult to obtain every possible value—especially in field survey studies—as some employees may be absent, on vacation, taking sick leave, or otherwise unable or unwilling to participate in a research project.

Block Design

In the *block design*, a group is divided into two subgroups, and members in one subgroup interact with those in the other subgroup. Similar to the round-robin design, the block design is also reciprocal. Consider a group that includes 6 members (1 through 6), in which members 1, 2, and 3 interact with members 4, 5, and 6. This block design would yield two sets of observations:

the upper-right section and the lower-left section, as illustrated in Table 1. Note the two subgroups need to be arbitrary or have no effect. In such a case, the design is called the *symmetric block design*. The symmetric block design provides a solution in studies that would present an excessive burden on participants' time or attention if a full round-robin was used. As shown in Table 1, compared to the round robin design, the symmetric block design reduces the number of other people each actor needs to rate or interact with—in this example from five to three. If the two groups are distinguishable in some way, such as by gender in a speed-dating study, the design is called an *asymmetric block design*. For instance, Cronin (1994) used this design to study interactions between buyers and sellers. He employed a block design so that each seller met multiple buyers and each buyer met multiple sellers. As Cronin (1994, p. 72) noted, the 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."

Half Block Design

The *half block design* is one half of the block design, such that members 1, 2, and 3 rate members 4, 5, and 6 but not vice versa. This is a non-reciprocal design because each person is either an actor or a partner for a given measurement. An example of a half block design is presented in Table 1. The half block design is perfect to collect DDD for behaviors and perceptions that are not bi-directional. Indeed, the half-block design is used in many rating studies (e.g., Biesanz, 2010) where the targets being rated are presented stimuli (e.g., photos, videotape). There are also many potential workplace phenomena where researchers might find the half-block design useful. For example, research on recruitment and selection processes, in which hiring managers judge job applicants who do not judge them back, could use the half-block design. The primary limitation of this design, however, is that it does not capture the interactive nature of social interaction.

Challenges for Estimating SRM Parameters

As we reviewed earlier, there are two major approaches suggested for estimating the SRM parameters, namely an analysis of variance (ANOVA) approach (Kenny et al., 2006; Kenny & La Voie, 1984) and a multilevel modeling (MLM) approach (Kenny et al., 2006; Snijders & Kenny, 1999). Most of the early SRM papers used the ANOVA approach, which estimates the SRM variances and correlations using the expected mean squares and cross-products of the random effects (the group effects, the actor effects, the partner effects, the relationship effects). Its formulas were first implemented in two FORTRAN programs—SOREMO and BLOCKO. The former one was developed for the analysis of the round-robin design while the latter one was developed for the analysis of the block design. These FORTRAN programs are difficult to use (e.g., the data preparation and formatting are very demanding, and these 90s programs are complicated to setup on today's computers); and, unlike wine, software does not improve with the passage of time. As a remedy, Schmukle et al. (2010) developed TripleR, a more user-friendly package for the R environment—open source and freely available statistical software—that estimates SRM based on the same ANOVA approach. TripleR is limited, however, to datasets collected using a full round-robin design.

Furthermore, there are numerous drawbacks associated with SRM estimated by the ANOVA approach (Kenny & La Voie, 1984). First, the ANOVA approach can produce out-of-range estimates (e.g., negative variances, correlations that exceed 1.0 or be less than -1.0). Second, it poses stringent requirements on the data (e.g., no missing values). Third, when examining the influence of covariates on the SRM effect, researchers need to adopt a two-step approach—first calculate the SRM effect, and then use the SRM effect for subsequent regression analysis. This is problematic because the estimated variability of the SRM effect in the first step is not considered in the second step of the analysis, and thus it usually limits the accuracy of the statistical analysis.

To solve these problems, scholars (Kenny et al., 2006; Snijders & Kenny, 1999) suggested the use of an MLM approach to estimate SRM. Within the MLM approach, scholars view the SRM as a multilevel model and use maximum likelihood to estimate its variance and covariance parameters (Snijders & Kenny, 1999). In a reciprocal design (i.e., round-robin design and symmetric block design), the SRM can be considered a crossed random effects model in which the random effects of actor and partner are partly correlated. In a non-reciprocal design (i.e., half block design), DDD is one-sided, and thus the SRM is a typical multilevel model with two random factors (one for actor and the other for partner) without generalized and dyadic reciprocity correlations. The main advantages of the MLM approach are that missing values can be easily handled without imputation, unbalanced group sizes are easily accommodated, and the effects of fixed predictors such as age or gender can be directly estimated within a single model and estimation.

Accompanying its significant strengths are complexities that present tremendous challenges that make estimating SRM with the MLM approach daunting for many researchers. First of all, many widely-used conventional MLM software programs (e.g., SPSS, SAS, and MLwiN) are closed-source packages that require users to purchase a commercial license. Further, each of these packages requires users to invest significant time to learn its idiosyncratic (and often not user-friendly) programming language. Even though scholars (e.g., Knight & Humphrey, 2019) have developed solutions of conducting SRM analyses with the MLM approach in R, researchers who do not have prior knowledge of using R programming language may still find it difficult to draft and execute the code needed to manipulate dyadic datasets and run the SRM. These challenges are exacerbated for SRM with reciprocal designs, for which the MLM is particularly complicated to specify. Most MLM software programs assume that random effects are uncorrelated, and thus researchers need to first create a set of dummy variables for each individual actor and partner within the group (denoted a_1 to a_n for the actors and p_l to p_n for the partners, where n is the size of the largest group in the DDD set; see Snijders & Kenny, 1999) and impose constraints on the variance–covariance matrix of the random slopes for these dummies. This approach cannot currently be done in the MLM routines within SPSS or HLM, as these programs do not allow users to specify constraints. Even within programs that do allow users to specify constraints (e.g., MLwiN, SAS, R), the precise method for doing so is idiosyncratic to a given program, usually tedious for the programmer, and prone to human error. Therefore, considering these challenges, a freely-available, accessible, and user-friendly tool that is specifically designed for SRM would help organizational scholars to analyze their DDD set.

Introduction to SRM_R

The 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 R (or any other software) on their local machines, nor do they need to specify any R-code. Instead, within SRM_R all computations are executed in the cloud, through a web browser, and the complicated data transformations and programming specifications (i.e., MLM equation code, dummy variable creation, and equality constraints) are automatically performed behind the scenes. After execution, users receive through their web browser a summary description of the results and an accompanying interpretation. A major goal of this program is to eliminate the barrier for organizational researchers who are interested in using appropriate statistical models to study relational phenomenon.

Currently, SRM_R can perform SRM analyses for three DDD designs: round-robin, symmetric block, and half block. For a DDD that is reciprocal (i.e., round-robin design and symmetric block design), 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 using Snijders and Kenny's (1999) approach, which creates dummy variables for each actor and partner. For a DDD that is non-reciprocal (i.e., half block design), it uses a simple linear mixed model estimated with the *lme4* package for R (Bates et al., 2015). In addition, SRM_R allows for the inclusion of fixed variables in the MLM equation. For estimating degrees of freedom, SRM_R relies on the default method within the lmer function of lme4. For group-level predictors, degrees of freedom are the number of groups minus the number of predictors plus one. For other predictors, the degrees of freedom are the total number of non-missing data values minus the total number of predictors plus one. Lastly, as many readers are unfamiliar with SRM, SRM_R provides a considerable amount of explanatory language to help researchers interpret the results of and draw conclusions from their SRM analyses.

An Illustrative Example and Dataset Preparation

To illustrate the usage and functionality of SRM_R, we focus on the interpersonal behavior of advice seeking. Prior studies have considered advice seeking as a relational phenomenon that can be shaped by individual characteristics of an advice seeker (i.e., actor) and an advice provider (i.e., partner), as well as aspects of relationship between the two (Lee & Duffy, 2019; Morrison & Vancouver, 2000). For our illustrative example, we collected DDD on advice seeking behavior from the members of project groups in a large state-owned telecommunications company located in China. Our sample comprises 228 individuals nested within 47 groups of 4 or 5 members; yielding a total of 884 directed dyadic observations. The project groups' main responsibility was to help clients develop new telecommunication technologies and offer customized business solutions for their clients.

All 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 2-item scale adapted from previous research (Alexiev et al., 2010; McDonald & Westphal, 2003) ("I seek opinions from [partner name] when I have problems or face difficulty at work" and "I solicit advice from [partner name] about work", $\alpha = .80$). Prior to the round-robin measurements of advice seeking behavior (approximately one week before), we administered a self-report survey to measure participants' individual differences, including gender (1 = female, -1 = male) and proactive personality. Proactive personality was measured using a 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" ($\alpha = .74$). There were no missing values for our study.

To illustrate the use of SRM_R for investigating the relational nature of employees' advice seeking, we focus our analysis on the following research questions:

Questions of Variance: ***What is the source (or locus) of advice seeking—the group, the individual (actor and partner), or the relationship?***

The findings of some studies (e.g., Ji et al., 2017; Woolley et al., 2013) suggest that the members of some groups seek out advice from one another to a greater extent than the members of other groups—perhaps due to group climate (i.e., a group variance explanation). However, other studies (e.g., Lim et al., 2019; Ma et al., 2019) indicate that the degree to which someone seeks advice from others may be a function of their own individual characteristics (i.e., an actor variance explanation). And, other studies direct attention to an “advisor” perspective (e.g., Zhang et al., 2022), revealing that some people tend to provide more advice than others (i.e., a partner variance explanation). The findings of social network research (e.g., McDonald & Westphal, 2003) underscore, however, the importance of considering the unique relationship between an actor and a partner (i.e., a relational variance explanation). Using SRM_R, we consider and assess all of these explanations simultaneously.

Questions of Reciprocity: ***How does one person’s advice seeking toward others relate to others’ advice seeking toward them?***

Given that we are focused on advice seeking as a dyadic phenomenon (Lee & Duffy, 2019; Morrison & Vancouver, 2000), it may be interesting to explore patterns of reciprocity that occur. As described in the overview of SRM above, a reciprocal design permits examining generalized reciprocity and dyadic reciprocity. Regarding generalized reciprocity for advice seeking behavior, we can use SRM_R to shed light on the degree to which prolific advice seekers tend to attract high levels of advice seeking from others. And, regarding dyadic reciprocity, we can address the question of whether there is reciprocal advice seeking behavior within a given pair of team members.

Questions of Explanation: ***Given these findings, how do group, individual, and relational attributes explain this variance?***

In work settings, advice seeking can facilitate employees’ acquisition of the content required to adapt successfully (Berger, 1979; Miller & Jablin, 1991). As an important “learn the ropes” strategy, advice seeking has been found to be associated with heightened role clarity and improved job performance (e.g., Ashford & Black, 1996; Bauer et al., 2007). Thus, understanding what factors may drive group members to seek advice from one another becomes critical. In the current illustration, we are particularly interested in whether advice seeking between group members is a function of two characteristics—gender and proactive personality (i.e., participants' disposition toward taking action to influence their environment; Crant, 2000; Seibert et al., 1999).

Table 2 displays one group from the larger illustrative DDD set. To prepare a dataset for SRM_R, the researcher must organize the DDD in long format, such that each row is one directed dyadic observation—one group member's rating of another group member. Four columns in this DDD are needed for SRM_R: the group identifier, the actor identifier, the partner identifier, and one column for the outcome variable (i.e., actor's advice seeking from partner). Actor and partner identifiers need not be unique to the group; that is, they can be from 1 to *n*, where *n* is group size, in all the groups. These identifier variables instruct SRM_R on how to handle interdependence in the data. In our demo DDD set, partially shown in Table 2, the four columns are called "GID", "AID", "PID" and "Y", but any other name can be assigned to these columns.

------- Insert Table 2 about here -------

In addition to these identifier variables, Table 2 also shows the general structure of how predictors can be included in a DDD set. Each of the predictors used in our illustrative example is described below:

GX1—Percent of female members in groups (group level predictor).

GX2—Group average of members' proactive personality (group level predictor).

AX1—Actor's gender (1 = female and -1 = male; actor level predictor).

AX2—Actor's proactive personality (actor level predictor).

PX1—Partner's gender (partner level predictor).

PX2—Partner's proactive personality (partner level predictor).

RX1—Same vs. different gender, i.e., actor gender × partner gender (relationship level predictor).

RX2—Similarity of actor's and partner's proactive personality, i.e., Absolute difference between an actor's and a partner's proactive personality (relationship level predictor).

The researcher must include any desired predictor variables in the DDD set created before beginning to use SRM_R. Note that in the DDD set, the lowest level of analysis is the directed dyadic rating. Thus, values located at any level higher than this, including symmetric relational variables (e.g., RX1 and RX2 above), are repeated. Very often DDD have missing data. For instance, a team member may not be at work the day of the survey, and so their data would be missing. SRM_R does not impute missing data; instead, the MLM estimation proceeds without these values. Also, if any covariate is missing, that case would be dropped.

User Instruction and Features

In the remainder of this paper, we explain how to use the SRM_R with the round robin DDD set of advice seeking. Figure 1 displays the SRM_R graphical user interface, which currently relies on an RShiny framework. Readers can directly access the graphical user interface for SRM_R at https://davidakenny.shinyapps.io/SRM_R/. Indeed, we encourage readers to access the app, download the sample data, and follow along with the illustrative example below by running it on their own. The navigation bar at the top with red tabs lets the users navigate between "Social Relations Model Estimation," "Help & Contact," and "Updates" screens. The "Updates" screen details modifications in the program.

------- Insert Figure 1 about here -------

We begin with an introduction of the terms in the "Social Relations Model Estimation" page. The function of each tab is briefly described below. The information in the first two green-colored tabs on the left-hand side of the screen is required to estimate the basic form of SRM:

Select Data. The first step is to upload the input DDD dataset organized in long format. To do so, on the opening SRM_R screen, users click the green tab labeled "Select Data." The program accepts file in either SPSS (.sav) or Excel comma separated variables (.csv) format. After selecting the format, the users then search for the file on their device and select that file. A message "Upload complete" will be shown when dataset is uploaded successfully. The DDD set used in our illustrative example is included in the SRM_R app so that researchers can reproduce the analyses in this paper and experiment with the software using known results. To access the illustrative DDD set, users should choose "Example Data" in the scrolling list of "Input Data File Type" on the "Select Data" tab.

------- Insert Figure 2 about here -------

Variables, Design, & Terms. The second step is to denote the reciprocal nature of the selected dataset, and specify the Group, Actor, Partner and Outcome identifier variables. To do so, the user should click on the green tab of "Variables, Design, and Names." By default, SRM_R presumes that the design is reciprocal (i.e., round robin and block design). However, if the design is non-reciprocal (i.e., half block design), the user should uncheck the "Data Reciprocal" box. The user then needs to find in the dataset the numeric variables that denote group, actor, and partner, as well as the outcome variable. In the present example, we choose "GID", "AID", "PID" and "Y" from the list of variable names as shown in Figure 2. One can also name the outcome for the text and tables, which we have done to "Advice Seeking." If needed, the user can also change the default names of “Actor” and “Partner” to, for example, “Seeker” and “Recipient” for the text output. One can change “group” or “groups” to “team” or “teams” or whatever the user chooses.

------- Insert Figure 3 about here -------

The next three black tabs are additional, optional specifications for the model. They are:

Predictor Variables. The user can choose to include predictors (fixed covariates) into the SRM model in this tab. These predictors must be numeric variables. When “Predictor Variables in the Model” tab is checked, variable names (other than the selected identifiers) are displayed. The user can select predictors that account for the Outcome Variable. The default option for the variable names is “Same Names As In The Dataset,” but the user can use the “Enter Names” option to rename predictors in a given textbox, with each predictor name separated with a comma. For example (see Figure 4), if the user wants to include all predictors in our example DDD set, they can click the checkboxes “GX1”, “GX2”, “AX1”, “AX2”, “PX1”, “PX2”, “RX1”, and “RX2” indicating predictors of the model, and input the following text to rename these predictors:

> *Percent of female members in groups, Group average of members' proactive personality, Actor's gender, Actor's proactive personality, Partner's gender, Partner's proactive personality, Same vs. different gender, Similarity of actor's and partner's proactive personality*

Alternatively, users can choose “SRM_R Creates Names” such that SRM will automatically generate variable names for predictors.

Moreover, to make the intercept more meaningful, users may wish to center the predictors. When “Center Predictor Variables” is checked, three centering options “Grand Mean

All", "Grand Mean Those Variables Without a Zero" and "Grand Mean Selected Variables" are displayed. In our example, we grand-mean center any continuous variables, so we select "Grand Mean Selected Variables" and check "GX1", "GX2", "AX2", "PX2" and "RX2" as shown in Figure 4. Last but not least, when "Predictor Variables in the Model" is unchecked, a null model (intercept model without predictors) is estimated.

------- Insert Figure 4 about here -------

Group Effect. Users can choose to estimate the group effect as either random or fixed (i.e., a set of $k - 1$ group dummy variables are created where k is the number of groups, which are included as covariates), or set the group variance to zero. For this example, we use the default option in which a random intercept is estimated to account for the group effect.

Technical. In this tab, users are allowed to change the alpha value for significance testing and methods of estimating parameters (either REML or ML) and optimizer (either "optim" or "nlminb" for reciprocal designs and "bobyqa" and "Nelder-Mead" for non-reciprocal designs).

Once the run is configured, users can click the blue button labeled "Estimate the SRM Now!" The results then appear on the right-hand side of the screen and users can select the blue horizontal tabs to view the Text, Tables, or Computer Output:

Text. A verbal summary of the main results from the study are provided. The purpose of this text is to aid a user in two ways. First, the text helps a user understand the DDD set used in the analysis, including the number of unique groups, actors, partners, and cases and the prevalence of missing data. Second this text explains the SRM results, including the fixed and random effects, as well as a test of equal actor and partner variances for reciprocal design.

Tables. Among the tables included are the descriptive statistics of the predictor variables and the outcome, the results for the fixed effects, and the SRM variances and correlations.

Computer output. Included is the *R* setup, output of the basic run, and resulting variance-covariance matrix of predictor effects.

The last two purple tabs on the left-hand side of screen allow downloading of the data and a report of the results.

Download New Dataset. The user can download a dataset needed for a re-analysis of the dataset on one's own. If the data are reciprocal, dummy variables necessary for the Snijders and Kenny's (1999) approach are automatically attached in the downloaded dataset. The R syntax is also given in the Computer Output section. Reproducing the results locally would require calling the custom SRM class for R at http://apknight.org/pdSRM.R, as explained by Knight and Humphrey (2019).

Download Output. Users can choose to save the output file into docx, html, or pdf formats.

SRM_R has numerous error checks. The key one is a check on whether the model converges. For most data, the default settings work fine. Yet, users may sometimes experience convergence issues. Such non-convergence is typically a sign that something is not quite right with the specification of the model or the data. Typical problems could be wrong data organization, too many missing values, and (almost) no actor or/and partner variance. If, after inspecting their data, users believe nothing is wrong, making changes on model specifications, estimation procedure or the optimizer may help model to convergence. Note that sometimes a sub-model may fail to converge and if so, there would not be a significance test for that component. Other error checks include: if the design is not reciprocal, the user is notified, the user can make that change. Also, if there are group-level predictors, the user cannot choose to treat the group effect as fixed.

Of note, SRM_R is designed to facilitate iterative data analysis, such that if users want to make changes to their model, they can simply revisit the tab on the left-hand side, make the changes, and again click the blue *"Estimate the SRM Now!"* button.

Demonstration of SRM_R

After introducing the function of each tab, in this section, we illustrate how SRM_R can help researchers address substantive research questions through our analyses of advice seeking behavior.

Testing Questions of *Variance* and *Reciprocity*

Answering the first two research questions we posed above requires researchers to first partition the variance in a dyadic measurement. For our illustrative example, this entails estimating how much the rating of advice seeking is attributable to characteristics of groups, actors (i.e., advice seekers), partners (i.e., advice providers), and relationships. To do so, we estimate a null model—a SRM without fixed-effect predictors—in SRM_R.[1] Following the steps outlined above, we provide the information needed in the two mandatory green-colored tabs "Select Data" and "Variables, Design, & Terms"). Then, after clicking "Estimate the SRM Now!" the results appear on the right-hand side of the screen.

[1]One can view the null model as a mis-specified model if covariates are needed in the model and excluding covariates can lead to wrong conclusions about variance components. Alternatively, including a covariate can potentially remove "too much" variance of a component if it is merely another measure of the criterion variable. As SRM_R is reactive, enabling users to change the analysis based on previous results, we suggest researchers may adopt an iterative approach to examine null model first and learn if they should include covariates. Of note, management studies (e.g., Joshi & Knight, 2015) often adopt such an iterative approach.

In the *Table* tab, SRM_R gives a table of the random effects (see Figure 5). To answer the "Questions of Variance" that we proposed above—that is, to determine whether advice seeking is a function of the group, the actor, the partner, or the unique relationship between two people—researchers can examine the relative variance in each random effect component. The results in Figure 5 show that nearly half the variance (46.3%) in advice seeking is located at the relationship level. Of note, this relationship component comprises both relationship and error variance—we should be wary of concluding that all this variance is due to meaningful relational characteristics. Also, in line with prior research, individual level characteristics also help explain variance in advice seeking (actor variance = 44.7%, partner variance = 9%, both $p < .001$). Yet, group variance essentially equals zero and is not statistically different from zero ($\chi^2 = 0.001$, $p = .980$, *n.s*), indicating that group context likely does not explain variance in employees' advice seeking behavior.

------- Insert Figure 5 about here -------

Figure 5 also shows the generalized correlation and the dyadic correlation, which indicate the degree of reciprocity in advice seeking and can be used to answer the "Questions of Reciprocity" that we posed above. As Figure 5 shows, we found a non-significant generalized correlation of advice seeking ($r = .057$, $p = .663$, *n.s.*), indicating that there is no evidence to claim advice seekers tend to attract advice seeking from others. The dyadic correlation of advice seeking, however, is significant and positive ($r = .216$, $p < .001$), indicating there is reciprocal advice seeking behavior within a given pair of team members. We reproduce the text provided in the *Text* tab, which summarizes in plain language the SRM results regarding the random effects (see Appendix B).

Testing Questions of *Explanation*

Apart from the partitioning of variance and reciprocity correlations, in the next step of our illustration, we explore the impact of gender and proactive personality on advice seeking behavior (questions of explanation) by including fixed effect predictors in the model. Following Knight and Humphrey's (2019) approach, in preparing the dataset, we included two group level variables (GX1: Percent of female members in groups; GX2: group average of members' 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), as well as two relationship level variables (RX1: Same vs. different gender; RX2: Similarity of actor's and partner's proactive personality). After estimating the null model, users can immediately go to the *Predictor Variables* tab and enter these predictors into the model. Within the same tab, we check *Center Predictor Variables* and grand-mean center continuous variables (GX1, GX2, AX2, PX2 and RX2) to make the intercept more interpretable[2]. Once completed, users click "Estimate the SRM Now!" The results, again, appear on the right-hand side of screen.

Starting at the group level analysis, as Figure 6 shows, neither of the group level predictors helps to explain why advice seeking behavior is higher in some groups than others. Specifically, the percent 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'

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[2]Centering is also important in MLM in the interpretation of effects (Enders & Tofighi, 2007). Because in the SRM there are at least four different levels, centering issues become even more complicated. Besides discussion by Banchefsky et al. (2016), there is relatively little discussion in the literature on how to appropriately center fixed covariates within the SRM.

proactive personality (*b* = 0.497, *p* = .250, n.s.). The lack of significant predictors at the group level makes sense, given the lack of meaningful group-level variance as reported above.

Then, at the individual level of analysis, we consider both actor and partner characteristics with respect to gender and proactive personality. With respect to actor characteristics, actor's proactive personality is significantly and positively related to advice seeking behavior (*b* = 0.312, *p* = .033). This positive coefficient indicates that those who are higher in proactive personality tend to seek more advice, in general, than those who are lower in proactive personality. Actor's gender, however, has a non-significant relationship with advice seeking behavior (*b* = 0.126, *p* = .344, n.s.).

Next, with respect to partner characteristics, partner's gender helps explain who tends to receive more advice seeking. The results in Figure 6 show that, compared to men, women are more often to be the target of others' advice seeking behavior (*b* = 0.173, *p* = .038). Partner's proactive personality has a non-significant relationship with advice seeking behavior (*b* = -0.140, *p* = .123, n.s.).

Finally, at the relationship level, the interaction term between actor gender and partner gender sheds light on whether more advice seeking from same vs. different gendered pairs. Specifically, the results in Figure 6 indicate a positive interaction effect, suggesting that more advice seeking occurred in pairs of group members of the same gender than of different genders (*b* = 0.144, *p* = .032). Similarity of actor's and partner's proactive personality has a non-significant relationship with advice seeking behavior (*b* = -0.060, *p* = .558, n.s.).

------- Insert Figure 6 about here -------

Discussion

Although recent research has increasingly recognized the need to adopt social relations designs, analyses are infrequently conducted at the dyadic level with appropriate statistical tools (Krasikova & LeBreton, 2012). Furthermore, for those who are not familiar with SRM, analysis can be extremely difficult and error-prone. To address these concerns, we have introduced and demonstrated how DDD can be analyzed using the app SRM_R. Specifically, we described features of the SRM_R, a freely-available and easily-accessible online application that performs social relations analyses with multilevel estimation. In addition, we demonstrated the functionality of the SRM_R by using it to examine *questions of variances* (e.g., what is the source of advice seeking?), *questions of reciprocity* (e.g., how does one person's advice seeking toward others relate to others' advice seeking toward them?) and *questions of explanation* (e.g., how do dyad members' gender and proactive personality explain variance of advice seeking?). As we discuss below, the introduction of SRM_R will help to reduce barriers that currently inhibit management researchers from exploring important dyadic phenomena in groups. In addition, we describe several limitations of SRM_R and possible improvements.

Implications for Organizational Research: Removing Barriers for Dyadic Research

Whereas methodologists may be very interested in the process of estimating the parameters of a statistical model, organizational researchers are much more interested in exactly how they can answer their questions. However, when it comes to dyadic research, many organizational researchers do not know how to handle the DDD sets they collect, and consider the complicated steps in social relations analyses as a "necessary evil" merely to please the demands of editors, reviewers, and coauthors. In the ideal, the SRM should open the door to understanding for researchers interested in dyadic phenomena—not make it impassable with data manipulation challenges and technical obstacles. Although we have seen more researchers adopt social relations methods to investigate organizational phenomena in recent decades, dyadic research in organizational studies is still in its infancy. 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).

The SRM_R app is developed to address this problem, aiming to bridge the gap between methodologists and organizational researchers in social relations analyses. Indeed, the SRM_R is part of a larger project DyadR[3]—a cluster of web programs that help researchers conduct and understand dyadic data analyses. The overarching purpose of DyadR, including SRM_R, is to automate complicated dyadic data analyses and to present the results in a straightforward and accessible way for researchers. With SRM_R, researchers can perform social relations analyses at ease by simply pointing and clicking the required information (i.e., name of variables or types of analyses) without having to deal with all the complicated steps. In other words, organizational researchers do not need to bother to learn how to handle the complicated steps in SRM.

One potential disadvantage of SRM_R, though, is that it may discourage researchers to study the statistical background of SRM. We agree this may happen, but at the same time, its ease of use actually removes the barrier for beginners who want to kickstart their investigation of the dyadic phenomenon. Curious researchers can access the R syntax behind SRM_R in the “Computer Output” section and read relevant information from Snijders and Kenny (1999). By introducing SRM_R, we hope to promote a more effective understanding of SRM and its application in organizational settings.

Limitations of and Future Developments for SRM_R

[3]Readers can access all programs under DyadR by visiting http://davidakenny.net/DyadR/DyadRweb.htm.

Although SRM_R greatly simplifies the analysis of DDD, it does have limitations. First, the multilevel estimation implemented in SRM_R assumes that SRM effects are random effects that are normally distributed. That said, all analyses within SRM_R should be limited to normally distributed outcome measures. If the outcome measure were dichotomous (e.g., help or not help) or a count (how often someone asks for help), SRM_R would be unable to analyze such data. For such dichotomous data, users may consider other alternative statistical models. One option is the p2 model of van Duijn et al. (2004), like SRM, partitions a dichotomous outcome measure into group-level, individual-level, and dyad-level components.

Second, SRM_R is limited to univariate outcomes. That is, the program could not conduct a full bivariate analysis—decompose each of two round-robin variables into SRM components and compute additional correlations among these SRM components. Additionally, within the SRM, self-ratings can be extensively analyzed and their association with actor and partner effects can be measure and removed to study self-enhancement. These features are currently not available in the initial release of SRM_R, but we are exploring adding them in future updates. In the meantime, the user can use covariates to examine bivariate relations of two round robin variables and determine each of effects of actor and partner self-ratings on dyadic outcome variable. Relatedly, because the program only allows for univariate outcome, SRM_R is unable to perform latent variable analyses that separate error from relationship effects—even though researchers may have multiple items in measuring outcome variable.

Finally, 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 that cannot be changed within the program. Thus, SRM_R cannot currently handle DDD sets collected from the asymmetric block design or the block round-robin design, and does not allow users to add random slope in the model or implement longitudinal analyses with random effects. Users who wish to conduct more complicated analyses may need to download the R syntax in the Computer Output section, as well as their configured dataset, and perform these analyses locally.

Conclusion

The SRM has been an important tool to test hypotheses in organizational research. It is a method that is especially appropriate when groups or teams are studied in organizations. However, performing a social relations analysis using currently-available options is complex and time-consuming for researchers new to dyadic analyses and/or novices in computer programming. We have in this paper shown how the app SRM_R can be used to assist in not only analyzing DDD, but also in interpreting the results. We hope that SRM_R will foster the more frequent use of SRM to examine organizational phenomena occurred at dyadic level.

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Table 1

Social Relations Designs in Group of Six Members

1. Round-robin design

	Partner					
Actor	***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}	

2. Block Design

	Partner					
Actor	***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}			

3. Half Block Design

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

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

Table 2

An Illustration of a Directed Dyadic Dataset 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* = Percent of female members in groups. *GX2* = Group average of members' 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 vs. different gender (Actor's gender × partner's gender). *RX2* = Similarity of actor's and partner's proactive personality (|Actor's proactive personality – Partner's proactive personality|)

Figure 1
Initial SRM_R Graphical User Interface

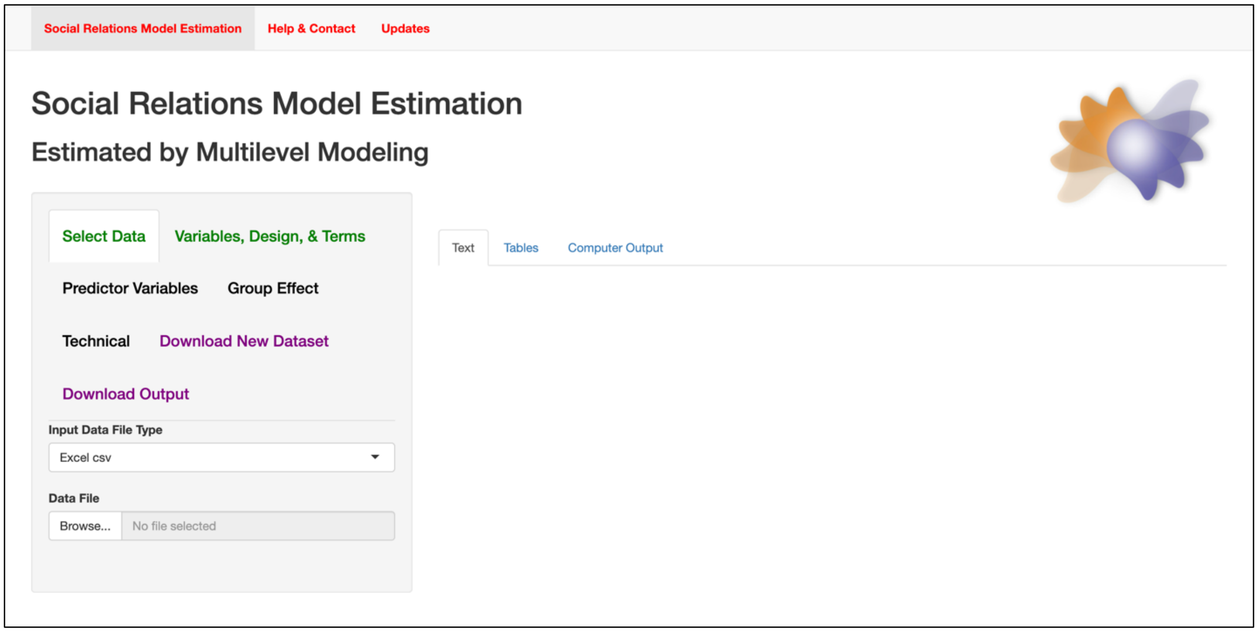


Figure 2

View of Select Data Tab

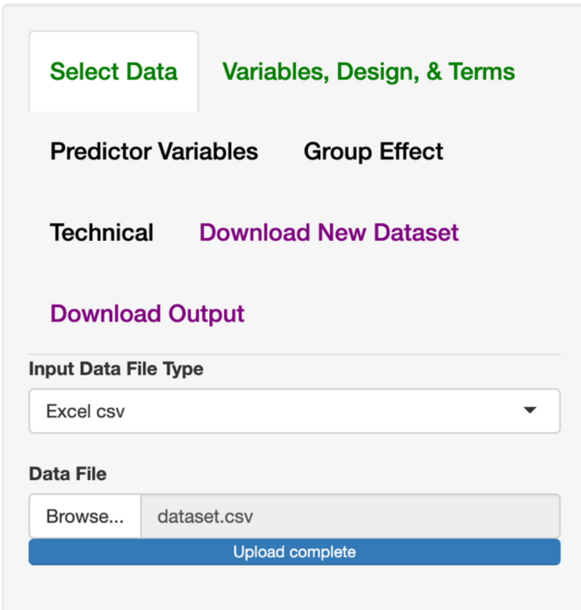
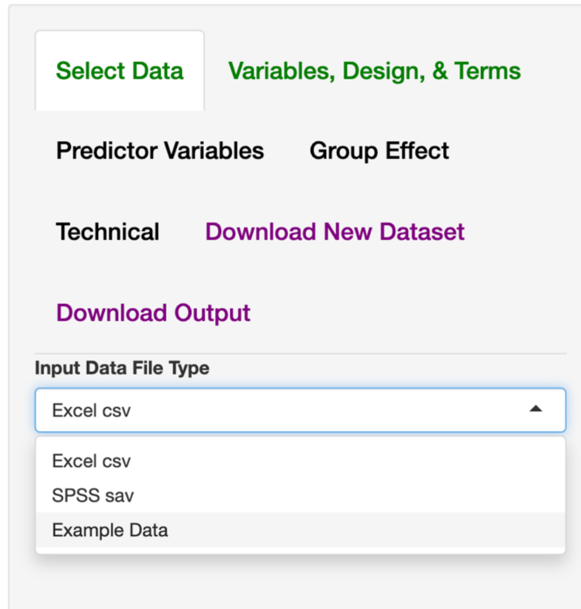
(a) Selecting Data from the Local Computer	*(b) Selecting Example Data*
	

Figure 3

View of Variables, Design, & Terms Tab

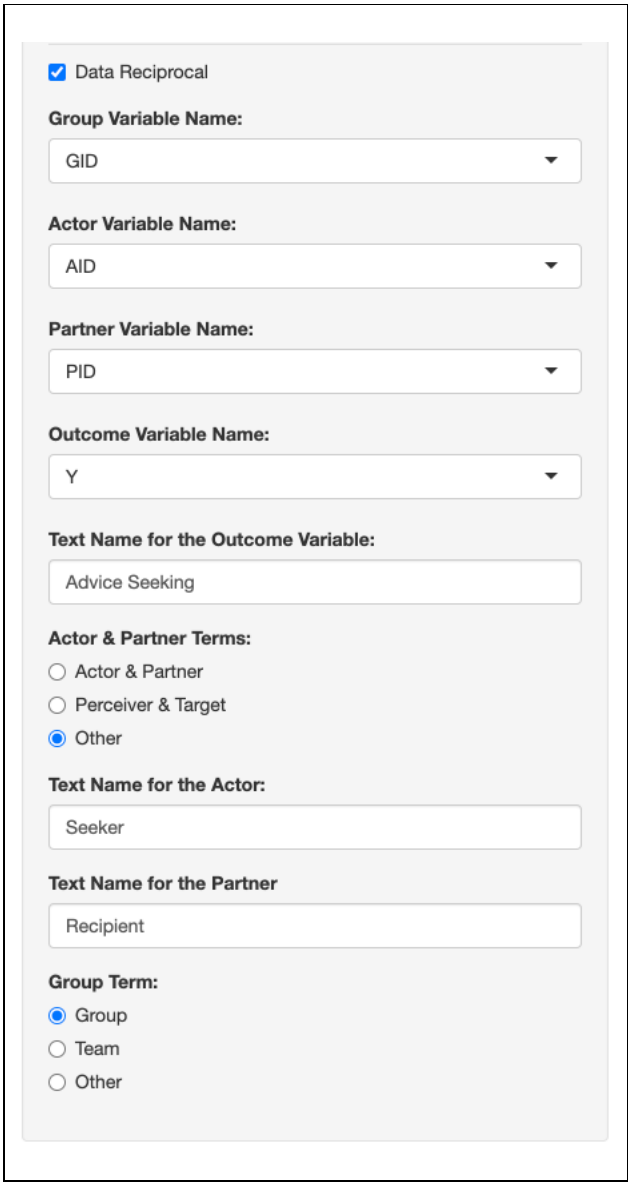


Figure 4

View of Predictor Variables Tab

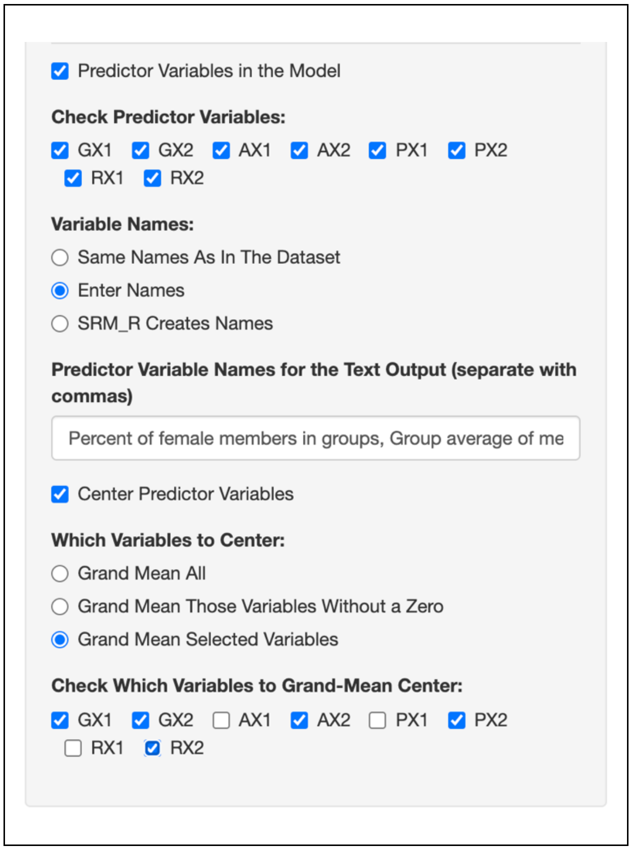


Figure 5

View of Table Tab Showing Social Relations Analyses Results of Advice Seeking (Null Model)

Text Tables Computer Output

Table 1: Descriptive Statistics

Variable	Mean	SD	Minimum	Maximum
Advice Seeking	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 6

View of Table Tab Showing Social Relations Analyses Results of Advice Seeking with Fixed Effect Predictors

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
Percent of female members in groups	-0.593	-1.422	to	0.235	44	.156
Group average of members' 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 personality	-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

Appendix:

A. Sample tables from SRM_R output of the illustration

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
Percent of female members in groups	-0.593	-1.422	to	0.235	44	.156
Group average of members' 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 personality	-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 illustration example

Text reproduced for the null model

Model:

SRM_R conducts a Social Relations analysis of directed dyadic data. The design is reciprocal in that seekers are also recipients 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 Setting:
SRM_R conducts a Social Relations analysis of directed dyadic data. 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 Percent of female members in groups, Group average of members' 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 personality and their names in datafile are GX1, GX2, AX1, AX2, PX1, PX2, RX1, and RX2. The predictor variables at the group level are Percent of female members in groups and Group average of members' 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 Percent of female members in groups is 0.156 with a p value of .156. The effect of Group average of members' proactive personality is 0.250 with a p value of .250. The effect of Actor's gender is 0.344 with a p value of .344. The effect of Actor's proactive personality is 0.033 with a p value of .033. The effect of Partner's gender is 0.038 with a p value of .038. The effect of Partner's proactive personality is 0.123 with a p value of .123. The effect of Same vs. different gender is 0.032 with a p value of .032. The effect of Similarity of actor's and partner's proactive personality is 0.558 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.