Looking at dyads: A primer on actor-partner analysis in marriage research

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Appearing in:

Weisfeld, C. C., Weisfeld, G. E., & Dillon, L. M. (Eds.) (2018). *The Psychology of Marriage: An Evolutionary and Cross-Cultural View*. Lanham, MD: Lexington Books.

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From the building block of social networks, to the basis of a monogamous romantic relationship, and to the simplest structure of social interactions, the basic unit of social interactions and relationships is the dyad—a group of two. Through studying married couples and romantic relationships, we can study factors shared by both partners (e.g., relationship length) as well as factors specific to each individual (e.g., each person's relationship satisfaction). However, as relationship researchers, we must also examine inter-individual processes between both members. Accounting for how one partner might influence the other has been central to much theory in relationships. For instance, attachment theory (Bowlby, 1982) holds that parents' care and interactions with an infant will shape infants' perceptions and expectations of close relationships throughout life. Depending on whether an infant develops a secure or more insecure attachment, this style of attachment will later influence others' perceptions and social interactions with the person (e.g., Berlin, Cassidy, Appleyard, 2008). Indeed, building theories on interpersonal relationships and interactions requires analyses of more complex, dynamic interactions among people. This type of analysis contrasts from the analytic approach supplied by the oft-used ANOVAs, t-tests, and standard regressions, tools originally developed to analyze data from potatoes, beer brewing, and the orbits of comets—not humans and their dynamic, interactive social relationships (Eden & Fisher, 1929; Gauss, 1809; Livingston, 2004).

The purpose of this chapter is to thus provide a brief primer on dyadic analyses. We orient this chapter to introduce researchers to analytical and methodological issues when examining dyadic data from marriages. We also highlight new trends, limitations, and future directions for dyadic analysis in the field. In doing so, we wish to point the reader toward authoritative comprehensive guides by which to conduct these analyses such as those of Kenny, Kashy, and Cook (2006). Additionally, our introduction to this methodology primarily focuses on the analysis of cross-sectional dyadic data. For in-depth discussions of dyadic longitudinal modeling, we point the reader toward other methodological reviews, such as those of Ackerman and colleagues (Ackerman, Donnellan, Kashy, & Conger, 2012). Dyadic analysis requires less-commonly used statistical techniques such as multilevel linear modeling (MLM) and structural equation modeling (SEM). For background on these techniques, we refer readers to comprehensive guides to conducting MLM (e.g., Luke, 2004; Snijders, 2011) and SEM (e.g., Bollen, 1989; Kline, 2016; Raykov & Marcoulides, 2006; Ullman & Bentler, 2003).

Harnessing Interdependence

An apt starting point to champion the use of dyadic analyses in relationship science is nonindependence (interdependence). When a variable is nonindependent, scores in one group member are often related to scores in another group member. For instance, when a student in a classroom is experiencing elevated stress, other students are likely to be as well, although the source of this nonindependence may vary (e.g., taking an exam, challenging course content). Marriages, and, more broadly, all social relationships, have a hefty amount of nonindependence/interdependence. This nonindependence takes three forms. First, marriages have nonindependence in that both members are affected by mutually experienced external factors ("*common fate*"). These sources of common fate nonindependence could be environmental, situational factors both couple members endure, or group-level relationship factors (e.g., economic hardship, housing quality, household income). Factors in marriages also involve *mutual influence*—another type of nonindependence—between members. For example, if one partner is experiencing positive affect, so will the other, and this perhaps may create a reciprocal feedback loop of positive emotionality. Finally, and importantly, marriages may also have *partner effects*. With partner effects, a distinct variable in one partner may affect a different variable in the other. For example, recent research in married couples suggests that having elevated depression and anxiety symptoms predicts shorter sleep durations in individuals' romantic partners one year later (Revenson et al., 2016).

It is well known that nonindependence is a substantial problem for many commonly used data analytic techniques (Bliese & Hanges, 2004; Heck & Thomas, 2000; Kenny, 1996; Kenny & Judd, 1986). Often, the statistical techniques that researchers employ to study social processes are ill-equipped for dealing with nonindependence or assume that the data points are independent. The key reason for this is that more conventional statistical tests such as ANOVA and regression analysis assume that all units observed must be statistically independent of each other. A high degree of interdependence can bias statistical models that assume statistical independence (O'Connell & McCoach, 2008), inflating the likelihood of type I errors (e.g., Bliese & Hanges, 2004).

However, we as researchers would not necessarily benefit by eliminating, reducing, or controlling for nonindependence (or interdependence) from our data. Instead, interdependence must be modeled with our methods. Although it is a statistical nuisance, interdependence has critical theoretical meaning for the study of relationships. As we reviewed, all of the common sources of interdependence in relationships (common fate, mutual influence, and partner effects) have bearing on some unique theoretical processes. Thankfully, dyadic analysis offers tools for assessing interdependence and processes within the dyad.

Dyadic Analysis

Dyadic analysis is a constellation of approaches and techniques designed to assess and account for interdependence within groups of two. Whereas more conventionally used parametric statistics (e.g., ANOVA, regression) assume that all observations are independent, dyadic data analysis can use statistical models to quantify and account for the interdependence. More broadly, the statistical analyses used by dyadic data analysis (e.g., multilevel modeling, structural equation modeling) can also account for larger groups that may have interdependence beyond the dyad.

In dyadic analysis, researchers distinguish between several different types of variables related to the structure of a dyad. *Between-dyad variables* are factors that are quantitatively common between two dyad members (e.g., the length of a romantic relationship, the number of children cared for by a cohabitating couple), and always have the same value for each member of the dyad. On the other hand, *within-dyad variables* will systematically differ between dyad members, but be of equivalent frequency across dyads (e.g., numerically-coded values of gender within heterosexual couples, ranks of players in individual tennis competitions). Moreover, each dyad member must have different values of a within-dyad variable, yet the distribution of these different values will be the same across all dyads in an analysis. To illustrate, a study examining dyadic interactions between patients and physicians will typically have one patient and one physician in each dyad. The role of each person in this dyad will always be different within each dyad, yet each dyad in the data will contain the same distribution of the patient/doctor role. Lastly—and commonly used in the dyadic analysis of couples' data—are *mixed variables*. Mixed variables occur when different values are observed within each dyad member, and values can vary across couples (e.g., relationship satisfaction of each partner in a relationship, personality traits of each partner).

A critical feature of a dyad is often whether the two members of a dyad can be distinguished from each other in some fashion, typically a within dyad variable. When dyad members can be distinguished on this basis, this is referred to as *distinguishable dyads.* If not, the dyad members are considered *indistinguishable.* For instance, if a sample consists exclusively of heterosexual couples, the couple members could be considered distinguishable on the basis of gender, whereas same-sex couples are indistinguishable on that basis. The difference between distinguishable and indistinguishable dyads is important to researchers because it can affect model specification and statistical power. For models with distinguishable dyads, it is possible to estimate specific parameters for each category of member in the same model. For example, one might want to estimate whether actor and partner effects differ between distinguishable members, or describe the individual effects for the distinguishable members. Researchers have also argued that it is important to avoid making dyads distinguishable when there are no substantive differences in the distinguished dyad members (Kenny et al., 2006), testing for the presence of empirical distinguishability before assuming it exists (Ackerman et al., 2011). [1]

The Actor-Partner Interdependence Model (APIM)

Although dyadic analysis safeguards the researcher against drawing conclusions about their data that are biased by interdependence, dyadic analysis also allows one to draw substantive conclusions from interdependence itself. One key piece of knowledge gained from this approach is that dyadic analysis allows researchers to uniquely study the interpersonal processes of relationships. Many dyadic designs take the approach of the actor-partner interdependence model

[1] Methodologists have cautioned against the tendency for distinguishable dyads, and moreover, analyzing men and women separately, to overemphasize gender differences (Ackerman et al., 2011).

(APIM; Kashy & Kenny, 2000; Kenny, 1996). This model estimates the influence of variables specific to one person (e.g., their behavior, personality traits) on other variables within the same person (e.g., relationship satisfaction)—termed *actor effects*. This model also estimates the influence of variables within one person influencing variables within another dyad member—termed *partner effects*. Beyond the ability to account for interdependence, this type of analysis can yield substantive information about social processes in dyads, revealing how dyad members might influence each other (e.g., how one partner's emotionality might affect the other partner's relationship satisfaction). Overall, the APIM approach is suitable for assessing actor and partner effects. However, alternative approaches to assessing different types of interdependence, such as the common-fate model (Ledermann & Kenny, 2012) and the mutual-feedback model (Kenny, 1996; Woody & Sadler, 2005) may prove useful for other types of research questions less related to interpersonal influence in dyads.

APIM models assume that the same variables are measured in each member of the dyad. This requirement may not be fulfilled by every dataset or research method (e.g., if wives completed a measure that husbands did not). Additionally, the APIM approach must use predictor variables and dependent variables that are measured on the level of the individual. Moreover, predictors specific to the dyadic members (e.g., husbands' and wives' relationship responsiveness) must predict outcomes specific to the members (e.g., husbands' and wives' relationship satisfaction) rather than a variable that pertains to the couple as a whole (e.g., length of a romantic relationship).

To illustrate the concept of APIM, we provide an example where a researcher is investigating how stress predicts relationship satisfaction within couples (See Figure 1). This is the standard way of illustrating the APIM. Here, the predictor, stress, is measured in both married partners, as is the dependent outcome, relationship satisfaction. This analysis allows the researcher to use each individual's level of stress to predict his or her own level of relationship satisfaction (actor effects), such as the actor effect from Partner 1's stress to Partner 1's relationship satisfaction (A_{p1}), and the actor effect from Partner 2's stress to Partner 2's relationship satisfaction (A_{p2}). Importantly, this model also allows the researcher to examine processes between partners, such as the partner effect of Partner 1's stress on Partner 2's relationship satisfaction ($P_{p1 \rightarrow p2}$), or alternatively, the partner effect of Partner 2's stress on Partner 1's relationship satisfaction ($P_{p2 \rightarrow p1}$). There are additional parameters in this model, such as the residual variance of the partners' relationship satisfaction (E_{p1} *and* E_{p2}*;* i.e., variability not explained by either partners' stress), the covariance between the predictors (r_x; the covariance between Partner 1's stress and Partner 2's stress), and the covariance between the residual variances (r_y). This model could be construed as representing a distinguishable dyad, since separate parameters might be estimated for partner 1 and partner 2 in models where partner 1 and partner 2 represent different values of distinguishability (e.g., different genders). However, in a structural equation modeling context, constraining the actor effects (A_{p1} and A_{p2}) and partner effects ($P_{p1 \rightarrow p2}$ and $P_{p2 \rightarrow p1}$) would transform the estimation of this model to represent an indistinguishable dyad. Methodologists assert that APIM of indistinguishable dyads is easiest to implement using multilevel linear modeling (MLM). For an example of how to interpret an empirical example of APIM data, we refer readers to our supplemental section on APIM analysis.[KMW1]

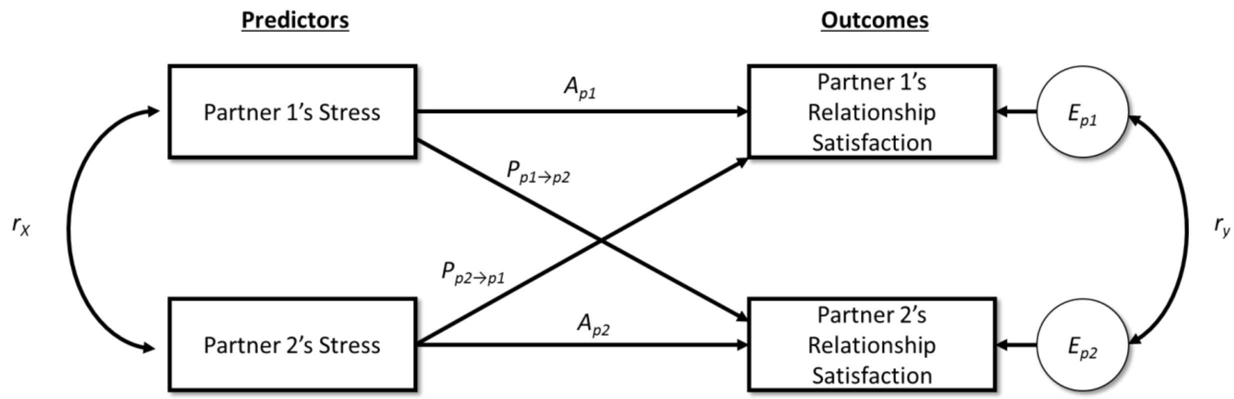

Figure 1. An illustration of the APIM for a couple. r_X = covariance between the predictors; r_y = residual nonindependence not accounted for by the actor and partner effects; A_{p1} = Actor effect for partner 1; A_{p2} = Actor effect for partner 2; $P_{p1 \rightarrow p2}$= Partner effect from Partner 1 to Partner 2; $P_{p2 \rightarrow p1}$ = Partner effect from Partner 2 to Partner 1; E_{p1} = residual variance for partner 1; E_{p2}= residual variance for partner 2; r_x = covariance between each dyad member's predictor variable; r_y = covariance between the dyad members residual variances.

Getting Down to Brass Tacks: Using Dyadic Analysis

Much of dyadic analyses is implemented through multilevel linear modeling (MLM) or structural equation modeling (SEM), which can account for interdependence in multiple ways. Some ways of performing dyadic analysis are easier depending on the software. For instance, syntax for performing simple dyadic APIM analyses has been supplied for popular software such as SPSS and SAS by methodologists (e.g., Kenny et al., 2006). This software permits the researcher to make small adjustments to the syntax so that it may better fit their data, provided their dataset is set up correctly (we discuss this later). On the other hand, more complex models such as cross-lagged longitudinal dyadic designs (e.g., assessing actor and partner effects across multiple time points) are often more easily implemented with SEM, provided the researcher has enough background in this statistical method.

In MLM, the data have a hierarchical structure whereby observations are clustered within higher order units, such as college faculty members (level 1) being clustered into academic departments (level 2), which are in turn nested within a college or university (level 3). In multilevel dyadic analysis, each dyad member (a lower, level 1 unit) is nested within each dyad (a higher, level 2 unit). In this type of analysis, there are regressions conducted on the level of the individual, and regressions on the level of the dyad. Dyadic MLM combines the effects on both levels into one model, while accounting for interdependence occurring within the dyad, or more broadly, any higher level unit.

In structural equation modeling (SEM), separate latent variables (unobserved variables that are inferred through a combination of measured variables) are typically created representing the predictors and outcomes measured individually in each dyad member, in a similar structure to that of Figure 1. Pathways from the predictor (or exogenous) variables pointing to the outcome (or endogenous) variables can take the form of actor and partner effects. Often in SEM, researchers seek to have over-identified models as these allow for the model fit to be evaluated. In an over-identified model, the number of known values in a model is greater than the number of free parameters, allowing a unique solution to be estimated for all parameters in the model. APIM models in SEM are typically just-identified (contain an equal number of known values and free parameters) unless constraints are placed on the model (e.g., by fixing parameters to be equal or fixed at specific values). This allows researchers to estimate parameters in the model but does not allow researchers to substantively evaluate model fit. Conducting dyadic analysis with SEM is primarily geared toward distinguishable dyads (Cook, 1994), but researchers have developed some approaches for SEM with indistinguishable dyads (Olsen & Kenny, 2006; Woody & Sadler, 2005).

Data Structure

Altogether, the data in dyadic analysis can take one of two structures: dyad structure, and pairwise structure (Kenny et al., 2006). We illustrate each of these structures using our example of married couples' stress and relationship satisfaction, shown below in Table 1. Both data structures indicated in the table are permutations of the very same data. Through the use of common restructuring tools available in most mainstream statistical packages, it is easy to shift one's data between these two structures.

The first of these, the *dyad structure*, is designed so that each row represents a dyad. Variables for each member of the dyad are indicated in separate rows. In the example in Table 1, the data have separate stress and satisfaction scores for persons 1 and 2, whereas the between-dyad variable relationship length describes the dyad as a whole. This dyad structure is typically used in conceptually distinguishable dyads (e.g., men vs. women). Since this structure treats the dyad as the only examined unit, it is convenient to analyze these dyadic data with more conventional statistics.

The second of these structures, *pairwise structure*, is more appropriate for indistinguishable dyads than dyad structure and lends itself to multilevel modeling. In this structure (see Table 1), each row represents an individual, and each dyad takes up two rows. There are two identification variables indicating a person's membership in the dyad and a within dyad variable providing identification with the dyad (e.g., person 1 vs. person 2). In distinguishable dyads, it is sometimes the case that researchers will use the distinguishing variable (e.g., gender) to distinguish members of the dyad instead of the person indicator variable. In this example, the between-dyad variable, relationship length, is the same for each dyad member. However, the mixed variables of stress and satisfaction are represented as actor and partner variables. In this example, actor stress and satisfaction are the self-reported stress and satisfaction of the participant in each column, whereas partner stress and satisfaction represent those of the other dyad member or partner.

These two structures are the most commonly used in dyadic analysis. However, some researchers have used "one-with-many" structures and the "social relations model" structure (for reference, see Kenny, Kashy, & Cook, 2006). It is recommended that researchers keep multiple options of data structures available, as the very structure of the data will determine what types of analyses are used in dyadic analysis.

Table 1. Data Structures for Dyadic Analysis.

Dyad Structure

Dyad	Person 1 Stress	Person 1 Satisfaction	Person 2 Stress	Person 2 Satisfaction	Relationship Length
1	2	4	3	2	2
2	2	2	4	4	4
3	2	4	3	5	1
4	5	3	1	3	2

Pairwise Structure

Dyad	Person	Actor Stress	Actor Satisfaction	Partner Stress	Partner Satisfaction	Relationship Length
1	1	2	4	3	2	2
1	2	2	2	2	4	2
2	1	3	2	4	4	4
2	2	4	4	2	2	4
3	1	2	4	3	5	1
3	2	3	5	2	4	1
4	1	5	3	1	3	2
4	2	1	3	5	3	2

Forefronts and Advanced Applications of Dyadic Analysis in Couples

Thus far we have primarily illustrated how dyadic analysis could be used in the most basic of dyadic designs and the APIM. However, dyadic analysis can occur in many permutations and forms. Below, we discuss three advances in dyadic analysis: longitudinal models, mediation, and analyses of groups of couples.

Longitudinal models. With longitudinal modeling, researchers are interested in the implementation of change in couples over time (Ackerman et al., 2012). In this approach, both the dyad and time provide a source of interdependence. Because of this, MLMs with three levels are often used, with the dyad-level variables modeled on level 3, the individual-level variables modeled on level 2, and time-specific variables modeled on level 1. Since data from couples-are collected simultaneously, the persons and days are typically crossed, rather than having days nested within persons. One common research method-used in this approach is the daily diary study (e.g., Muise et al., 2013; Muise & Impett, 2015, Study 2; Otto et al., 2015). We refer interested readers to detailed descriptions of longitudinal dyadic analysis provided by Ackerman and colleagues (2012) as well as Bolger and Shrout (2007).

Process analysis in couples. Researchers are also paying attention to the statistical processes between dyad members in couples, in terms of both mediation and moderation. Statistical mediation occurs when independent variables affect outcomes through the process of an intervening third variable, the mediator (Baron & Kenny, 1986; Hayes, 2009). This area of research is crucial for establishing the explanatory mechanisms of effects in marriage data. Although research on mediation has been well-established for non-independent models (for review, see Hayes, 2009, 2013; Iacobucci, 2008; MacKinnon et al., 2007), methodologists are developing methods of assessing mediation within dyads and other nonindependent data structures (e.g., Ledermann & Macho, 2009; Ledermann, Macho, & Kenny, 2011).

Studies of multiple interacting couples. Recent researchers have adopted dyadic analysis to study interacting couples. These "double-couple" studies suggest that friendly, novel interactions with another couple may increase positive affect and closeness (Slatcher, 2010), as well as increase passionate love (Welker, Baker, Padilla, Holmes, Aron, & Slatcher, 2014). They also provide preliminary evidence that friendly intergroup couple interactions may reduce prejudice (Welker, Slatcher, Baker, & Aron, 2014). In the first of this emerging work, Slatcher (2010) randomly assigned pairs of couples to participate in a novel, high self-disclosure discussion task (developed by Aron et al., 1997) or a low self-disclosure “small-talk” discussion task, and measured positive affect and closeness. This paper adapted the APIM approach to model how the experimental condition affected positive affect and closeness, along with how positive affect mediated the effect of the experimental condition on closeness using path analysis. The path model of this type of analysis is displayed in Figure 2). Structural equation modeling is especially well-suited to conducting this type of analysis, which allows for incorporation of distinguishable factors (e.g., males vs. females), but also indistinguishable factors (one couple vs. the other couple) and mediators (e.g., positive affect).

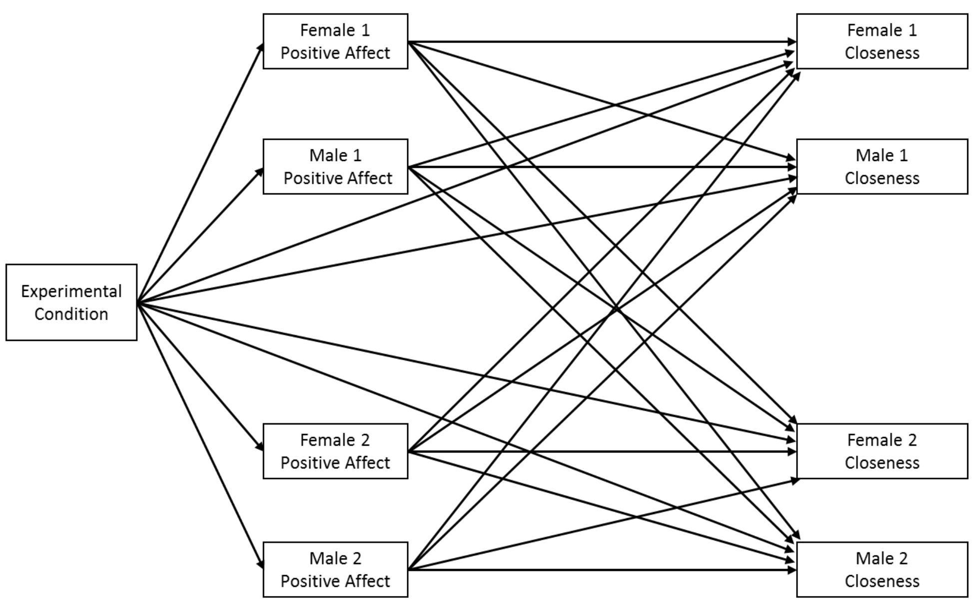

Figure 2. Double-couple mediated Actor-partner Interdependence Model (APIM) used by Slatcher (2010). For ease of viewing, this figure does not include correlated variances and errors from the model.

Future Directions and Current Limitations to Dyadic Models

Effect Sizes. One of the hallmark benefits of conventional statistics such as correlations, regressions, and ANOVAs is that effect sizes such as Pearson's *r* or Cohen's *D* can be used to make standardized assessments of statistical effects across different studies and analyses. Multilevel modeling approaches with dyadic analysis do not provide easy-to-understand estimates of effect size. In structural equation modeling, standardized path coefficients and some measures of model fit (e.g., the root mean square residual) can be used as indices of effect sizes (see Kelley & Preacher, 2012 for a review). In MLM, the most commonly used effect size metric is probably the "pseudo R^2" statistic (Kreft & De Leeuw, 1998), which provides an estimate of the variance explained for any random parameter. But generally, a current limitation of dyadic analysis is the lack of a simple statistic such as an effect size *r* or Cohen's *d* that can be used to compare dyadic effects across studies and across methodologies (i.e., across SEM and MLM).

Power analysis. Analysis of statistical power and sample size has been of growing concern in data analysis since the inception of Cohen's (1988) innovations in developing power analysis. Researchers have been quick to develop a wide variety of tools to determine sample size and statistical power for more conventional statistics such as correlations, regressions, and ANOVA (e.g., Faul, Erdfelder, Lang, & Buchner, 2007; Hintze, 1996). However, for the types of analyses often used in dyadic analysis, development of power analytic tools has lagged behind. Part of the complicated nature of determining sample sizes and power for multi-level models is due to the variability of samples at different levels and hierarchies of data analyses. For instance, multilevel data with students nested within classrooms, which are in turn nested within schools will have considerable variability with the number of classes and students within each class. The other complication lies in the varying degrees of interdependence between predictor measures and outcome scores which can affect statistical testing and increase the number of dyads needed to ensure adequate statistical power (Ackerman et al., 2011). Notably, researchers have developed some preliminary tools for two-level multilevel power analysis (see Snijders, 2005 for a review), which may be of particular use for simple dyadic designs (Snijders & Bosker, 1993; see http://www.stats.ox.ac.uk/~snijders/multilevel.htm#progPINT). For structural equation modeling, there has been plentiful discussion of the necessary sample size (e.g., Kline, 2015; Muthén & Muthén, 2002; Tanaka, 1987; Wolf et al., 2013). Researchers have also developed tools for a priori and post-hoc power analysis for testing the overall fit and specific parameters within structural equation modeling (Hancock, 2006). Notably, from the framework of structural equation modeling, Ackerman and colleagues (2011) have provided a tool for determining the number of dyads needed to ensure .80 statistical power given a convention alpha of .05, given expected correlations between predictors and outcomes, as an expected or assumed effect size of an actor or partner effect. [KMW2]

Toward replicable, well-powered dyadic research

At this point in social psychological research, concerns of research reporting false positives, or type I errors, have been very high (e.g., Murayama et al., 2014; Simmons et al., 2011). Although researchers are moving toward greater efforts for replicability in psychology (e.g., Open Science Collaboration, 2015), the costs and difficulties in the feasibility of collecting data from dyads makes replicating research especially challenging for relationship researchers. In addition, relatively large amounts of data are often needed for adequate statistical power to conduct successful replications. For example, based on the power calculations of Ackerman and colleagues (2011), a sample of 212 couples would be needed to estimate the most common effect size in social psychology as an actor or partner effect (r = .20, compare to r = .21 from Richard, Bond & Stokes-Zoota, 2003), assuming moderate degrees of interdependence between the predictor and outcomes in each couple member (*r*s = .30). Given the feasibility difficulties in conducting couples research, most couples studies are likely under-powered. This increases the likelihood of Type II errors. Additionally,-feasibility difficulties may push researchers away from direct replication studies, particularly when scientific norms value novel research over replication. But as the field of psychology demands more replication, the replicability and efficiency of couples research may lag behind other areas of social psychology. Nevertheless, this movement is advancing (Campbell, Loving, & LeBel, 2014; Finkel, Eastwick, & Reis, 2015).

We argue that the difficulties of couples research make it even more important to conduct replication studies. The feasibility and economic costs of replicating a couples study are greater than those of a similarly designed individual-level study (never mind the costs and difficulties of running the original study!). However, a far more dire consequence to consider is the time, costs, and effort researchers may have spent trying to conduct couples studies based on the theoretical consequences of false positive findings. Consider that Researcher A runs a dyadic study on couples, and publishes an influential paper. Researcher A's research involved more work and compensation than more typical individual studies. Now, Researchers B, C, and D are fascinated by Researcher A's findings, and decide to conduct follow-up studies without replicating the initial effect. Because the initial effect is flawed, Researchers B-D observe null results. The feasibility and economic costs of this cascading barrage of null follow-up studies to Researcher A's type I error will no doubt be far more costly to scientists than a direct replication. Extending the findings of tenuous, un-replicated couples research is a dire circumstance, and overall, the field will benefit from greater replication in couples research.

Conclusion

From data collection to analysis, studying couples is a challenge. With this chapter, we hope that current and future romantic relationship researchers will be primed with the knowledge to analyze and discover more about couples. Although dyadic analysis can be challenging to implement, it is critical to understand the nature of dyadic analysis for not only the analysis of data, but also the planning stages of research design. The field greatly needs to design studies that can test hypotheses that are dyadic in nature. We hope that this chapter captures the value of using the APIM in relationship research, providing researchers with new tools to collect data, and more importantly, build new theory.

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