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Analyzing Dyadic Data From Small Samples: A Pooled Regression Actor–Partner Interdependence Model Approach

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Abstract
The authors describe an approach to analyzing dyadic data that can be utilized with the smaller samples often available to researcher–practitioners working with couples in counseling. Specifically, the authors describe how to use the actor–partner interdependence model (APIM), a common dyadic data analysis tool, using a pooled regression approach that is appropriate for smaller sample sizes. An example is provided using data collected from a study of the role of expectancies in couple counseling outcomes. Additional data from the example study are provided in Appendix A for interested readers who want to practice the techniques they describe.

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quantitative, program, research, evaluation

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Counselors work in a variety of settings (e.g., schools and clinics), and they often are encouraged to participate as researcher–practitioners in evaluating the services they provide (Hays, 2010; Sprenkle, 2003). This requires developing competence and expertise in methods of data analysis that are appropriate not only for the setting but also for the available data. For some situations, the research techniques may be relatively straightforward, whereas in other settings, the nature of service provided and data collected make the situation more complicated.

This is the case for counselors who work with pairs, such as romantic dyads. In situations involving romantic couples, counselors may be interested in the outcomes of counseling for both members of the couple (e.g., adjustment) and how precounseling variables (e.g., expectations about counseling) and couple characteristics (e.g., length of relationship) relate to these outcomes. Appropriate techniques for analyzing

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data collected from couples, called dyadic data analysis techniques, are relatively new in the field of social sciences; their use has not yet widely spread outside of laboratory-based research with couples (Kenny, Kashy, & Cook, 2006). Thus, counselors may not be aware of appropriate techniques. Furthermore, if they do seek out resources on conducting dyadic analyses, they may be discouraged by the large samples required for most types of dyadic analyses (e.g., structural equation modeling and multilevel modeling). Thus, researcher–practitioners may miss an opportunity to learn more about the clients they serve and also contribute to the greater body of research on the experiences of couples in counseling and the outcomes of their services.

However, there are a few techniques available for these researchers, and the purpose of this article is to describe one of them. In this article, we describe an approach to analyzing dyadic data that can be utilized with the smaller samples often available to researcher–practitioners working with couples in counseling situations. Specifically, we describe how to use the actor–partner interdependence model (APIM; Cook & Kenny, 2005), a common dyadic data analysis tool, using a pooled regression approach that is appropriate for smaller sample sizes. The outline of this article is as follows. First, we describe the rationale behind dyadic data techniques. Then, we provide an overview of the APIM, and, finally, we explain and illustrate how to apply the APIM to small samples using the pooled regression technique. An example is provided using data collected from a study of the role of expectancies in couple counseling outcomes. Additional data from the example study are provided in Appendix A for readers who are interested in practicing the techniques.

Rationale for Dyadic Analysis Techniques

The Problem of Nonindependence

In the social sciences, observations and data points frequently are not independent, for a variety of reasons. Observations may be dependent because they are from related groups, share some common feature, or are arranged sequentially in time. Related groups within data most commonly arise when individuals are nested within a grouping variable. For dyads, people are nested within a couple. Nonindependence is important for two reasons.

First, dependence among observations violates a key assumption of most inferential statistics, that the errors in observations are independent. In other words, once the study variables are accounted for, the remaining (error) variance for each person is not related to the error variance of any of the other study participants. For couple members, this usually is not a reasonable assumption because members of the couple often have other sources of variation in common that are not accounted for by the study variables. If the errors are correlated in reality but this correlation is not modeled, the variance estimates produced are not accurate. Because these variances are used to compute standard errors and tests of statistical significance, the resulting inferential statistics are biased (Kenny, 1995; Kenny & Judd, 1996). The direction of this bias depends on the size and direction of the nonindependence; in some cases, the tests are too conservative and in others, they are too liberal (Cook, 1998; Kenny, 1995; Kenny & Judd, 1996). In the case of couple data, observations from the two members of the couple usually are positively related, leading to an underestimation of the standard errors and an increased risk of Type I error (Newsom, 2002), or concluding that an effect is present when there is none.

Second, researchers may actually be interested in the interdependence among people and observations. Information about the degree to which members of a couple influence one another addresses key research questions in the study of relationships. Ignoring interdependence between members of a couple limits the information available to answer questions of influence.

Methods for Addressing Nonindependence

Several methods for dealing with interdependence among couples' data have been developed. First, some researchers choose to split couple data and treat each member of the couple as an independent unit for the purpose of analysis (Kenny, 1995; Kenny, Kashy, & Cook, 2006). If data from both members of the couple are then analyzed at the same time, this approach does not remedy the problems inherent in nested observations. Errors may be over- or underestimated and interdependence cannot be modeled.

This has led other researchers to analyze data separately for each group of individuals if the members of the dyad are distinguishable by some feature such as gender. Using this approach, partners are analyzed as separate groups. This does not violate the assumption of independence because only one individual per dyad is analyzed in each analysis; however, this approach makes it impossible to analyze shared variance or differences within and between couples (Kenny, 1995). Furthermore, this approach assumes that the two members of the couple differ on the variables of interest, which may not be the case.

Others choose to combine data from both individuals to create a single couple score. Data are added or averaged to create one score representative of the total or average couple observation (Kenny et al., 2006). Because there is only one observation per couple, the independence assumption is not violated. Though popular, this approach is conceptually and methodologically problematic. Conceptually, it implies that individuals within couples are so similar that they can be combined into one person, and that the relationship can simply be represented by a sum of the parts; most researchers and practitioners who work with couples would disagree with this assumption. Methodologically, differences in partners' scores are obscured when they are combined (e.g., 50 and 100 can be combined for a score of 150 and an average of 75, as can two scores of 75), which results in the loss of valuable information (Kenny et al., 2006) and the inability to model differences within dyads.

Finally, a fourth approach to couple data is to analyze only the data from the member of the couple with the most extreme score (Kenny et al., 2006). This approach is commonly used in studies of phenomena, such as psychopathology or depression, in which individual's scores are very different. Though the assumption of independence is not violated, analyzing data from only one member of a couple eliminates the dyadic aspect of the data.

None of these methods are ideal. Although each method approaches nested observations from a slightly different perspective, all attain independence of data points at the expense of valuable information about dyadic relationships. Rather than working to eliminate interdependence among observations, Kenny et al. (Kashy & Snyder, 1995; Kenny, 1995; Kenny & Judd, 1996; Kenny et al., 2006) have developed the APIM. The APIM is a conceptual model and set of related statistical techniques specifically designed to capture and model sources of dependence in data gathered from dyads.

The APIM

Important Concepts in Dyadic Analysis

Before describing specific APIM techniques, it is helpful to have an understanding of the concepts and considerations involved in dyadic analysis. These have important implications for the choice of appropriate analytic procedures.

Types of dyads. A central consideration is whether the dyads are distinguishable or indistinguishable. For dyads in which members are distinguishable by a meaningful characteristic (e.g., gender in heterosexual partnerships), the statistical analysis of the APIM is straightforward because the dyad members can be ordered based on their score on this variable (i.e., women can be assigned one score and men another) and thus assigned a specific role in the analysis. When members are not distinguishable on a meaningful characteristic (e.g., same-sex roommates), they can only be assigned such a role randomly, which inappropriately introduces artificial differences between members that may not really exist. Thus, analysis procedures often need to be different for indistinguishable dyads, and in many cases, these analyses are more complicated. The procedures

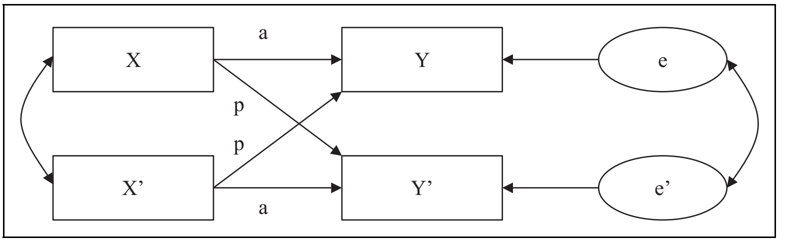

Figure 1. The actor–partner interdependence model, where X = data for Partner 1 at Time 1; Y = data for Partner 1 at Time 2 or outcome; X′ = data for Partner 2 at Time 1; Y′ = data for Partner 2 at Time 2 or outcome; e = error; a = actor effects; p = partner effects. Adapted from Cook and Kenny (2005) and Kenny (1995).

we illustrate here apply to distinguishable dyads; researcher–practitioners who wish to analyze data from indistinguishable dyads are encouraged to consult Kenny, Kashy, & Cook (2006) for adaptations to these procedures.

Types of dyadic variables. A primary requirement of most dyadic analyses is that the outcome variable and at least one predictor variable are measured using the same instruments for both members of the couple. Usually, the outcome variable is continuous, as for the analyses presented here. Analyses involving a categorical outcome variable (e.g., whether clients terminate counseling) are more complex, and interested readers are encouraged to consult Kenny et al. (2006) for further information. Predictor variables may be either categorical or continuous and are classified as one of the three types (Kenny et al., 2006): (a) between-dyads, in which scores are the same for both members of the dyad but differ between dyads (e.g., whether the members of the couple are cohabiting); (b) within-dyads, for which partners' scores within the dyad are different, but the average score is the same for all dyads (i.e., the distinguishing variable; in heterosexual partnerships this might be the individual's gender); and (c) mixed variables, for which values vary both between and within dyads (expectations regarding counseling is the mixed variable used in the analyses here, but most psychosocial variables are mixed).

The APIM was specifically developed to investigate differences in the effects of mixed predictor variables both within and between dyads. Researchers often are interested in questions related to within- or between-dyad predictor variables as well (e.g., whether males and females differ in mean scores on a particular variable), and thus we also illustrate how to conduct these types of analyses as part of an overall analysis plan for dyadic data.

Overview of the APIM

The APIM (Cook & Kenny, 2005) is based on a framework in which dyadic data are obtained at two time points or as an independent variable and outcome of interest. Individual data are retained, which allows for estimation of both individual and dyadic effects (Kenny, 1995). Figure 1 shows the general conceptual model underlying the APIM. The two central components of the APIM are the *actor effect* and the *partner effect*. The actor effects, the straight lines noted by *a* in Figure 1, are the estimate of an individual's impact on herself or himself; they are intraindividual effects. Interdependence is modeled through the partner effect, represented by the diagonal lines and noted as *p* in Figure 1. A partner effect is the degree to which a person's outcome is influenced by the partner's score on the predictor variable. In the APIM, both types of effects are estimated together, so that actor effects are estimated while controlling for partner effects and vice versa (Cook & Kenny, 2005; Kenny, 1995). The APIM can thus accurately model interdependence in dyadic data.

Two additional features of the APIM are noteworthy. First, independent variables are correlated, as represented by the curved bidirectional arrow between X and X'. This controls for shared variance in the outcomes that is due to members of the couple being similar on the predictor variables. If either X variable predicts a Y variable, it can be done while controlling for the other X variable (Kenny, 1995). Second, the error terms (denoted e and e') are allowed to correlate, as represented by the curved, double-headed arrow between them. The extent to which the X variables do not predict the Y variables is included in the model as error. If the actor and partner effects were the only source of variation in Y, when the partner effect is removed, Y and Y' should no longer be correlated. This is rarely the case because there are many likely sources of covariation in Y and Y' other than the partner effect (Kenny et al., 2006). Allowing the errors to correlate means that they can be related even after the covariation due to partner effect is removed. Specifying this type of correlation models makes it possible to model the presence of nonmeasured sources of interdependence found in dyad members.

Options for Analysis of the APIM

The APIM can be estimated using any of several statistical methods; the most common is structural equation modeling, although multilevel modeling also is used. The disadvantage of these techniques, however, is that they require a larger sample size (e.g., at least 100 dyads for structural equation modeling; Kline, 2005) than may be available to many researcher–clinicians working in common counseling settings. However, there is a strategy for APIM analyses that is appropriate for smaller sample sizes—the pooled regression approach. In the following sections, we describe and illustrate the steps involved in conducting such an analysis.

Example Data

Participants

The data we use for examples come from a study of the role of client expectancies in couple counseling (Tambling, 2008). The participant group included both members of 12 couples recruited from a general population who requested couple counseling at a university-based clinic in the southeastern United States. Eight of the couples were married, and four identified their relationship as committed heterosexual. On average, the couples had been partnered 49 months (SD = 63) or approximately 4 years. Participants were predominantly White (n = 22; 85%); two were Latino American (8%), one was Asian American (4%), and one participant did not report this information. Most had at least a bachelor's degree, (n = 18; 75%), and reported household incomes ranged from less than $5,000 annually to more than $40,000, with an equal distribution across income groups. Client age ranged from 21 to 45, with an average of 29.5 years.

Procedures

Potential clients phoned the clinic to request services and completed an intake assessment over the phone. At that time, clinic staff notified clients of the opportunity to participate in the project. For couples who consented, counselors instructed the clients to remain in the clinic after the first and fourth sessions to complete various measures relevant to couple counseling. Data are present for 12 couples at the first session and four couples at the fourth (outcome) session.

Measures

Outcome variable. The outcome variable in the example study was individuals' scores on the Revised Dyadic Adjustment Scale (RDAS; Busby, Crane, Larson, & Christensen, 1995). The RDAS consists of 14 items, measured on a Likert-style scale, designed to measure adjustment in relationships on three subscales: consensus, satisfaction, and cohesion. The subscales can be summed to create a total score representative of marital satisfaction, with higher scores indicating increased distress (Crane, Middleton, & Bean, 2000).

Predictor variables. The original study included three predictor variables: (a) clients' expectations and preferences about counseling, operationalized

Table 1. Data Used in Example Computations

Case	$RDAS4_M$	$RDAS4_F$	FC_M	FC_F	FC_{MC}	FC_{FC}	$RDAS4_{DIFF}$	G_M	G_F	G_{DIFF}	FC_{DIFF}	$FCIN_M$	$FCIN_F$	$FCIN_{DIFF}$	$RDAS4_{AVG}$	FC_{AVG}	$FCIN_{AVG}$
1			4.72	6.16	−0.66	0.79		1	−1	2	−1.44	−0.66	−0.79	0.13		0.06	−0.72
2	55	56	5.88	4.94	0.51	−0.44	−1	1	−1	2	0.94	0.51	0.44	0.07	83	0.04	0.47
3	55	55	4.94	5.00	−0.44	−0.38	0	1	−1	2	−0.05	−0.44	0.38	−0.82	82.5	−0.41	−0.03
4			5.94	6.05	0.56	0.68		1	−1	2	−0.11	0.56	−0.68	1.24		0.62	−0.06
5			5.33	5.16	−0.05	−0.21		1	−1	2	0.16	−0.05	0.21	−0.26		−0.13	0.08
6	53	40	6.11	5.77	0.73	0.40	13	1	−1	2	0.33	0.73	−0.40	1.13	73	0.56	0.17
7			4.72	4.83	−0.66	−0.55		1	−1	2	−0.11	−0.66	0.55	−1.20		−0.60	−0.06
8		48	5.33	5.88	−0.05	0.51		1	−1	2	−0.55	−0.05	−0.51	0.46		0.23	−0.28
9	48	48	4.50	4.44	−0.88	−0.94	0	1	−1	2	0.05	−0.88	0.94	−1.82	72	−0.91	0.03
10			5.83	6.72	0.45	1.34		1	−1	2	−0.88	0.45	−1.34	1.80		0.90	−0.44
11			4.44	4.55	−0.94	−0.82		1	−1	2	−0.11	−0.94	0.82	−1.76		−0.88	−0.06
12			5.33		−0.05			1	−1	2		−0.05					

through the Expectations about Counseling Questionnaire–Brief Form (EAC-B; Tinsley, Workman, & Kass, 1980); (b) individual's level of distress, operationalized through the Symptom Distress subscale of the Outcome Questionnaire (Lambert et al., 1996); and (c) readiness for change, operationalized through the University of Rhode Island Change Assessment (McConnaughy, Prochaska, & Velicer, 1983). The example analyses presented in this section are conducted using one of the EAC-B subscales. Data required to estimate models using the remaining EAC-B subscales and the other predictor variables are included in Appendix A, and interested readers are encouraged to use that data to practice the analysis techniques presented in the remainder of this article.

The EAC-B consists of 66 items, measured on a 7-point scale, arranged within four factors: facilitative conditions (FC; e.g., "I expect the counselor to be friendly and warm towards me"), personal commitment (PC; e.g., "I expect to take responsibility for making my own decisions"), counselor expertise (CE; e.g., "I expect the counselor to know how to help me"), and nurturance (N; e.g., "I expect the counselor to give me support"). Each statement is prefaced by the words "I expect to" or "I expect the counselor to" and address many common expectations about counseling (i.e., "I expect to talk about my presenting concerns"). Scores on the EAC-B are obtained by summing the responses to the items assigned to each factor and dividing by the number of items on the factor.

Example Analyses

In this section, we present the steps to conduct a pooled regression APIM analysis using the EAC-B FC subscale as the predictor variable.

Structuring the Data Set

For distinguishable dyads, the data should be arranged in "dyad" format as shown in Table 1, which contains the data used in the example computations. This means that each line represents a dyad; for this case of heterosexual couples, each member of the couple's scores on each variable are entered onto the same line (e.g., EAC-B FC subscale scores are labeled as FC_M and FC_F for male and female members of the dyad, respectively).

Preliminary Analyses

Descriptive statistics. Consistent with best practices for quantitative analyses, researchers should first evaluate descriptive characteristics of the data. Because the APIM relies on adaptations of conventional regression techniques, researchers should evaluate whether their data meet minimum criteria for those types of procedures, including linear relationships among variables and reasonable amounts of measurement error. Cohen, Cohen, West, and Aiken (2002) provide an excellent overview of procedures analysts can use to evaluate these assumptions.

As an additional step at this stage, the analyst can investigate mean differences across levels of the distinguishing variable (e.g., whether men and women differ in their mean scores on any of the study variables) through paired samples *t* tests. For the example data, such analyses showed that men and women did not differ in their mean scores on any of the study variables. It is important to note, however, that this does *not* mean that the dyads can be treated as indistinguishable because other criteria must also be met (see Kenny et al., 2006).

Measuring nonindependence. For distinguishable dyads, determining the degree of nonindependence between dyad members involves computing the correlation between the members' scores. To accurately measure the nonindependence in the outcome variable, however, the effects of the predictor variables should be controlled. This is accomplished by computing the partial correlation between the members' scores on the outcome variable (RDAS at the fourth session), controlling for the independent variable (each subscale of the EAC-B). Because we have multiple independent variables and thus a set of measures for which we want to evaluate nonindependence, we could also conduct a canonical correlation analysis. In this test, one member's

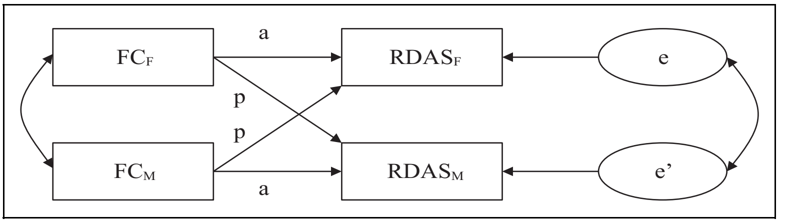

Figure 2. Model tested in example calculations, where FC_F = expectations about counseling facilitative conditions subscale score for female member of dyad at intake; $RDAS_F$ = revised dyadic adjustment scale score for female member of dyad at fourth session; FC_M = expectations about counseling facilitative subscale score for male member of dyad at intake; $RDAS_M$ = revised dyadic adjustment scale score for male member of dyad at fourth session; e = error; a = actor effects; and p = partner effects.

scores on all of the variables are used to predict the other member's scores (it does not matter which is used in which position; Kenny et al., 2006).

An important consideration is how much nonindependence needs to be present to conclude that a dyadic analysis is necessary (i.e., the amount of interdependence that would bias tests of statistical significance in a meaningful way if the dyadic structure was ignored). Kenny et al. (2006) suggest a correlation of .45; they further recommend using a liberal significance level of .20 when testing for nonindependence (in contrast to .05). Given these criteria, a sample size of at least 28 dyads is necessary for adequate power to test for such an effect. With fewer than 28 dyads, as in the example data set, nonindependence must be assumed.

Steps in Conducting the APIM Analysis

In this section, we show how to compute the actor effect, partner effect, and associated parameters. The pooled regression approach to estimating the APIM is based on ordinary least squares regression (Kenny, 1995). In this method, two regression equations are estimated and the results are pooled together to obtain the parameters (Kashy & Kenny, 2000; Kenny et al., 2006). One of the equations tests the within-dyad effects of the predictor variable; the other tests the between-dyad effects. Estimates of the magnitude of the actor and partner effects are obtained when the results of the two regressions are pooled; these estimates can be interpreted as unstandardized regression coefficients. The significance is tested using the *t* statistic.

We used the pooled regression approach to analyze the research questions depicted in Figure 2: Do scores on the EAC-B FC subscale at intake predict RDAS scores at the fourth session? Are actor effects significant? Are partner effects significant? and Do these effects differ by gender?

Creating new variables. To investigate effects of the distinguishing variable (i.e., gender), several new variables must be created according to procedures outlined by Kenny et al. (2006). Some are similar to variables created for a regular multiple regression (e.g., interactions), whereas others may not be immediately intuitive (e.g., constants for gender). Some are used in the within-dyads regression, whereas others are used in the between-dyads regression.

An additional consideration at this point in the analysis is whether and how to make zero a meaningful value for the variables being used as predictors (Kenny et al., 2006). A common way to do this is to "center" the predictor variables by subtracting the mean on that variable from each individual's score. It is important to note that the mean used in these calculations should be for the entire sample, rather than separate means for the levels of the distinguishable variable (i.e., it is not advisable to compute the mean score for men and then subtract that from men's scores and then do the same for the women). Centering the variables using the mean of the entire group is not required, but it does make the interpretation of the results more straightforward, as will be illustrated in the following sections. Thus, we create new variables called, for example, FC_{MC} and FC_{FC}, which are used to create the other variables described in the following sections.

Variables for within-dyads regression. The within-dyads regression is based on differences between the dyad members. First, we create a new variable using the difference between the dyad members' scores on the outcome variable (RDAS at fourth session). In the data set shown in Table 1, this is called $RDAS4_{DIFF}$. Next, two constants indicating the gender of the couple members must be created. Therefore, each dyad has G_M that equals 1 and G_F that equals -1. These constants are used to create a gender difference contrast (G_{DIFF}), which always equals 2. Third, a difference scores for the mixed predictor variable is created ($FC_{DIFF} = FC_{MC} - FC_{FC}$). Fourth, we create the interaction between gender and the mixed predictor variable by multiplying each member's predictor variable score by his or her gender variable (e.g., $FCIN_M = FC_{MC} \times G_M$). We also create a difference score for this interaction, $FCIN_{DIFF} = FCIN_M - FCIN_F$.

Variables for between-dyads regression. The between-dyads regression is based on the average of scores within the dyad. First, we create a dyad-level average for the outcome variable ($RDAS4_{AVG}$). Second, we create an average for both the subscale scores, $FC_{AVG} = (FC_{MC} + FC_{FC})/2$, and the subscale by gender interaction, $FCIN_{AVG} = (FCIN_M + FCIN_F)/2$. Gender is not included directly because each dyad has both a male and a female member, so the average does not vary between dyads.

Step 1: Within-dyads regression. In the within-dyads regression, the difference between each partner's scores on the outcome variable ($RDAS4_{DIFF}$) is predicted by three variables, all of which are similar to what might be included in a conventional regression, except they are based on difference scores: (a) the difference between each partner's scores on the predictor variable, FC_{DIFF}; (b) the gender difference, G_{DIFF}; and (c) the difference in the interaction between the predictor variable and gender, $FCIN_{DIFF}$. The direction of the difference between variables is arbitrary (i.e., we could subtract men's scores from women's or vice versa), so the intercept should not be estimated in the within-dyads regression (Kenny et al., 2006). This can be done in statistical package for the social sciences (SPSS) by unchecking the "include constant" choice in the "Options" function of the linear regression command. This results in the within-dyads regression equation shown in Equation 1,

$$RDAS4_{DIFF} = b_{w1}(FC_{DIFF}) + b_{w2}(G_{DIFF}) + b_{w2}(FCIN_{DIFF}) + E_{wi}. \quad (1)$$

Conducting this regression in SPSS procedures the following:

$$RDAS4_{DIFF} = -8.50(FC_{DIFF}) + 3.84(G_{DIFF}) + 5.52(FCIN_{DIFF}) + E_{wi}.$$

If we had not conducted tests earlier to determine whether men and women differed in their average RDAS scores at the fourth session, we could investigate that using the G_{DIFF} coefficient from this regression (as reported earlier, the difference between men and women is not significantly different from zero).

Step 2: Between-dyads regression. The between-dyads regression involves predicting the dyad mean of the outcome variable ($RDAS4_{AVG}$) using the dyad mean of the predictor variable (FC_{AVG}) and dyad average of the interaction between the predictor variable and gender ($FCIN_{AVG}$). This results in the between-dyads regression equation shown in Equation 2.

$$\text{RDAS4}_{\text{AVG}} = b_{b0} + b_{b1}(\text{FC}_{\text{AVG}}) + b_{b2}(\text{FCIN}_{\text{AVG}}) + E_{bi}. \quad (2)$$

Conducting this regression in SPSS produces the following:

$$\text{RDAS4}_{\text{AVG}} = 7.68 + 11.03(\text{FC}_{\text{AVG}}) + -17.01(\text{FCIN}_{\text{AVG}}) + E_{bi}.$$

Step 3: Estimating actor and partner effects. The regression coefficients from these two equations then are used to estimate the actor and partner effects for each of the mixed predictor variables (FC and FCIN; Kenny et al., 2006). This is accomplished using the appropriate coefficients from the within- and between-dyads regressions, as in Equation 3,

$$\text{actor} = \frac{(b_b + b_w)}{2} \text{ and partner} = \frac{(b_b - b_w)}{2}. \quad (3)$$

Thus, for FC, the effects are computed as follows:

$$\text{actor}_{\text{FC}} = \frac{(11.03) + (-8.50)}{2} = 1.27, \text{and}$$
$$partner_{\text{FC}} = \frac{(11.03) - (-8.50)}{2} = 9.77.$$

Although we have not evaluated yet whether these coefficients differ significantly from zero, conceptually they are interpreted as follows. For FC, the actor effect of 1.27 means that each point above the mean score on FC is associated with an RDAS score at the fourth session that is 1.27 points higher; therefore, individuals who have higher expectations for FC at the outset of counseling have higher RDAS scores at the fourth session. The partner effect means that for each point an individual's partner is above the mean on FC, he or she has an RDAS score at the fourth session that is 9.77 points higher.

For the variable FCIN, the actor and partner effects are computed in the same way, $\text{actor}_{\text{FCIN}} = -5.75$ and $\text{partner}_{\text{FCIN}} = -11.26$. These coefficients (if statistically significantly different from zero) indicate whether the actor and partner effects are moderated by gender. Because we coded men as 1 and women as -1, we compute these differences as follows. For men, we take the original actor coefficient (1.27) and add the interaction actor coefficient (5.75) to get a value of 7.02, and for women we subtract the interaction coefficient to the original coefficient ($1.27 - 5.75 = -4.48$). This means that the actor effect for women is actually negative, whereby women who score one point above the mean on FC at intake have a lower RDAS score at fourth session; for men, higher FC scores at intake are associated with higher RDAS scores at fourth session. The partner effect for women's FC on men's RDAS is 21.03 [9.77 – (−11.26)], which means men whose partners have higher FC scores have higher RDAS scores at fourth session; the partner effect for men's FC on women's RDAS is –1.49 [9.77 + (–11.26)].

Step 4: Interpreting the results. Actor and partner effects can be interpreted as unstandardized regression coefficients, so a t statistic is used to determine whether these effects differ significantly from zero. Because actor and partner effects are computed using coefficients from two separate regressions, the standard errors of both original coefficients must be pooled, using the formula shown in Equation 4 (Kenny et al., 2006),

$$SE_p = \sqrt{\frac{s_b^2 + s_w^2}{4}}. \quad (4)$$

Following this equation, the calculation for the variable FC from the example data is as follows:

$$SE_p = \sqrt{\frac{s_{b1}^2 + s_{w1}^2}{4}} = \sqrt{\frac{5.43^2 + 7.61^2}{4}} = \sqrt{\frac{29.49 + 57.91}{4}} = \sqrt{21.85} = 4.67.$$

For FCIN, the standard error is 7.73. To obtain the t statistic, the actor and partner effects are divided by the pooled standard error, first for the FC variable,

$$t_{\text{actor}} = \frac{a}{SE_i} = \frac{1.27}{4.67} = 0.27 \text{ and}$$
$$t_{\text{partner}} = \frac{p}{SE_i} = \frac{9.77}{4.67} = 2.09.$$

For FCIN, t(actor) = 0.74 and t(partner) = -1.45. The degrees of freedom for these tests are calculated as in Equation 5 (Kenny et al., 2006),

$$df = \frac{(s_b^2 1 + s_w^2)^2}{\dfrac{s_b^4}{df_b} + \dfrac{s_w^4}{df_w}}. \tag{5}$$

Following this equation, the calculations for the variable FC are as follows:

$$df = \frac{(s_b^2 1 + s_w^2)^2}{\dfrac{s_b^4}{df_b} + \dfrac{s_w^4}{df_w}} = df = \frac{(57.91 + 159.26)^2}{\dfrac{3353.81}{4} + \dfrac{25365.15}{4}}$$
$$= \frac{47162.81}{838.45 + 6341.29} = 6.74.$$

For FCINTER, the degrees of freedom are 10.19. Note that the degrees of freedom may be fractional. To test the statistical significance of the t statistic, examine a t table and locate the cut-off value for the desired level of significance with the correct number of degrees of freedom. In the case of fractional degrees of freedom, the recommendation is to be conservative and round down (Kenny et al., 2006). A review of published t tables showed that neither the actor nor the partner effect was significant for either variable. Neither the actor nor the partner effect of scores on the FC subscale of the EAC-B predicted fourth session RDAS scores, and these effects did not differ by gender. Although these results are presented here for illustration only and should not be interpreted substantively, it is important to note that a potential reason that some effects were not statistically significant from zero may be due to the small sample size, which reduced the power to detect anything but an extremely large effect.

Discussion and Suggestions for Implementation

In this article, we have described and illustrated a pooled regression APIM approach to analyzing dyadic data from a small sample of dyads. This method can be implemented using conventional statistical software and hand computations. Thus, it is appropriate for researcher–clinicians who want to find out more about their clients but do not have the sample size necessary to conduct APIM analyses using structural equation modeling or multilevel modeling.

This method has several advantages over other approaches used to analyze these types of data. The primary benefit is that researchers can investigate actor and partner effects (i.e., keep both members of the couple in the same data set) while accounting for the interdependence between the members of a couple. This results in more accurate statistical inferences as well as more nuanced and relevant information that the researcher–clinician can use to inform his or her practice. The ability to conduct these analyses using hand computations presents a significant advantage due to its simplicity, but it also introduces a potential source of error in the computations. Because of this, it is recommended that someone not familiar with the study confirm the computations. This individual would ideally be familiar with the APIM and regression-based statistical models but blind to the research questions of the study.

When using these techniques, a few cautions must be considered. First, the dyad-level data must be amenable to regression-based analyses. Also, because the pooled regression approach is based on conventional regression techniques conducted using standard statistical software, it cannot accommodate missing data; thus couples are deleted if they do not have data on a specific variable. This can result in a significant reduction in sample size and decrease the power of statistical tests. An additional disadvantage is that the pooled regression technique for distinguishable dyads assumes homogeneity of variance across levels of the distinguishing variable (i.e., in this case that men and women have the same variance in their RDAS scores).

Table 2. Data for Further Analyses

Case	PC_M	PC_F	CE_M	CE_F	N_M	N_F	SD_M	SD_F	U_M	U_F	$RDAS_M$	$RDAS_F$
1	4.82	6.67	4.56	5.00	4.08	5.17	47	54	101	116	7	33
2	6.76	6.45	5.89	3.78	5.67	5.00	19	27	94	89	55	54
3	5.20	5.26	4.45	4.33	4.42	4.17	40	19	103	88	53	54
4	5.64	6.34	5.78	6.22	5.58	5.58	9	39	113	104	8	
5	5.68	5.44	4.33	3.67	5.00	4.75	24	42	99	109	59	59
6	5.93	6.51	4.33	5.00	5.50	4.25	13	48	96	63	52	40
7	5.04	4.99	4.56	4.33	4.50	4.25	25	22	91	108	50	58
8	5.00		4.67	4.11	4.42	4.58	13	17	103	109	48	44
9	4.89	5.42	4.11	4.11	4.17	3.67	40	39	101	113	47	46
10	5.95	7.00	4.56	6.89	4.92	6.67	45	66	106	131	46	31
11	5.13	5.00	4.00	2.89	4.25	3.50	32	19	101	93	49	43
12	6.73	6.50	5.45	5.11	4.75	4.75	35	37	122	122	43	32

Despite some cautions, the pooled regression approach to the APIM offers researchers in clinical settings an alternative to individually focused analyses. Using the APIM, researcher–clinicians can account for, explicitly model, and investigate interdependence among dyad members, which increases their potential to conduct and apply research that is relevant to their work in counseling settings.

Appendix A

This appendix contains complete data for the other EAC-B subscales and the three additional predictor variables from the example study (presented in Table 2) as well as potential research questions to use with them (presented in text). Interested readers are encouraged to use these data to practice the analysis techniques presented in this article and check their computations against those we present here.

Additional Predictor Variables: Other EAC-B Subscales

For the effect of the PC factor on RDAS scores, actor and partner effects were not significant for either the subscale score, actor $= -8.03$, $t(4.94) = -2.03$, $p = .11$, and partner $= 6.66$, $t(4.94) = 1.68$, $p = .17$, or the interaction between the subscale score and gender, actor $= 15.83$, $t(3.31) = 3.17$, $p = .05$, and partner $= 12.58$, $t(3.31) = 2.52$, $p = .09$.

For the CE factor, the results were also not significant for either the subscale score, actor $= -1.52$, $t(3.09) = -0.20$, $p = .85$, partner $= 4.42$, $t(3.12) = 0.58$, $p = .60$, or the interaction between the subscale score and gender, actor $= 7.45$, $t(4.07) = 1.70$, $p = .164$, and partner $= -1.28$, $t(4.07) = -0.29$, $p = .78$.

For the nurture factor, results were not significant for either the subscale score, actor $= 12.68$, $t(5.63) = 3.37$, $p = .01$, partner $= -3.74$, $t(5.63) = -1.00$, $p = .363$, or the interaction between the subscale score and gender, actor $= -14.46$, $t(3.35) = -2.95$, $p = .060$, partner $= -12.84$, $t(3.35) = -2.62$, $p = .079$. It is noteworthy that the test for the actor effects of the nurture factor would be significant if not for the Bonferroni correction.

Additional Predictor Variable: University of Rhode Island Change Assessment

The University of Rhode Island Change Assessment (URICA; McConnaughy et al., 1983) was used to measure client stage of change. The URICA is a 32-item self-report measure on which individuals rate their agreement on a 5-point scale with statements reflecting each stage of change. The URICA was designed to provide a continuous score of readiness to change (McConnaughy et al., 1983). The URICA contains four subscales: (a) precontemplation, for example, “I am not the problem one, it doesn’t make sense for me to be here”; (b) contemplation, for example, "I have a problem and I really think I should work on it"; (c) action, for example, "I am finally doing some work on my problem"; and (d) maintenance, for example, "It worries me that I might slip back on a problem I already have, so I am here to seek help." Subscale scores are obtained by summing subscale items; summing the scores on contemplation, action, maintenance, and the reverse-scored precontemplation scale results in a total score indicating readiness for change.

The potential research question to use with this predictor is whether URICA scores at intake predict RDAS scores at the fourth session. To determine if the actor or partner effects for URICA scores on RDAS at fourth session were significant, a pooled regression test of the APIM was conducted. Results were not significant for either the URICA score, actor $= 0.05$, $t(3.97) = 0.064$, $p = .952$, partner $= -0.12$, $t(3.97) = -0.16$, $p = .88$, or the URICA by gender interaction, actor $= -0.07$, $t(3.46) = -0.08$, $p = .94$, partner $= 0.02$, $t(3.46) = 0.02$, $p = .99$.

Additional Predictor Variable: Symptom Distress Subscale of the Outcome Questionnaire

Data representing individuals' level of individual distress were obtained from scores on the Symptom Distress (SD) subscale of the Outcome Questionnaire (Lambert et al., 1996). The Outcome Questionnaire consists of three subscales (Symptom Distress, Interpersonal Relationships, and Social Role), but critics have suggested that only the SD subscale be used, as it is the most reliable and valid and has the strongest links between individual items and the factor (Mueller, Lambert, & Burlingame, 1998; Vermeersch, Lambert, & Burlingame, 2000).

The potential research question for this predictor is whether SD subscale scores at intake predict RDAS scores at the fourth session. To test this, a pooled-regression test of the APIM was conducted. Results were significant for the SD score, *actor* $= -1.58$, $t(4.05) = -19.82$, $p <$ 0.00, and *partner* $= 0.83$, $t(4.05) = 10.40$, $p <$ 0.00, but not the SD by gender interaction, *actor* $= 0.19$, $t(4.01) = 1.38$, $p = 0.23$, or *partner* $= 0.12$, $t(4.01) = 0.90$, $p = 0.42$.

Additional Predictor Variable: Revised Dyadic Adjustment Scale

A final potential research question concerns whether RDAS scores at intake predict RDAS scores at the fourth session, also tested through a pooled regression APIM. Results were significant for the actor effect for the RDAS score, *actor* $= 1.26$, $t(5.65) = 7.47$, $p <0.00$, but not the partner effect, *partner* $= 0.13$, $t(5.65) = 0.93$, $p = .39$, or either effect for the RDAS by gender interaction, *actor* $= 0.16$, $t(6.58) = 0.83$, $p = 0.43$, and *partner* $= 0.13$, $t(6.58) = 0.86$, $p = 0.42$.

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