It is an honor and privilege to be asked to comment on the 12 papers in this special issue of the *Journal of Pediatric Psychology* on Family Assessment. In most of the papers in this issue, the family member who was assessed was a parent whose child had been diagnosed with a serious chronic condition. It should be clear that when a family member is assessed that measurement reflects not only the respondent but also reflects the other family members, the respondent’s relationship to the other family members, and the whole family. Consider the study by Knafl et al. (2009) in which they asked 579 parents, 414 mothers, and 165 fathers (father is used throughout this paper, even though in some cases the father may not be the biological father of the child), of a child with a chronic medical condition to complete a 53-item Family Management measure which measured six dimensions: Child’s Daily Life, Condition Management Ability, Condition Management Effort, Family Life Difficulty, Parental Mutuality, and View of Condition Impact. If we consider the Parental Mutuality dimension (e.g., “I am pleased with how my partner and I work together to manage our child’s condition”), this scale reflects on the respondent, the respondent’s partner, the child, the respondent–partner relationship, respondent–child relationship, the partner–child relationship, and the family.

My own area of expertise is not in the assessment of families per se, but in the analysis of data when measures are used to study families. I have primarily focused on the fundamental social unit in the study of families and that unit is the dyad. Almost all of what I know about dyadic data analysis is contained in the book *Dyadic Data Analysis* (Kenny, Kashy, & Cook, 2006). I believe that research in this area would benefit by thinking about the data in terms of dyads and in this short note, I outline some possibilities. As I hope to show, by using dyadic analysis, one can learn more about what is occurring in families.

Before I begin my discussion of dyadic data analysis, I wish to make one suggestion about assessment. Many of the articles in this issue assess multiple dimensions. For instance, I mentioned earlier that Knafl et al. (2009) assessed six dimensions of Family Management. An important, but sometimes forgotten, issue in assessment is discriminant validity. The question of discriminant validity is whether the two scales correlate too highly, making them not two distinct constructs but just one. The complicated way to assess discriminant validity is to perform a confirmatory factor analysis and determine whether the latent variables correlate too highly (i.e., greater than \( \pm .85 \)). An alternative and simpler way to do so is as follows: First, correlate the two scales. Second, divide that correlation by the square root of the product of the two scales’ reliabilities. (Normally, the reliability coefficient used would be a Cronbach alpha coefficient.) Third, make sure that the corrected correlation is not too large, e.g., less than \( \pm .85 \). Because, most of the studies in this issues conducted factor analyses on the entire set of items (not just the items separately for each scale) most of scales discussed in this paper have good discriminant validity. For instance, Palmer et al. (2010) conducted separate confirmatory factor analyses for three scales for mothers and fathers and found decent convergent validity; however, one correlation was relatively large, being .788.

Researchers are generally aware today of issues of non-independence in family data. It can be problematic to analyze family data with individual as unit because significance testing results will likely be wrong because the two dyad members’ responses are dependent. Violation of the independence assumption can sometimes lead to too liberal a significance test (which is well recognized), but it can sometimes lead to too conservative a test, a test that is under-powered. One strategy to handle nonindependence (e.g., employed by Benzies et al., 2010; Berlin, Davies,
Silverman, & Rudolph, 2009; Celano, Klinnert, Holsey, & McQuaid, 2009) is to collect data from only one person to eliminate dependence. Another strategy is to gather data from two or more members, and likely mistakenly treat them as if they were independent individuals. For this reason, most of the articles present separate analyses for the two dyad members. That is, the analyses are split into two parts: mother and father (e.g., Marsac & Alderfer, 2010) or parent and child (e.g., Dunn et al., 2010).

Separate analyses do get around the problem of violating the independence assumption in significance testing, but they have their own drawbacks. First, by splitting one’s sample into two parts one reduces power in each and some important results might well be missed. Second, by analyzing the data separately, one is sure to obtain somewhat different results in each group inviting the interpretation of differences when in fact there are none. Third, by conducting separate analyses (or collecting data from only one person), one does not measure the correspondence in the responses of the two dyad members. Fourth, sometimes there is no clear way to split the members into two groups, as in the case of siblings or twins.

Better than splitting the sample in half is to perform a truly dyadic analysis. A dyadic analysis has the following properties:

1. All the data are analyzed in one analysis.
2. Dyad is considered in the analysis and not ignored (as would happen if individual were the unit of analysis).
3. Nonindependence of responding of the two dyad members is directly measured.

In the remainder of the article, two different types of dyadic analysis are discussed. First, is the use of regression-type models and second is factor analysis. Both sorts of analysis are conducted in this special issue.

Here, we consider a possible dyadic analysis of the effect of one variable (X) on another (Y) where one or both of the variables are dyadic variables. There are three possibilities: X is dyadic and Y is not, Y is dyadic and X is not, and both X and Y are dyadic. Considered here is how to do a dyadic analysis for each of these, using one of the studies in this issue as an example.

First, we wish to measure the ability of a variable to predict another variable where the predictor variable is dyadic, measured from two family members, and the outcome variable is not dyadic. Consider the study by Palmer et al. (2009) where Relationship Quality, as assessed by both the mother and father are used to predict the adolescents’ Metabolic Control of their diabetes (see their Table 1). The analysis of this question using dyadic analysis might be best done using structural equation modeling (SEM). We treat the two Relationship Quality variables as exogenous, and so correlate them, and we draw a path from each to Metabolic Control. Note the unit of analysis would be family. We use full information maximum likelihood or FIML to handle the fact that data from some families are missing, mainly the father’s measure of Relationship Quality. Using SEM, we can test the extent to which the two Relationship Quality effects are equal, by setting the two paths equal and seeing if the fit worsens. If the fit does not worsen, then single estimate, pooled across mothers and fathers, gives the relationship to Metabolic Control more precisely than the two separate coefficients. A similar analysis could have also been conducted by Barzel, & Reid, G. (2011) in their study of the effects of maternal and paternal co-parenting on the child’s externalizing and internalizing behavior.

Second, we wish to measure the ability of a variable to predict another variable, where the outcome is dyadic, but the predictor is not. Consider the study by Jastrowski Mano, Anderson Khan, Ladwig, & Weisman (2009) on the effect of child’s reports of pain (P_C) on maternal and paternal Quality of Life (Q_M and Q_F). We could again use SEM to measure these effects, but multilevel modeling (MLM) can be used to estimate a model in which PC simultaneously predicts Q_M and Q_F. We need to create a data file in which the unit is parent and so there are two records for each family, a mother record and a father record. The data file would have the parent’s Quality of Life measure (Q), the child’s pain level (P_C), a family identification variable (Family), and the parent’s gender (Gender) on each line of the data file. We can use any MLM program. I illustrate here how Mixed Models within SPSS can be used. The syntax is as follows:

MIXED Q WITH P Gender
/FIXED= P Gender P*Gender
/PRINT=SOLUTION TESTCOV
/REPEATED=Gender | SUBJECT(Family) COVTYPE(UNR).

I assume that Gender is effect coded (e.g., 1 for father and −1 for mother). Note that just one effect of Q on P is estimated, which is the pooled estimate for both mothers and fathers. The test of P by Gender interaction evaluates whether the effect of P on Q differs for mothers and fathers. Finally, the “REPEATED” command provides an estimate of the nonindependence in the two quality of life measures by correlating the errors in husband and wife measures.

Third, we wish to measure the ability of a variable to predict another variable where both of the variables are dyadic, measured from two family members. Consider Barzel & Reid (2010) who might have examined whether
Marital Satisfaction (S), measured from the mother’s (SM) and father’s perspective (SF), predicted Maternal and Paternal Co-parenting (CM and CF), in 161 families in which the child has type 1 diabetes. We note because there are two predictors, SM and SF, and two outcomes, CM and CF, there are four possible paths. Using the Actor-Partner Interdependence Model (APIM; Kenny et al., 2006), two of these paths are called actor paths: the effect of SM on and CM and the effect SF on and CF. It is this path that we usually think of. The other two paths are called partner paths and are the effect of SM on and CF and the effect of SF on and CM. In some sense the partner paths are more interesting than the actor paths, because they capture interpersonal influence. The APIM can be estimated using MLM or SEM (see Chapter 7 in Kenny et al., 2006).

I now turn to the issue of using factor analysis with dyadic data. Here, we return to the Palmer et al. (2009) study. They conducted three-factor confirmatory factor analysis, separately for mothers and fathers. If all the data were analyzed in one analysis (see Chapter 6 in Kenny et al., 2006), we could test the following hypotheses: First, are the factor loadings the same for mothers and fathers? This is a key question as it establishes that the latent variable has the same meaning for both members. Second, are the factor means and variances the same for mothers and fathers? Third, are the latent variable correlations the same? Fourth and perhaps most importantly, we can examine agreement by seeing what the correlations are for mothers and fathers. For example, returning to Palmer et al. (2009), we can assess where mothers and fathers agree about Relationship Quality or for Kaugars et al. (2010) we can assess whether maternal and paternal parenting styles, as measured from behavioral observation, are similar. So parenting styles, we might ask if the father has a controlling style, does the mother also? It would seem that in many of the studies in this special issue a key question is whether husband and wife or parent and child agree when the same construct is measured from both of them. The assessment of agreement is very useful if the researcher seeks to combine the two measurements into a single measure, as was done by Kelly, Holmbeck, & O’Mahar (2010) for parents of children with spina bifida.

The focus in this paper is on dyadic analysis, but families are more than a collection of dyads. Some papers in this special issue collect data from triads (e.g., Jastrowski Mano et al., 2009): mother, father, and child. Sometimes we might want to study the child and all of his or her significant relationships (e.g., parents, siblings, and grandparents). Dyadic analysis of mother–father and parent–child is then just one important way to start in our understanding of the family.

Most of the investigators in this special issue have shown that key concepts can be measured in families where children have a serious chronic condition. Moreover, they show that such measures can be reliably and validly measured. It is my hope that these measures can be used to study families and that dyadic data analysis will be one of the tools used in those investigations. Dyadic analysis does require using more complicated analyses like SEM or MLM. However, by using these methods, researchers are better equipped for a wider, more interesting, and more clinically relevant set of questions.

Conflicts of interest: None declared.

References


