Multilevel Modeling Approaches to the Study of LGBTQ-Parent Families

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One of the most central pursuits of family theory and research is to better understand and explore the dynamics of interpersonal family relationships. Understanding these relationships is furthered by collecting information on multiple family members (Jenkins et al., 2009). There is a growing body of LGBTQ research that draws from the experiences of multiple family members (Carone, Lingiardi, Chirumbolo, & Baiocco, 2018; Farr, 2017; Goldberg & Garcia, 2015, 2016; Pollitt, Robinson, & Umberson, 2018). Unfortunately, by their very nature, family members' experiences are interdependent, and this interdependence complicates the analysis of data from multiple family members (Atkins, 2005; Bolger & Shrout, 2007; Jenkins et al., 2009; Sayer & Klute, 2005). With the right analysis strategy, this interdependence can also be a rich source of information about family processes.

Data interdependence precludes the use of many statistical methods that assume the errors are independent, such as ordinary least squares (OLS) regression or standard analysis of variance (ANOVA). Several statistical methods that take into account the dependency in family members' outcomes are available to researchers and have become the standard in family research journals. Many of the most commonly used approaches, however, are easiest to employ when one distinguishes family members on the basis of some characteristic meaningful to the analyses (Sayer & Klute, 2005). For example, in parent/child dyads, one can easily distinguish dyad members on the basis of whether they are the parent or child (Shih, Quiñones-Camacho, Karan, & Davis, 2019). In research on heterosexual couples, partners are most commonly distinguished on the basis of gender (assuming a binary male/female conception of gender; Claxton, O'Rourke, Smith, & DeLongis, 2012; Kuo, Volling, & Gonzalez, 2017; Perry-Jenkins, Smith, Wadsworth, & Halpern, 2017; Raudenbush, Brennan, & Barnett, 1995). Such approaches to distinguishing partners on the basis of gender, however, are clearly not useful to researchers of same-sex couples. In some cases, same-sex partners may be distinguished on the basis of some other characteristic, such as biological versus nonbiological parent (Goldberg & Perry-Jenkins, 2007; Goldberg & Sayer, 2006), where that distinction is relevant to the analyses. In other cases, however, no such

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meaningful distinctions can be made – for example, in many analyses of same-sex nonparent couples or same-sex adoptive parents, wherein neither partner is the biological parent. In these instances, alternate statistical models must be employed.

This chapter discusses the challenges faced by researchers analyzing data from multiple family members, with a focus on couples. It addresses advances in research methods using multilevel modeling (MLM). MLM, which is a fairly straightforward extension of the more familiar OLS multiple regression, provides one of the more versatile and accessible approaches available to model couple and family data (Sayer & Klute, 2005). As such, it is becoming a common method for LGBTQ-parent family researchers to examine data collected from two (or more) individuals nested within a couple or family (e.g., Carone et al., 2018; Farr, 2017; Goldberg & Smith, 2017). We begin by discussing the role of MLM in family research, in general, and in dyadic (or paired) data, more specifically. Next, we consider some of the common difficulties encountered by scholars examining LGBTQ-parent family data. We then describe the basic multilevel models available to researchers analyzing (a) cross-sectional and (b) longitudinal dyadic data. Next, we address the application of these models to analyses of multiple informant data, when multiple family members provide reports of the same outcome. In addition, we present some considerations that researchers using these statistical methods should take into account.

Multilevel Modeling in Family Research

The use of MLM became more common in family journals at the end of the last decade (e.g., Kretschmer & Pike, 2010; Soliz, Thorson, & Rittenour, 2009), a trend that has continued, particularly in research on heterosexual couples (e.g., Kuo et al., 2017; Perry-Jenkins et al., 2017). Yet the adoption of MLM by researchers who study LGBTQ couples and families was initially somewhat slower. In part, this is because the area of LGBTQ couples and families was relatively new in the 2000s, and much of the early research was qualitative and exploratory as opposed to quantitative (see Goldberg, 2010, for a review). In addition, those studies that used quantitative methods tended to rely on fairly small sample sizes of LGBTQ couples and families (e.g., Goldberg & Sayer, 2006; Patterson, Sutfin, & Fulcher, 2004), thereby decreasing power and the ability to detect effects. Small sample sizes may lead researchers to use methods other than maximum likelihood methods, an estimation technique used in multilevel modeling, which perform best with large samples (Raudenbush, 2008). An additional barrier to using multilevel modeling with same-sex couples is when members of couples or dyads are not clearly distinguishable from one another on the basis of some central characteristic such as gender (i.e., members are “indistinguishable” or “exchangeable”). This scenario requires methods designed to take this indistinguishability into account. Treating dyad members as indistinguishable requires the use of MLM approaches that may be less familiar to many family researchers, including LGBTQ-focused researchers, given the field’s overall focus on the (binary gender) based distinguishable model.

In comparison to MLM, structural equation modeling (SEM), an alternate method for the analysis of dyadic data, provides more flexibility in many areas, such as the ability to place constraints on estimates of all parameters of the model, a wider range of model fit indices, and a more sophisticated analysis of the effects of measurement error for latent variables (Ledermann & Kenny, 2017). Unfortunately, SEM is much more complex, can be challenging to learn, requires specialized software, and requires much larger sample sizes (over 200 cases, and therefore dyads, when analyzing latent variables) (Ledermann & Kenny, 2017). In addition, Ledermann and Kenny (2017) suggest that SEM is often more straightforward for the analysis of data from distinguishable dyads, whereas MLM is often more straightforward for indistinguishable members. Further, MLM is available in most software packages. Consequently, we will focus on MLM, although later in the chapter, we will briefly describe some types of analyses that can only be done in an SEM framework. For further discussion and helpful comparisons of the advantages of MLM versus SEM in examining dyadic data, see Ledermann and Kenny (2017), as well as Hong and Kim (2019).

A fairly large body of work discusses the application of MLM to heterosexual couples using models for distinguishable dyads (Bolger & Shrout, 2007; Hong & Kim, 2019; Ledermann & Kenny, 2017; Raudenbush et al., 1995; Sayer & Klute, 2005). Much less work is available on its application to indistinguishable couples (Kenny, Kashy, & Cook, 2006; Ledermann & Kenny, 2017). There is a clear need to bring together recent advances in several areas: (a) the analyses of indistinguishable dyads; (b) advances in longitudinal analyses of indistinguishable dyads (Kashy, Donnellan, Burt, & McGue, 2008); (c) the analyses of mixed samples, such as analyses including female couples, male couples, and heterosexual couples (Ledermann, Rudaz, & Grob, 2017; West, Popp, & Kenny, 2008); (d) multiple informant models (Georgiades, Boyle, Jenkins, Sanford, & Lipman, 2008); and (e) the important limitations to using MLM (Hong & Kim, 2019; Ledermann & Kenny, 2017), especially when examining dyads and other small groups (Raudenbush, 2008). Consequently, this chapter focuses on multilevel modeling approaches to analyzing dyadic data when couple members can be considered indistinguishable. While these approaches are valuable for the study of same-sex couples, they are also useful in the study of twins, friends, roommates, and other types of relationships where members cannot be distinguished from each other based on some meaningful characteristic (Kenny et al., 2006). For this reason, the information presented in this chapter may be useful and relevant to family scholars more generally.

Family theorists from a wide range of perspectives, including family systems theory, life course theory, social exchange theory, symbolic interaction theory, conflict theory, and social ecological theory, have long been interested in the relationships between family members and how those relationships affect family members. For example, family systems theory views individuals as part, not only of a family, but also of multiple, mutually influencing family subsystems (Cox & Paley, 1997). Individuals' experiences and their dyadic relationships with other family members affect not only those directly involved but other individuals and relationships within the family system as well. Life course theory examines changes in the intertwined lives of family members over the life span (Bengtson & Allen, 1993). Finally, ecological theory posits the importance of understanding the family as a central social context that influences all of the individuals within it (Bronfenbrenner, 1988). Research examining data from multiple family members allows researchers to start to tease apart these complex family relationships. For example, Georgiades et al. (2008) examined multiple family members' reports of family functioning (N = 26,614 individuals in 11,023 families). Using MLM enabled them to distinguish shared perceptions of family functioning from unique individual perceptions.

Collecting information from more than one individual per family allows for the examination of the association between family members' scores (Bolger & Shrout, 2007). Multilevel modeling provides a means of disentangling the variability in the outcome. The variability in the outcome (i.e., the variance) is due to two sources: within-family variability and between-family variability. MLM methods provide a means for separating the variability in the outcome into these two sources, as well as appropriately testing both family-level and individual-level predictors of that variability.[1] It is not surprising, therefore, that MLM has become widely used in family research (e.g., Kretschmer & Pike, 2010; Kuo et al., 2017; Perry-Jenkins et al., 2017). The

[1]It should be noted, however, that one should be wary of the inference tests of the parameter estimates of variance components based on models examining dyadic data, as they are known to be low powered due to the small number of individuals per group/dyad (Maas & Hox, 2005; Raudenbush, 2008). The fixed effects, however, are quite reliable.

nature of family research has subsequently led to adaptations of MLM approaches to suit the specialized needs of this field. This has occurred, most notably, in the area of modeling couple data (or dyadic data more generally), starting with the early models to examine cross-sectional (Barnett, Marshall, Raudenbush, & Brennan, 1993) and longitudinal (Raudenbush et al., 1995) data, and developing to address more specific needs in family research, such as the examination of diary data (Bolger & Shrout, 2007) or the complex interactions between partners in the Actor–Partner Interdependence Model (APIM; Campbell & Kashy, 2002; Cook & Kenny, 2005; Garcia, Kenny, & Ledermann, 2015).

Key Issues in Analyzing Data from LGBTQ Couples and Families

The Issue of Dependence

It is important to clarify why special statistical methods may be required when analyzing data from multiple family members. One of the central assumptions underlying conventional statistical methods such as OLS regression and standard ANOVAs is that the residuals (errors) are independent. This assumption is untenable in the case of dyadic or family data. Partners who are in a relationship are likely to have outcome scores that are similar, and this similarity or dependency must be taken into account when performing statistical analyses. Failure to take into account dependence in the outcome scores results in inaccurate estimates of the standard errors leading to both Type I and Type II errors, depending on the direction of the dependence and level of predictor variable (Griffin & Gonzalez, 1995; Kenny et al., 2006; Kenny & Judd, 1986). In addition, failure to account for dependency in the outcome can also lead to incorrect estimates of effect sizes (Kenny et al., 2006).

There are a number of reasons why family members' outcomes may be associated (Kenny et al., 2006). For example, partners may have chosen each other at least partly on the basis of shared interests in community involvement (mate selection). Alternately, a small family income may affect the financial confidence of all of the members of a particular family (shared context). Similarly, family members who live together are likely to be affected by each other's moods and behavior (mutual influence), perhaps even in the negative direction (e.g., individual time spent on housework). Statistical methods such as paired sample t-tests and repeated-measures ANOVA do adjust the estimates for the dependency in the outcome and can be used to answer many basic research questions. For example, a researcher may investigate if lesbian mothers and their teen daughters have mean differences in the level of conflict they report in their relationship. MLM provides a means of better understanding the relationship between those two family members' reports on the same outcome, breaking down the variance into that which occurs within families and that which occurs between families. In addition, it enables the examination of the effects of both individual-level (e.g., age or stress level) and family-level (e.g., number of children or family income) variables (Kenny et al., 2006; Sayer & Klute, 2005). In other words, instead of treating the dependence between family members' reports as a nuisance to be adjusted for, MLM enables researchers to treat this dependence as interesting in its own right and to explore predictors of it.

The Issue of Distinguishability

When studying same-sex couples, researchers are often faced with an additional methodological difficulty. For example, most analyses of heterosexual couples within family studies distinguish between the two members of the couple on the basis of a binary distinction between male and female genders (Claxton et al., 2012; Kuo et al., 2017; Perry-Jenkins et al., 2017; Raudenbush et al., 1995). In research on same-sex couples, distinguishing partners by gender is not an option. In some instances, same-sex partners should be distinguished on the basis of some other characteristic, if that distinction is important for the analyses conducted. For example, in Abbie Goldberg's work on lesbian couples who used alternative insemination to become parents (N = 29–34 couples), she distinguished between the biological mothers and the nonbiological mothers and found differential predictors of relationship quality and mental health across the transition to parenthood (Goldberg & Sayer, 2006; Goldberg & Smith, 2008a). Other distinguishing features that may be relevant to analyses might be work status (e.g., working/not working, in single-earner couples), primary/secondary child caregiver status, or diseased/not diseased (O'Rourke et al., 2010).

It is important that the distinction between dyad members is justified by the research questions being asked and the analyses being conducted and is thereby meaningful in a substantive sense. As it is always possible to find some distinguishing feature, however arbitrary, it is important to carefully evaluate whether the distinguishing feature is in fact relevant.[2] There are, for example, times when distinguishing partners within heterosexual couples based on gender may not be relevant to the analyses being conducted (Atkins, 2005; Kenny et al., 2006). The use of a particular distinguishing feature should be supported by the theoretical frameworks guiding the research, by prior research findings suggesting that this is a meaningful distinction, and by empirical investigation of the data being examined (Kenny et al., 2006). Kenny and Ledermann (2010) contend that distinguishability must be supported empirically. In other words, if dyad members are to be treated as distinguishable in the analyses, distinguishability analyses should be conducted to give empirical support for this decision. Kenny et al. (2006) describe an Omnibus Test of Distinguishability conducted using SEM that examines the means, variances, covariances, effect estimates, and intercepts in a model in order to show that the data support distinguishing dyad members. MLM techniques can also be used to test for distinguishability, although distinguishability in predictor variable means and variances cannot be assessed using MLM (Kenny et al., 2006).

There are also methods that can be used within the context of multilevel modeling to empirically support the use of a particular feature to distinguish between dyad members. Consider, for example, Goldberg and Smith's (2008b) analyses of social support and well-being in lesbian inseminating couples, where partners were distinguished by whether or not they were the biological mother of the child. The MLM approach for distinguishable dyads provides separate parameter estimates for the two partners based on the distinguishing feature (in our example, biological mother or nonbiological mother). Researchers can test whether these estimates are statistically significantly different from each other, by fitting a second model, in which these two separate parameter estimates are constrained to be equal. Model comparison tests are then used to determine which model is a better fit to the data. If there is no significant decrement in model fit, then there is not enough of a difference in the partners' estimates to justify the estimation of two separate parameters. If there is a decrement in model fit, this supports the decision to treat partners as being meaningfully distinguished on the basis of the selected distinguishing feature (i.e., in this case, biological versus nonbiological mother).

Even when there are theoretical and empirical reasons to distinguish between partners, it is possible that researchers will find that only some parameter estimates differ between them. Those parameters that are not found to be significantly different can then be constrained to be equal, creating a more parsimonious model. Such an approach was used in Goldberg and Smith's (2008a) examination of changes in the anxiety of lesbian inseminating couples over time (N = 34

[2]One question that is worth considering, for researchers, is whether partners in so-called heterosexual or different-sex couples actually identify as male and female. Assumptions about gender identity are routinely made in family research – and should perhaps be revisited and avoided by explicitly asking parents or partners about their self-identified gender, with a range of possible gender identity options.

couples). Their analyses revealed that while the effect of some factors such as neuroticism did not significantly differ for biological and nonbiological lesbian mothers, other factors did have a differential effect on biological and nonbiological mothers. Work hours and proportional contribution to housework were related to higher levels of anxiety only for biological mothers, while high infant distress and low instrumental social support were related to greater increases in anxiety only in nonbiological mothers. Such differential findings strongly supported the decision to distinguish partners on the basis of whether or not they were the biological mother.

MLM Approaches to Analyzing Data from Indistinguishable Dyads

As noted, in many cases in LGBTQ couple research, a salient, distinguishing feature will not be available for researchers. Having a distinguishing feature allows the researcher to assign each member to a group based on that distinction and then examine these separate groups in the analyses. As a result, some researchers may be tempted to deal with the lack of a distinguishing feature on which to assign dyad members to groups by randomly assigning members to one of the two groups (e.g., partner A and partner B) and then treating them as if they were distinguishable or by using an arbitrary characteristic to distinguish them (see Kenny et al., 2006). The problem with such an approach is that it can lead to erroneous findings. The assignment to a group is purely arbitrary and, yet, findings will differ depending on how the individuals are assigned. For example, when examining couple data, one of the first questions a researcher may want to consider is "How correlated are partners' scores?" Once the researcher has distinguished between the two partners and assigned them to separate groups, the researcher can simply examine the correlation between the two partners' scores. Unfortunately, however, the estimate of this correlation will differ depending on the way in which partners were assigned to groups (see Kenny et al., 2006, for a more detailed discussion of this issue).

Cross-sectional Model for Indistinguishable Dyads

Multilevel modeling provides a relatively simple extension of OLS regression, which takes into account the nesting of data within families or couples. In this statistical approach, the variance in the outcome is partitioned into the variance that occurs *within* couples (how partners differ from each other) and the variance that occurs *between* couples (how couples differ from each other). Predictors, both those that vary by couples (such as number of children and length of relationship) and by partner (such as age or mental health status), can then be added to explain this variance. In the model for the cross-sectional analysis of dyadic data, the multilevel model generally used to examine individuals who are nested within groups (such as students within classrooms, workers within organizations, or patients within hospitals) is commonly adapted to deal with the fact that dependence in dyads can be negative (because there are exactly two members in each group). For example, one common adaptation is in the specification of the error structure (i.e., using compound symmetry), whereby the dyad members' residuals (errors) are modeled as correlated as opposed to including a random dyad intercept in the model as would be the more traditional MLM specification. Group/dyad variance can only be positive and thus, the random intercept model can only handle positive dependence, but in a correlated errors model it can accommodate negative dyadic dependence as well as positive dependence. The random intercept model is described in detail below.

The MLM approach to indistinguishable dyads is actually a simpler model, in terms of the number of parameters to be estimated, than the one more commonly used model for distinguishable dyads (Kenny et al., 2006). Several studies of same-sex couples have used this approach (e.g., Goldberg & Smith, 2008b, 2009b, 2017; Kurdek, 1998). For example, in his early pioneering work in the field, Lawrence Kurdek (2003) used this approach to analyze differences between gay and lesbian cohabiting partners' relationship beliefs, conflict resolution strategies, and level of perceived social support variables in a sample of 80 gay male and 53 lesbian couples.

	FAMID	MEMBER	FAMSUP	A1AGE	P1AGE	A1EDUC	P1EDUC	A1PINC	P1PINC
1	1	1	3.10	43	43	5	5	$9.50	2.10
2	1	2	1.45	43	43	5	5	$2.10	9.50
3	2	1	3.50	40	53	5	6	$9.00	14.00
4	2	2	1.95	53	40	6	5	$14.00	9.00
5	3	1	2.85	36	37	5	6	$4.50	9.50
6	3	2	3.50	37	36	6	5	$9.50	4.50
7	4	1	1.85	38	41	4	2	$6.60	3.85
8	4	2	3.55	41	38	2	4	$3.85	6.60

Fig. 1 Example of a Level-1 (within-couples) data file for the analysis of cross-sectional dyadic data

Fig. 2 Example of a Level-2 (between-couples) data file for the analysis of cross-sectional dyadic data

	FAMILYID	lesbian	PrivAdop	PubAdopt	IntAdopt
1	1	1	1	0	0
2	2	1	1	0	0
3	3	1	0	0	1
4	4	1	1	0	0
5	5	1	1	0	0
6	6	1	0	1	1
7	7	1	0	0	1
8	8	1	1	0	0

The most basic model is an unconditional model, with no predictors at either level; this is often referred to as a random intercept model (Raudenbush & Bryk, 2002). This model provides estimates for the grand mean of the outcome across all couples as well as estimates for the two sources of variability: within-couples and between-couples. We calculate the proportion of variance that is due to between-group differences, or the intraclass correlation coefficient (ICC), from these two estimates of variability: the between-couples variance divided by the total variance (the sum of the within-couples and between-couples variances).[3] The ICC provides two central pieces of information: (a) the extent of the dependence within couples on the outcome and (b) the proportion of variance that lies *between* couples versus the proportion that lies *within* couples. Any ICC larger than a few percentage points indicates a degree of dependence on the data that cannot be overlooked and justifies the use of MLM.

It is easiest to understand multilevel models if one looks at the levels separately. In the cross-sectional model for dyads, Level 1 provides the *within*-couple model, in which individual responses are nested within couples, while Level 2 provides the *between*-couples model. Examining the structure of the data for the two levels, as required by the software program HLM, can help one better understand the distinction between these levels; see Figs. 1 and 2 (Raudenbush, Bryk, & Congdon, 2004). In Eq. (1) of the unconditional model, the intercept, β_{0j}, represents average outcome score for each couple, and r_{ij} represents the deviation of each member of the couple from the couple average. This intercept is treated as randomly varying; that is, it is allowed to take on different values for each couple. The intercepts that are estimated for each

[3]The ICC is simply the estimate of the error correlation in the dyadic model that parameterizes the dependence within couples by way of a residual correlation as opposed to a between-couples variance term. The ICC estimates from these two approaches will be the same when maximum likelihood estimation is used in both models.

couple are treated as an outcome variable at Level 2. The intercept in the Level-2 equation, Eq. (2), γ_{00}, provides an estimate of the average outcome score across couples and u_{0j} represents the deviation of each couple from the overall average across all couples.

Level 1 (*within* couples; Eq. 1):

$$Y_{ij} = \beta_{0j} + r_{ij} \tag{1}$$

Level 2 (*between* couples; Eq. 2):

$$\beta_{0j} = \gamma_{00} + u_{0j} \tag{2}$$

where Y_{ij} represents the outcome score of partner i in dyad j, where $i = 1, 2$ for the two members of the dyad. In addition to the above "fixed effect" estimate (e.g., the γ_{00}), estimates of the variance of the "random effects" both within and between couples are provided (e.g., the variance of the r_{ij}'s and the u_{0j}'s). Predictors can then be added to the model, with those that vary within couples (e.g., partners' ages) added at Level 1 (Eq. 3):

$$Y_{ij} = \beta_{0j} + \beta_{1j}\left(\mathrm{Age}\right)_{ij} + r_{ij} \tag{3}$$

and those that vary between couples (e.g., length of time in a relationship together) added at Level 2 (Eq. 4):

$$\beta_{0j} = \gamma_{00} + \gamma_{01}\left(\mathrm{Relationship\ duration}\right)_{j} + u_{0j} \tag{4}$$

We can add a variable at Level 2 that provides us with a way to tease out important group differences in the couple averages, such as the type of couple. For example, in Abbie Goldberg's research on lesbian, gay male, and heterosexual adoptive couples, this multilevel modeling approach is used to provide estimates of means for each group (on reports of love, conflict, and ambivalence), as well as to test for differences in these means (Goldberg, Smith, & Kashy, 2010). To examine group means, a dichotomous variable is created that indicates the type of couple (e.g., gay male or heterosexual), which is then entered at Level 2. The intercept provides the mean level of the outcome for the reference group (lesbian, in this case), while the coefficient for the predictor (e.g., gay male) indicates the difference between that group and the reference group. An alternative parameterization of the effects of couple type suggested by West et al. (2008) is described below.

Considering Partner Effects

Personal relationship theory, which examines the predictors, processes, and outcomes of close relationships, has shown the importance of considering the role of partner characteristics in dyadic research (Kenny & Cook, 1999). It may not be immediately evident how such a model can be used to examine partner effects – that is, the association between one partner's predictor with the other partner's outcome score. It is helpful to think of these associations within the context of the Actor–Partner Interdependence Model (APIM; Campbell & Kashy, 2002; Cook & Kenny, 2005). Using this approach, one simultaneously considers the respondent's value on a predictor, such as age, as well as the respondent's partner's value on this predictor in relation to the outcome. For example, Fergus, Lewis, Darbes, and Kral (2009) found that in examining the HIV risk of gay men ($N = 59$ couples), it was important to consider not only individuals' own integration into the gay community, but also their partners' integration. In the MLM approach, both of these predictors are entered into the model at Level 1 (Kenny et al., 2006).

Level 1 (within couples; Eq. 5):

$$\begin{aligned} Y_{ij} = \beta_{0j} &+ \beta_{1j}\left(\mathrm{Actor\ race}\right)_{ij} \\ &+ \beta_{2j}\left(\mathrm{Partner\ race}\right)_{ij} + r_{ij} \end{aligned} \tag{5}$$

Level 2 (between couples; Eq. 6):

$$\begin{aligned} \beta_{0j} &= \gamma_{00} + u_{0ij} \\ \beta_{1j} &= \gamma_{10} \\ \beta_{2j} &= \gamma_{20} \end{aligned} \tag{6}$$

The APIM goes further, however, suggesting that it is necessary not only to consider both actor and partner characteristics as main effects, but also to consider the interaction between them (Garcia et al., 2015). The interaction term models the specific pairing of the two individuals in the couple. For example, the effect of parents' disciplinary style on the child's behavior may vary as a function of their partners' disciplinary style. In such a case, it would be important to test an interaction between actors' disciplinary style and partners' disciplinary style. Whenever the theoretical framework guiding the analyses and past research suggest the potential importance of such an interaction and sample size permits its inclusion, it is crucial that the interaction term be included (Cook & Kenny, 2005).

Modeling (Binary) Gender and Sexual Orientation Using the APIM Approach

Research in the field of personal relationships extended the APIM approach specifically to address the role of gender and sexual orientation (particularly in the area of partner preferences; West et al., 2008). West et al. (2008) argue for the need to include same-sex couples in research on the effects of partner gender (using a binary approach to gender). In addition, they contend that both actor gender and partner gender should be considered in analyses that examine data from both heterosexual (distinguishable) and same-sex (indistinguishable) couples. They propose what they term a "factorial method" that considers respondent gender, partner gender, and "dyad gender" (i.e., the difference between same-gender and different-gender respondents, where dyad gender is the interaction between actor and partner gender). They point out that examining group differences between female, male, and heterosexual couples without taking into account the gender differences within heterosexual couples may lead to an inadequate understanding of the data, as it conflates the scores for men and women within heterosexual couples. West and colleagues provide an example in which findings from a group difference approach (i.e., looking only at differences between female, male, and heterosexual couples) showed that female and male same-sex couples placed less importance on the social value of a partner (e.g., appeal to friends, similar social class background, financial worth) than heterosexual couples ($N = 784$ female couples, 969 male couples, and 4292 heterosexual couples). When within-dyad gender differences are taken into account, however, the results showed that it was not that lesbians and gay men placed less emphasis on the social value of a partner than heterosexuals, but that heterosexual *women* placed much more emphasis on the social value of a partner than gay men and heterosexual men, with lesbians placing slightly more emphasis on the social value than gay men.

Randi Garcia et al. (2015) delve further into the role of moderators in the APIM. Specifically, they describe many patterns of moderation effects that can be tested when adding moderators to the indistinguishable and distinguishable dyad APIMs, and they discuss modeling techniques using both MLM and SEM.

Examining Change Over Time in Indistinguishable Dyads

To get a better grasp of longitudinal multilevel models for dyadic data, it is useful to understand how change is modeled in a basic (nondyadic) multilevel model. The cross-sectional approach to dyads considered individuals nested within dyads, modeling individuals at Level 1 and couples at Level 2. When examining change over time, we are looking at multiple time points nested within each individual. Level-1 models change within individuals, while Level-2 models differences in change between individuals. There are essentially two MLM approaches to modeling change over time within dyads: (a) a 2-level model in which trajectories of change for both dyad members are modeled at Level 1, while between-dyad differences in change are modeled at Level 2 (Raudenbush et al., 1995); and (b) a 3-level model in which change over time within each individual is modeled at Level 1, individuals within dyads at Level 2, and between-dyad differences at Level 3 (Atkins, 2005; Kurdek, 1998; Simpson, Atkins, Gattis, & Christensen, 2008).

While conceptually, the 3-level approach might appear to make perfect sense, there is a statistical problem in terms of the random effects. That is, while it is a 3-level model in terms of the data structure, it is only a 2-level model in terms of the within-level variation. Consequently, most articles on dyadic multilevel modeling recommend the 2-level approach (Bolger & Shrout, 2007; Raudenbush et al., 1995; Sayer & Klute, 2005). Even proponents of the 3-level model admit to a reduction in power and related changes in findings when using this model in comparison to the 2-level model most easily used for distinguishable dyads[4] (Atkins, 2005). Deborah Kashy has developed an extension of the 2-level multilevel model generally used to examine change in distinguishable dyads, which can be applied in the case of indistinguishable dyads (Kashy et al., 2008). While Kashy's initial work was on twin research, more recent work has extended the use of this model to lesbian and gay male parents (Farr, 2017; Goldberg et al., 2010; Goldberg & Garcia, 2016; Goldberg & Smith, 2009a, 2011). For example, in a study of female, male, and heterosexual adoptive parents, this approach was used to examine preadoptive factors on relationship quality (love, conflict, and ambivalence) across the transition to adoptive parenthood (Goldberg et al., 2010; $N = 44$ female couples, 30 male couples, and 51 heterosexual couples). Parents who reported higher levels of depression, greater use of avoidant coping, lower levels of relationship maintenance behaviors, and less satisfaction with their adoption agencies before the adoption reported lower relationship quality at the time of the adoption. The effect of avoidant coping on relationship quality varied by gender. The use of a longitudinal model enabled Goldberg et al. (2010) to examine change in relationship quality across this transition as well: Parents who reported higher levels of depression, greater use of confrontative coping, and higher levels of relationship maintenance behaviors prior to the adoption reported greater declines in relationship quality.

The longitudinal model for indistinguishable dyads is very similar to the distinguishable dyad model in which trajectories for both dyad members are modeled at Level 1, with separate intercepts and slopes modeled for each member of the dyad (Raudenbush et al., 1995). The two partners' intercepts are allowed to covary, as are their rates of change (slopes). Due to the inability to distinguish between dyad members in the indistinguishable case, however, parameter estimates for the average intercept and average slope (the fixed effects) are pooled across partners as well as dyads (Kashy et al., 2008). In addition, drawing from approaches to modeling indistinguishable dyads in structural equation modeling (Olsen & Kenny, 2006; Woody & Sadler, 2005), this approach constrains the estimates of intercept and slope (if random) variance to be equal for partners.[5] Similar to the distinguishable model, two (redundant) dummy variables, P1 and P2, are used to systematically differentiate between the two partners. In other words, if the outcome score is from partner 1, P1 = 1, and otherwise P1 = 0; and, if the outcome score is from partner 2, P2 = 1, and otherwise P2 = 0. At Level 1 of the model (in which there are no predictors aside from Time), an intercept and slope for time for each partner is modeled:

Level 1 (within couples; Eq. 7):

$$\begin{aligned} Y_{ijk} &= \beta_{01j}\left(\mathrm{P1}\right) + \beta_{11j}\left(\mathrm{P1} * \mathrm{Time}\right)_{1jk} \\ &+ \beta_{02j}\left(\mathrm{P2}\right) + \beta_{12j}\left(\mathrm{P2} * \mathrm{Time}\right)_{2jk} + r_{ijk} \end{aligned} \tag{7}$$

where Y_{ijk} represents the outcome score of partner i in dyad j at time k, and $i = 1, 2$ for the two members of the dyad.

[4]The overtime model is more difficult to use for indistinguishable dyads than for distinguishable dyads because the elements of the covariance matrix of random effects need to be fixed to be equal across dyads in the indistinguishable case. Not all statistical software packages allow this custom specification.

[5]Estimates of within-person and between-person intercept-slope covariances are also constrained to be equal across members.

In this model, intercepts and slopes can vary between dyads. The inability to distinguish between dyad members would make it meaningless to have separate parameter estimates for member 1 and member 2; therefore, the parameter estimates for the fixed effects are aggregated across dyad members. In the Level-1 equation (Eq. 7), β_{01j} and β_{02j} represent the intercepts, for partners 1 and 2 in couple j, and estimate the level of depressive or anxious symptoms at the time of the adoption. Likewise, β_{11j} and β_{12j} represent the slopes for the two partners. These slopes estimate the change in the outcome over the transition to adoptive parenthood. Unlike the distinguishable model, however, the estimates for the intercepts and slopes are then pooled (β_{0ij} and β_{1ij}) creating only two Level-2 equations, one for the intercept and one for the slope.

Level 2 (between couples; Eq. 8):

$$\begin{aligned} \beta_{0ij} &= \gamma_{00} + u_{0ij} \\ \beta_{1ij} &= \gamma_{10} + u_{1ij} \end{aligned} \tag{8}$$

As these two equations show, the intercepts are pooled not only between but *within* dyads (i.e., across both i and j) to estimate the fixed effect, γ_{00}, which is the average intercept (or the average level of the outcome when Time = 0), and similarly, the slopes for time are pooled both between and within dyads to estimate the average slope, γ_{10} (or the average rate of change in the outcome across all partners).

The variance components are also pooled both between and within dyads. At Level 2, the variance in the intercept, Var(u_{0ij}), represents the variability in the outcome at the time of the adoptive placement, and the variance in the slopes, Var(u_{1ij}), represents the variability in how depressive or anxious symptoms change over time. The third variance component, Var(r_{ijk}), is the variance of the Level-1 residuals (or the difference between the observed values of the outcome and the predicted values from the fitted trajectories). The variance of the Level-1 residuals is constrained to be equal for both partners and across all time points. In addition to the variances, several covariances commonly estimated in dyadic growth models can also be included in this model. For example, the covariance between the two slopes estimating change for each person uniquely shows the degree of similarity in partners' pattern of change, to name one such covariance.[6]

Considerations When Modeling Change Over Time When modeling change, the reliability of the change trajectories will be greatly improved with a greater number of assessment points (Raudenbush & Bryk, 2002; Willett, 1989). In addition, the use of more assessment points allows researchers to examine more complex patterns of change. For example, research on heterosexual-parent couples has shown relationship quality and many mental health outcomes such as depression to follow curvilinear trajectories particularly across the transition to parenthood (Perry-Jenkins, Smith, Goldberg, & Logan, 2011). Such patterns cannot be captured with only three time points.

[6]In addition to the variances, Kashy et al.' (2008) model for analyzing longitudinal data from indistinguishable dyads provides estimates for several covariances. Dyadic growth models often include three covariances. First, the covariance between the intercepts estimates the degree of similarity in partners' outcome scores at the time of the adoption. Second, the covariance between the slopes estimates the degree of similarity in partners' patterns of change. Third, a time-specific covariance assesses the similarity in the two partners' outcome scores at each time point after controlling for all of the predictors in the model.

Two additional covariances are estimated using Kashy et al.' (2008) approach. An intrapersonal covariance between the intercept and slope can be estimated to examine, for example, if having higher depressive symptoms at the time of adoption is related to greater increases in depressive symptoms over time. An interpersonal covariance between the intercept and slope can also be estimated to examine, for example, if partners of individuals with high initial stress experience greater increases in stress over time. As some software such as SPSS does not allow for estimation of these covariances, these are not always included in the models (Goldberg et al., 2010; Goldberg & Smith, 2009a; Goldberg & Smith, 2011). As these covariance estimates are less important, and less likely to affect findings, the use of models with and without them may well be adequate for most research. In fact, identical patterns of results have been found with and without the covariance constraints in the existing published literature (Goldberg et al., 2010; Goldberg & Smith, 2009a; Goldberg & Smith, 2011).

Note that the software program HLM does not allow for either variances or covariances to be constrained.

While more time points are preferable, it is possible to fit the change models to examine change between two time points (i.e., a latent difference score). Goldberg and Smith (2009a) used this approach to examine changes in perceived parenting skill in lesbian, gay male, and heterosexual adoptive couples after the adoption of their first child. Examination of change between only two time points is essentially a difference score. While not ideal, the use of multilevel modeling to generate difference scores provides better estimates of change than observed difference scores, as it provides some correction for measurement error, and takes into account level as well as amount of change (O'Rourke et al., 2010; Sayer & Klute, 2005). (Note that SEM would accommodate further modeling of measurement error; Iida, Seidman, & Shrout, 2018.) For an example of using MLM to examine change between two time points in distinguishable dyads, see Goldberg and Sayer's (2006) examination of change in relationship quality in 29 lesbian inseminating couples across the transition to parenthood.

Additional data preparation is necessary to estimate change between two time points. With only two time points at Level 1, there would be too few degrees of freedom to estimate two fixed effects (an intercept and rate of change) and the residuals (or error) around the fitted regression line, unless additional information on the outcome was available and introduced into the modeling procedure. This additional information can be provided, however, by dividing the outcome measure into two parallel scales with comparable variance and reliability, allowing for the estimation of error (Raudenbush et al., 1995; Sayer & Klute, 2005).[7] In addition, the use of parallel scales provides a limited measurement component to the multilevel model and consequently a somewhat more accurate measure of both error and latent change scores. Future research, however, is needed to examine the reliability of the estimates for change from such models.

[7]Parallel scales are generally created based on the items' variance. First, the variances of all of the items in the scale are determined. The items are then assigned to each of the two scales on the basis of their variance. In other words, the item with the most variance would be assigned to scale A. The item with the second highest variance would go in scale B. The item with the third highest variance would also go in scale B. The items with the next highest variance would go in scale A, as would the next, and so forth.

Multiple Informants

In family research, one often attains multiple reports of the same outcomes. For example, a researcher examining the behavior of children of lesbian mothers may have both mothers report on the child's behavior. While structural equation modeling provides the best available method of handling data from multiple reporters, multilevel modeling may also be used to examine these data. By using reports from both parents, researchers can introduce a limited measurement component to the model. While this is a new area for LGBTQ research, it is a growing area in family research. A particularly interesting study was conducted by Georgiades et al. (2008) who used MLM to examine reports of family functioning gathered from multiple family members (N = 26,614 individuals in 11,023 families). While using reports from multiple members of the family provided a better measure of family functioning, the use of MLM enabled the researchers to distinguish shared perceptions of family functioning from unique individual perceptions, as well as to examine predictors of these perceptions.

Dyadic models such as those presented in this chapter can also be employed to examine reports from multiple informants. In the simplest application, MLM provides a composite score across multiple reporters, while taking into account the degree of association between dyad members' reports. This approach was used by Meteyer and Perry-Jenkins (2010) to examine change in fathers' involvement in childcare across the transition to parenthood in a sample of 98 heterosexual couples. The authors used a multilevel model with a single intercept and slope at Level 1 for each couple. The level of father involvement is estimated as this single intercept based on both mothers' and fathers' reports of father involvement; similarly, the single rate of change in involvement is based on both parents' reports of father involvement.

For indistinguishable dyads, this approach simply involves use of the indistinguishable model presented earlier in this chapter. For example, Goldberg and Smith (2017) examined the relationship between parents' involvement in children's schools and children's well-being as reported by both parents in a sample of 106 female, male, and heterosexual couples with adopted children. In the dyadic, cross-sectional model, the composite score for the dyad (dyad average; i.e., child well-being) is represented by the Level-1 intercept. MLM also estimates the correlation between the parents' scores, indicating the strength of the relationship between parents' reports within couples. Recall that in the MLM models, variance in the reports is partitioned into two sources: that which lies *between* dyads and that which lies *within* dyads. Predictors were then entered to explain this variance. At Level 1 (i.e., within couple), individual-level predictors included parent–school relationships at T1 (school involvement, parent–teacher relationship quality, parent–school contact about child problems, and perceived acceptance by other parents) and adoption-specific school experiences at T1 (parent input about classroom inclusion and parent–teacher conflicts related to adoptive family status). At Level 2 (i.e., between couple), couple and family-level variables (i.e., variables that varied between rather than within couples) were entered. These included family type (e.g., same-sex or heterosexual couple) and demographic control variables, such as child gender, child age, and private versus public school. Goldberg and Smith found that parent–school involvement was negatively related to later internalizing symptoms in children; providing input to teachers about inclusion and parent–teacher conflicts related to adoption were both positively related to later internalizing symptoms in children. Perceived acceptance by other parents was negatively related to later child internalizing and externalizing symptoms. School-initiated contact about child problems more strongly predicted higher externalizing symptoms among children in same-sex parent families than among children in heterosexual parent families.

With distinguishable dyads, the two-intercept model makes it easy to examine differential predictors of the two respondents' reports. For example, in the case of parent and child reports of child well-being, the model would include separate estimates for child reports and parent reports at Level 1. Predictors, such as family income, would be entered at Level 2. This model provides separate parameter estimates for the effect of income on parents' and children's reports. It is then possible to test whether these estimates are statistically different by constraining the two estimates to be the same and conducting model comparison tests (as discussed early in the section on distinguishability). This approach was used by Kuo, Mohler, Raudenbush, and Earls (2000), to examine the relationship between demographic risk factors and reports of children's exposure to violence (N = 1,880 children and 1776 parents). The researchers also used the traditional method of conducting analyses separately on fathers' and children's reports and found the results for individual parameter estimates to be very similar. However, it is only possible to statistically test for the differences between informants using the MLM (or SEM) approach, as the two reports must be modeled simultaneously.

Conducting similar analyses is not feasible in MLM using the indistinguishable model, as that model does not provide separate parameter estimates of the effects of a couple-level (Level-2) predictor on the two partners' reports (as the two partners are not distinguished). The APIM could, however, be used to examine differential effects of characteristics that vary for individuals. For example, one could examine the effects of individuals' own characteristics and their and partners' characteristics on individuals' reports.

An alternate approach for distinguishable dyads is to examine discrepancies between the reports of the two dyad members (Lyons, Zarit, Sayer, & Whitlach, 2002). Coley and Morris (2002) use this approach to examine discrepancies in mothers' and fathers' reports of father involvement in 228 low-income families. Specifically, reports of the outcome are regressed onto dummy indicators for the mother (−0.5) and father (0.5).

Discrepancy model: Level 1 (Eq. 9):

$$Y_{ij} = \beta_{0j} + \beta_{1j}\left(\text{indicator}\right) + r_{ij} \tag{9}$$

In this model, the intercept represents the *average* of the two parents' reports of father involvement, and the slope represents the *discrepancy* between the two reports, as there is exactly 1.0 unit between indicators. Predictors for the average and the discrepancy can then be added at Level 2. Coley and Morris (2002) found that parental conflict, fathers' nonresidence, and fathers' age, as well as mothers' education and employment, predicted larger discrepancies between fathers' and mothers' reports. Use of the discrepancy approach, however, requires the ability to differentiate between dyad members.

Beyond Basic Multilevel Moldels

While MLM provides many valuable approaches for the analysis of dyadic data, some analyses can only be done in SEM or are more easily done in SEM (by those already familiar with SEM), which we discuss only briefly. For example, mediation is most easily examined using SEM or using multilevel SEM (MSEM; Ledermann, Macho, & Kenny, 2011). Although, SEM is the preferred approach to examining mediation, strategies for examining mediation do exist within MLM framework. Kenny, Korchmaros, and Bolger (2003) provide a crude approach that consists of estimating the paths in separate models and then analyzing the results of the separately estimated models. In addition, Bauer, Preacher, and Gil (2006) developed an approach in which the data are restructured in order to test all effects.

In addition, SEM provides the ability to examine other models, such as the dyadic latent congruence model and the mutual influence model (which is similar to the APIM, but considers reciprocal effects), and to conduct confirmatory factor analyses using dyadic data and examine measurement invariance across distinguishable dyad members (Ledermann & Kenny, 2017). Common Fate Models (CFM; Galovan, Holmes, & Proulx, 2017; Iida et al., 2018; Kenny et al., 2006) and Common Fate Growth Models (CFGM; Ledermann & Macho, 2014) provide a better means to examine variables at the couple or family level than the MLM multiple informant model discussed above. (See Iida et al. (2018) for an excellent discussion comparing the uses of APIM, common fate, and a dyadic score model within an SEM framework.) Goldberg and Garcia (2016) used a CFGM in a sample of 181 couples with adopted children (56 female couples, 48 male couples, and 77 heterosexual couples). Specifically, they used the two parents' reports of their child's play as indicators of the child's behavior, as a family-level latent variable, and investigated parent-reported gendered play of children across three time points. Using this approach, they found that regardless of family type, the parent-reported gender-typed behavior of boys, but not girls, significantly changed over time (i.e., boys' behavior became more masculine).

The basic cross-sectional model and a longitudinal growth model can also be fit in SEM (although the growth model requires the same time intervals between measurements for all dyads). Hong and Kim (2019) present APIMs using MLM and SEM, showing how the estimates are essentially identical. However, Hong and Kim also prefer SEM over MLM, given the looser underlying assumptions regarding measurement and factor loadings in SEM, and the better selection of model fit indices available.

In an attempt to make dyadic SEM more accessible to researchers, Stas, Kenny, Mayer, and Loeys (2018) have made a simplified form of SEM analysis available through a web application *APIM_SEM* that allows one to easily fit basic APIMs for both distinguishable and indistinguishable dyads using one or two predictors and controlling for covariates. The free web application is available at http://datapp.ugent.be/shiny/apim_sem/.

Limitation of Dyadic Multilevel Modeling Due to Small Number of Families per Group

While multilevel modeling provides a useful method for examining family data, it also has important limitations. Most importantly, MLM is a large sample statistical approach; it is at its best when examining a large number of groups (like families) with a large number of individuals per group. Having too few groups or two few individuals per group (such with dyads) presents a power issue, as there is not enough information to reliably detect effects and can lead to a lack of precision in certain parameter estimates (Maas & Hox, 2005; Raudenbush, 2008).

Number of Families Required

Given the limited number of individuals in families and dyads, a large number of groups (at least 100) are required to obtain accurate estimates of the fixed effects, such as the intercept, rate of change, and the predictors, as well as their standard errors (Raudenbush, 2008). While there are alternative estimation procedures that provide more accurate estimates when there are a small number of units (groups or dyads) at the highest level (Level 2 for the models presented here) with many people per group, these alternatives cannot address the problem of the small number of individuals per dyad.

While having a sample of at least 100 dyads will provide accurate parameter estimates of the fixed effects and their standard errors, other parameter estimates lack precision due to the small number of individuals per dyad, specifically the estimates of the Level-2 variance components may be inaccurate (e.g., the amount of variability between dyads; Raudenbush, 2008). Consequently, researchers should not rely on statistical tests regarding the amount of variability when deciding whether or not to enter predictors into their model. In addition, the MLM estimates of individual scores for each dyad (the estimated Bayesian coefficients) are unreliable. This is of greatest concern with cross-sectional models, as well-fitting longitudinal models with assessments across multiple time points (i.e., more than two) allow for more accurate estimation. The unreliability of the estimates of variance should also raise concern with the accuracy of estimates of the ICC which is derived from the variance estimates.

Noncontinuous Outcomes

Another important limitation to having a small number of individuals per family or dyad is that these models should only be applied to the analysis of continuous outcomes (Raudenbush, 2008; but see Ledermann & Kenny, 2017, for a different perspective). When examining outcomes that are not continuously and normally distributed, such as categorical or count data, MLM cannot provide accurate estimates when there are only a few number of individuals per group, even if there are a large number of these small groups. When there are a large number of dyads, SEM or a generalized version of MLM would be the preferred approach to analyzing dichotomous or count data (or any other outcome that requires a link function to transform the outcome scores). Simulations have shown that generalized linear mixed models (GLMM) can provide reliable estimates in samples larger than 100 couples when the correlations within dyads are positive (Spain, Jackson, & Edmonds, 2012). Loeys and Molenberghs (2013) showed generalized estimating equations (GEE) to be a reliable and accessible alternative to GLMM (using a robust variance estimate), reporting that simulations demonstrated that GEE produce more reliable estimates than GLMM in smaller samples and when the within-dyad correlations are negative. Loeys and Molenberghs still recommend a sample size of more than 50 dyads to test an APIM, however. (For an excellent primer on GEE, see Loeys, Cook, De Smet, Wietzker, & Buysse, 2014.)

Goldberg, Smith, McCormick, and Overstreet (2019) use a GEE approach in their examination of predictors of health behaviors and outcomes in 141 parents in same-sex couples (76 women in 43 couples and 65 men in 39 couples). They found that parenting stress and internalized homophobia were most commonly associated with health behaviors and outcomes, but functioned differently in women and men. Women with high stress had greater odds of exercising at least 3 days a week, but women with high internalized homophobia had lower odds of exercising that much, while the effects were vice versa in men. In addition, men were more likely to report depression than women; and, men with low internalized homophobia more often slept less than 7 hours a week and reported greater alcohol intake than those with high internalized homophobia. Among all parents, those with multiple children and those who were unmarried had lower odds of exercising at least 3 days a week, while those with high stress had greater odds of depression and of a chronic health condition.

Future Directions

While there are still many areas requiring further development in the application of multilevel modeling to the examination of family data, the most important need in the area of LGBTQ family research is the need to make existing methods more available to researchers. In order to use MLM approaches to dyadic data analysis, researchers must learn both the basics of MLM and the inner workings of dyadic models. While multilevel modeling is increasingly being taught in departments such as family studies, human development, sociology, and psychology, they are still unavailable to students in many programs. Most researchers who study LGBTQ couples, parents, and families will need to seek out training beyond the courses they were offered in their graduate program. There are several training workshops analyzing dyadic data available across the country – many of these include SEM as well as MLM approaches. There are also, however, many useful resources available on the web (see Appendix A).

If researchers who study LGBTQ couples, parents, and families are unable to employ the statistical methods appropriate for their data and research questions, it hinders the development of the field. Researchers who are unfamiliar with the appropriate statistical methods to analyze their data are unable to publish, particularly in the leading journals in fields such as family studies, psychology, and others. In addition, they are often unable to capitalize on the richness of datasets. Currently, the greatest need in this area is to provide statistical training in methods such as multilevel modeling to junior and senior researchers and to facilitate collaborations between LGBTQ family researchers who lack this training and both established and emerging methodologists in the field of dyadic data analysis.

Appendix A: Online Resources for Dyadic Data Analysis

Overview of Dyadic Data Analysis
http://www.davidakenny.net/dyad.htm
Materials and Syntax to Accompany Kenny et al. (2006), *Dyadic Data Analysis*
http://www.davidakenny.net/kkc/kkc.htm
Multilevel Listserv
https://www.jiscmail.ac.uk/cgi-bin/webadmin?A0=multilevel

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