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Theoretical and methodological issues in relationship research: Considering the common fate model

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Abstract

Family and relationship researchers ask research questions at the dyadic- or family level, yet analyses are often conducted at the individual level. We review theoretical perspectives relative to studying families and dyads and note how they are connected with dyadic analysis techniques. We note differences in theoretical assumptions underlying the actor–partner interdependence model, the common fate model (CFM), and hybrid models that combine features of both and distinguish between the types of questions each addresses. Using third grade, sixth grade, and age 15 data from the National Institute of Child Health and Human Development study of Early Child Care and Youth Development ($N = 732$), we illustrate the value of using CFM and hybrid models to explore how family chaos is associated with couple conflict resolution and child behavior problems. Dyadic- and family-level analyses may offer additional insight into family functioning, and we provide recommendations for the use of CFM in furthering this line of inquiry.

Keywords

Adolescent development/outcomes, conflict, interaction, interdependence theory, structural equation modeling, systems theory

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Family and close relationship researchers have long been invested in studying relationship and family processes from multiple reporters, but the nonindependence of data complicates traditional data analysis methods. Indeed, the study of dyadic- and family-level research questions has seen significant growth in recent years (Ledermann & Kenny, 2012), and there are now many different models available to analyze these data, which—at a minimum—measure the same variables in both members of a dyad. In addition to providing the statistical means to account for the lack of independence between dyad or group members, these methodological advances permit researchers to explicitly model and explore interdependence. These advances also allow family and relationship researchers to ask questions about how interdependence between two or more partners influences other variables or how other variables might influence the interdependence present in a relationship. In asking such questions, Gonzalez and Griffin (2012) note that "interdependence is not treated as a nuisance that needs to be corrected but rather as one of the key psychological parameters to model" (p. 439). In this article, we explore two analytic methods capable of handling interdependence and continue to support Ledermann and Kenny's (2012) call for more dyadic research to employ the common fate model (CFM) when appropriate, as opposed to or in connection with the more popular actor–partner interdependence model (APIM).

Nearly all family and close relationships researchers implicitly or explicitly embrace the theoretical assumptions of interdependence in the research questions they ask and/or the methods they use. When scholars assume interdependence is a property of close relationships, they assert that an individual's thoughts, emotions, and actions are impacted not only by the individual but also by those connected to the individual (e.g., romantic partner, friend, child, etc.). Based on the fundamental assumption of interdependence, family and close relationship researchers use data from multiple members of the same relationship or group to explore the basic properties of interdependence. Some basic properties of interdependence might include one partner's degree of dependence on the other, the mutuality of dependence within the relationship (e.g., the degree to which two individuals' thoughts, behaviors, and emotions are linked in the relationship), the presence of individual outcomes (e.g., my behaviors and my partner's behaviors), the presence of joint outcomes that result from interdependence (e.g., family cohesion and relationship tension), or the correspondence of outcomes between interdependent partners (e.g., do my outcomes correspond or conflict with my partner's?; Kelley, 1979; Rusbult & Agnew, 2010; Rusbult & Van Lange, 2003; Thibaut & Kelley, 1978).

Fortunately, there are several statistical models that researchers can use to account for the interdependence inherent in close relationships. Kenny's Social Relations Model (SRM; Kenny, 1994; Kenny & La Voie, 1984) statistically models many of the theoretical assumptions outlined in relationship theories. The SRM includes components from the APIM (Kenny & Cook, 1999; see Figure 1), designed to model how individual partners' characteristics may be related to both their own and their partners' outcomes. The SRM also incorporates the distinct ideas from the CFM (Kenny & La Voie, 1985; see Figure 2) that represent how relationship- and family-level constructs may be related and the mutual influence model (Kenny, 1996) that models how

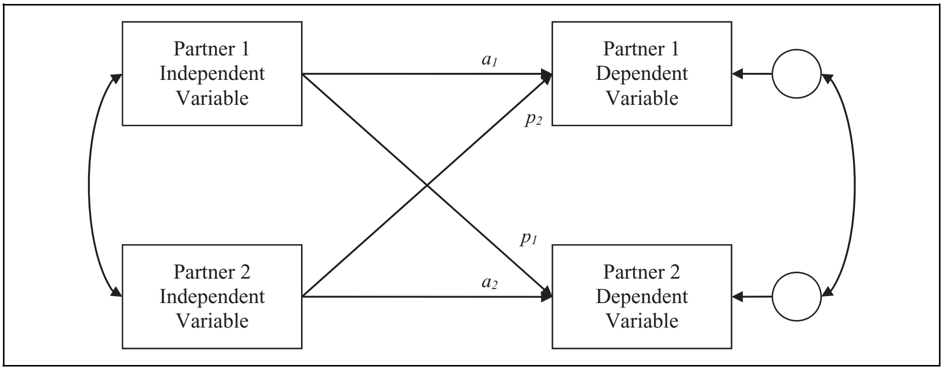

Figure 1. The actor–partner interdependence model. *Note.* Paths marked with *a* indicate actor effects. Paths marked with *p* indicate partner effects. The numbered subscripts correspond to each partner.

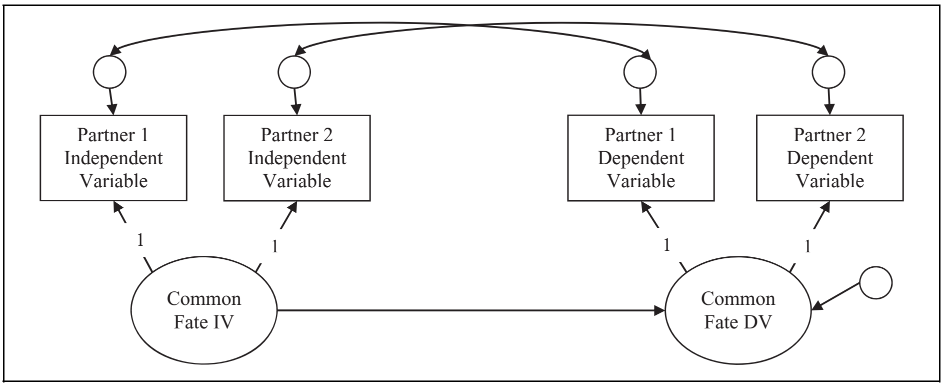

Figure 2. The common fate model. *Note.* Indicator variable intercepts are freely estimated, and the latent mean or intercept for the common fate variables are fixed to 0.

partners reciprocally influence one another. Thus, the SRM partitions the variance to include group-level effects, relationship-level effects for individuals within the group, and individual-level actor and partner effects. In using the SRM, researchers have increased our understanding of some unique dimensions of close relationships (Eichelsheim, Deković, Buist, & Cook, 2009; Halberstadt, Beale, Meade, Craig, & Parker, 2015). Given many researchers' unfamiliarity with the SRM and data structure considerations (e.g., multiple measures of the construct of interest), a full SRM analysis is not always possible or desirable. Thus, family and close relationship researchers have more often used the APIM and the CFM components of the SRM to model and understand relationship dynamics.

Researchers may question whether the APIM or CFM is most appropriate. Central to this question are issues related to the level of analysis. Indeed, despite the growth in scholars' use of dyadic- or family-level data and appropriate models for such data, it is still uncommon to see papers that appropriately distinguish between levels of analysis—that is, data that are collected from both dyad members but that occur at the individual level of analysis versus dyadic data that appear at the group level of analysis. This distinction informs the researcher's choice of analytic techniques and has theoretical implications, as it should inform the research questions being addressed in a study.

For the experienced dyadic researcher, embracing the interdependence inherent in dyadic data and selecting appropriate methods to best answer research questions about interdependence may be a relatively straightforward process. But for those new to the use of dyadic data or overwhelmed by the many options now available, selecting the best methodological technique can be a trying process. In writing this article, we have two primary goals. First, we discuss important theoretical and methodological considerations regarding when to use the CFM instead of the APIM and when to use hybrid models that incorporate elements of both the APIM and CFM. Second, we present five uses of the CFM and hybrid variations to illustrate how the CFM can be used to explore family-level and couple-level processes. Our hybrid illustrations further demonstrate how to test associations between group-level processes and individual behavior within the same family system. As the purpose of this article is not to discuss the technical components of each modeling strategy in depth, we refer the reader to sources that more thoroughly address the technical components (e.g., Kenny & Cook, 1999; Kenny, Kashy, & Cook, 2006; Ledermann & Kenny, 2012).

Although the CFM has been discussed in methodological circles since 1985 (e.g., Burk & Laursen, 2010; Conger, Rueter, & Elder, 1999), the method is still not widely used, and little discussion has occurred about when it may be a more appropriate choice than the APIM (see Ledermann & Kenny, 2012, for an exception). Our goal for including an illustration and discussion of the CFM in this article is to demonstrate how family and close relationship scholars can use this modeling technique to answer questions about the way family-level processes impact individual-, couple-, or family-level outcomes. To begin, we highlight key terminology used in the study of dyadic data and the methodological distinctions between the APIM and CFM. Next, we review the tenets of interdependence and systems theory, highlighting two of the theoretical perspectives best suited to explore interdependence. We then introduce our constructs of interest and offer an illustration of the CFM (Kenny & La Voie, 1985) and hybrid models (Ledermann & Kenny, 2012).

Nonindependence and interdependence

When discussing dyadic data, it is helpful to clearly define some basic concepts that will be referred to here. Nonindependence refers to the lack of statistical and theoretical independence between the reports of dyadic partners or members of a group, such as a family. Because all members share something in common—their relationship with one another—it cannot be assumed that members are independent of one another and neither are their scores on the variables that interest family and relationship scholars. While statistical independence can be assessed, theoretical nonindependence is often assumed. Interdependence refers to the relationships between partners and is more often used as a term implying the mutual influence between partners or members of a group that evolves over time (Thibaut & Kelley, 1978).

Level of measurement versus level of analysis

Another important component of dyadic data analysis is to distinguish between level of measurement and level of analysis. Level of measurement refers to the target of the items being asked of a respondent. For example, items from a common measure of depressive symptoms (the Center for Epidemiologic Studies Depression Scale; Radloff, 1977), such as, "Everything I did felt like an effort" target the individual—the individuals answering the question are reflecting only on themselves. An item such as "My husband and I get along well" targets the dyad, because the respondent is reflecting on a dyadic relationship that contains two parts (oneself and the partner). Level of analysis, on the other hand, refers to the level at which statistical dependence occurs (Kenny et al., 2006). For example, you might use the APIM to model the associations between two individual-level measurements (e.g., depressive symptoms and self-reported health) within marital dyads such that husbands' levels of depressive symptoms would be related to wives' reports of health. The level of analysis is dyadic because part of the variance of the outcome can be explained at the level of the couple—spouses influence each other's individual outcomes.

Distinctions between the APIM and CFM

In the CFM, interdependence is assumed to occur because dyad members are similar to one another due to the influence of a shared variable, which may be external to the relationship or a characteristic of the relationship itself. A critical question to ask when trying to decide whether the CFM is right for a given research question or design is whether dyad members are reporting on the same variable (Ledermann & Kenny, 2012) and whether the construct exists at the level of the dyad—or family—rather than the individual. For example, both dyad members may report on their level of depressive symptoms using the same scale. But reports of depression are self-referential and evaluate one's beliefs, behaviors, cognitions, and/or emotions. So while data may be available on both members' levels of depression, and their reports are likely to be correlated, the variable is not at the dyadic level of measurement and may be better suited for the APIM. The APIM allows the researcher to model the shared variance between individual reports of depression but assumes that similarities between partners are due not to a shared variable or force but to other processes (e.g., assortative mating; Kenny et al., 2006). Additionally, if partner reports are negatively correlated or correlations among the constructs are not consistent across partners, this suggests the constructs are individual-level rather than dyad-level constructs and would be better modeled with the APIM (Ledermann & Kenny, 2012). In contrast, a scale about the family's home environment that might contain items, such as, "The atmosphere in our home is calm" or "It's a real 'zoo' in our home," have the shared environment as the object of assessment—both spouses are influenced by the home environment that they share. If the research question is concerned with how this shared variable influences dyad members' shared outcome on another variable, the use of the CFM is appropriate.

Other examples of shared variables may include neighborhood quality, length of relationship, dyadic decision-making, or household income. These shared variables are assessed at the unit of the dyad and are usually referred to as between-dyad variables or as Level 2 variables in the multilevel modeling literature (alternatively, variables like depressive symptoms are considered Level 1 or within-person variables; Lüdtke et al., 2008). When the shared variable can be directly assessed, such as relationship length or household income, the variable can be modeled as an indicator whose value is the same (shared) for both members of the dyad (Newsom, 2002). In contrast, some variables, such as dyadic decision-making, are difficult to assess directly, and in this case, assessments are taken from both dyad members (Ledermann & Kenny, 2012). The shared variable is then best modeled as a latent variable with two indicators—one from each dyad member (Lüdtke et al., 2008; Maguire, 1999; Newsom, 2002)—a point we return to in our illustrative examples.

Theoretical and methodological foundations

Theorizing suggests that the properties of interdependent relationships may represent either individual- or group-level phenomena. Although the APIM and the CFM share a common theoretical assumption of interdependence, the two approaches diverge in the properties of interdependent associations that each models. In self-report research, the APIM uses variables that assess the unique perceptions of both dyad members (e.g., individual perceptions of relationship quality and individual reports of depressive symptoms) or self-reported demographic characteristics (e.g., education and age), while in observational research data from dyad members may include observations (e.g., ratings of emotionality) or physical or physiological measurements (e.g., heart rates). In its basic form, the APIM includes four primary paths of interest: two actor paths and two partner paths (see Figure 1), commonly termed "actor" and "partner" effects (e.g., see Cook & Kenny, 2005; Kenny & Cook, 1999). The two correlational paths in the model—one between the two partners' reports on the independent variable and one between the two partners' residual terms on the dependent variable—are also of interest. The correlation between the two independent variables represents the extent to which the two partners are similar to one another on the intrapersonal predictor variable. The correlation between the two residuals represents the nonindependence not explained by the APIM (Kenny et al., 2006). The APIM's basic assumption is that one dyad member's outcome can be predicted by both his or her own report on the independent variable and his or her partner, and in this way the APIM is best suited for analysis of the interrelatedness of dyadic partners.

In contrast to the APIM, the CFM (see Figure 2) explores theoretical associations about interdependence at the group level (Ledermann & Kenny, 2012). Patterns of reciprocity in relationships can lead to mutuality of dependence wherein partners—and indeed families—share an interdependent, relational experience (see also Drigotas, Rusbult, & Verette, 1999; Drigotas, Rusbult, Wieselquist, & Whitton, 1999; Rusbult & Van Lange, 2003). Thus, theoretically one or more members of the same group can report about their perception of shared processes within the group. For example, one member of the relationship can assess cohesion in the entire family group, reporting to what extent they agree with a statement like, "In our family we all work well together." Representing group-level phenomena with a common fate variable supports three key assumptions of interdependent systems within close relationships (Bowen, 1978; Day, Gavazzi, Miller, & van Langeveld, 2009; P. Minuchin, 1985; S. Minuchin, 1974).

First, as an interdependent system, the functioning of individuals is related not only to the individuals themselves but also to the behaviors between members of the system in which they are embedded (e.g., see Bowen, 1978; P. Minuchin, 1985). These processes at the group level may include implicit or explicit rules for all members, roles that are assigned and filled within the system, collective behaviors experienced and perpetuated within the system, or collective expectations shared by multiple members of the group. As such, researchers need to account for and explore nonindependence in the system, assuming that group-level phenomena may impact other group-level phenomena and/or individual-level phenomena.

Second, processes within a given system can operate in both direct and indirect ways. From a systemic perspective, these direct and indirect pathways create unique group-level contexts that may contribute to varying levels of other group-level phenomenon. For example, the shared perception of family cohesion may either directly or indirectly influence shared perceptions of emotional intimacy between the parents in the same family. These direct and indirect pathways create unique group-level contexts that may also impact individual-level phenomena, such as adult well-being or child outcomes. In this instance, a hybrid model (explained below) may best represent the theoretical assumptions represented.

Third, the whole "is greater than the sum of its parts and has properties that cannot be understood simply from the combined characteristics of each part" (Cox & Paley, 1997, p. 245). By altering one aspect of the group, the entire form of that group changes, subsequently altering expectations, norms, roles, goals, and equilibrium within the entire group. The APIM partially accounts for the patterns within a group or family. Importantly, the APIM does not model the system of behaviors between members that results in unique group-level phenomena addressed by these three key assumptions, whereas the CFM allows scholars to appropriately account for this theoretical assumption of group-level influence. Thus, unlike the APIM, in the CFM, the two partners do not influence each other; rather, the same variable or force influences both partners (Kenny et al., 2006), and the shared variance among dyad members on a given variable is of primary interest and is modeled as a dyadic variable. The unshared variance that remains for each individual's score on that variable is treated as error.

As we have argued, the CFM accounts for similarity, particularly similarity between individual members of a common group. Family system theorists argue that through unique relationship patterns, role configurations, and repeated explicit and implicit rules within a system, individuals in the same system may become more similar over time. In fact, the CFM may be a valuable methodological tool to capture such similarity reflected within the system. However, it is important to share some words of caution. Systems theories address more than similarity. They also address dissimilarity, actor effects, and partner effects. Each of these together will likely better reflect the "whole" that is "greater than the sum of its parts" than considering any one feature alone. For example, the dynamic patterns of behavior within the system may not only reflect a group-level similarity but also reflect group-produced dissimilarity. According to Plomin, Asbury, and Dunn (2001), the dynamic patterns within a given system may be as likely to produce difference between members of the group as they are to produce similarity within the group. Further, Murray Bowen, one of the founders of the family systems framework, believed that connectedness between family members is good but cautioned that too much similarity may be problematic for individual development. A lack of individuation might actually reflect dysfunction (Bowen, 1978).

We insert these cautionary remarks to remind our readers that neither the CFM nor the APIM alone will accurately assess the entire framework of the family system. As Cook and Kenny (2006) further demonstrated, unless the relationships at the individual level are also accounted for, the statistical presence of a group-level effect may be false. Bowen reminds us that individual-level and group-level similarities and dissimilarities are key patterns in understanding family systems. For these theoretical reasons, hybrid models might be equally as valuable as the CFM or APIM alone.

Hybrid models

By incorporating characteristics of both the APIM and the CFM in the same model—in what Ledermann and Kenny (2012) refer to as hybrid models—scholars can appropriately consider both individual- and group-level patterns inherent in the theoretical assumptions noted above. In a hybrid model, one or more individual-level variables (such as depressive symptoms) and common fate variables (such as family-level decision-making) are modeled to assess whether they are significantly associated. These models are capable of answering questions regarding whether a shared variable influences partners' or family members' individual outcomes (e.g., does family conflict impact each family member's levels of depression?) or whether individual-level variables impact a shared variable (e.g., does each family member's level of depression impact family decision-making?). These models also can be expanded to include more than one common fate variable or more than one individual-level variable, including the ability to answer process-oriented questions about potential mediation, moderation, or moderated mediation (Ledermann & Kenny, 2012; Ledermann & Macho, 2009).

Hybrid models may include several configurations of individual- and dyadic- or family-level variables; each is modeled differently. Individual-level variables for one person may also be assessed by multiple members of a family (Bauer et al., 2013; Byrne, 2010; Holmbeck, Li, Schurman, Friedman, & Coakley, 2002; Muschkin & Malone, 2007), which may reduce self-report bias (Orth, 2013). For example, a mother and a father may report on their child's behavior. These variables would be modeled like latent CFM variables, with reports from each individual serving as indicators. Because they are modeling individual-level constructs rather than dyadic-level constructs, models that include multi-informant variables would be considered hybrid models. Individual-level variables for multiple family members (e.g., husband's depression and wife's depression) are modeled using indicator variables that are correlated to account for interdependence between partners or family members, as would be done in the APIM. Finally, the dyadic- or family-level common fate variables are modeled as latent variables with indicators from each reporter, as would be done in the CFM.

An extension of the hybrid model, which more fully captures the interdependent and systemic assumptions noted above, is to account for shared *and* unique perceptions of the same construct (Dyer & Day, 2015). Researchers can also explore associations between these perceptions and other variables. For example, in exploring predictors of both shared and unique perceptions of father involvement, Dyer, Day, and Harper (2014) used CFM techniques and then saved the factor scores and residuals for use in regression models. An alternative to saving factor scores would be to estimate the unique and shared perceptions within a latent variable framework (Holmes, Galovan, & Proulx, 2014). Gustavson et al. (2012) employed this method to explore longitudinal relations among partners' shared and unique views of relationship quality and each spouse's depressive symptoms.

Illustrative examples

To support Ledermann and Kenny's (2012) call for more dyadic research to employ the CFM when appropriate, we present five uses of the CFM and hybrid variations that allow us to explore family and couple processes and how they may impact individual behavior. These models represent three primary constructs: chaos in the home environment, partner conflict resolution, and child behavior problems. As in all dyadic or group-level analyses, we have multiple reports (i.e., from mothers and fathers) of the same phenomenon.

Family chaos

In family systems frameworks, the shared microenvironment of the home becomes a backdrop for direct and indirect processes at the group level, including collective experiences, collective routines, and shared expectations among members of the group. Repetition of daily tasks offers structure and stability to the home environment. Such structure includes goals and values that give direction to activity within the family system (Weisner, 2010). The more chaos in the home environment, the less order in terms of explicit rules, clear boundaries, regular routines, and so on. Consistent with family systems theory, items on the Confusion, Hubbub, and Order Scale (CHAOS) assessment used here (Matheny, Wachs, Ludwig, & Phillips, 1995) ask respondents to consider the group-level environment of the home including routines, rules, noise, and patterns of behavior. The group-level wording adds to the validity of using the CFM over the APIM to measure the shared perceptions of the home environment (Ledermann & Kenny, 2012; see Measures section for exact wording).

Although it is more frequent to consider associations between chaotic home environments and children's development (Deater-Deckard, et al., 2009; Evans, 2006; Hanscombe, Haworth, Davis, Jaffee, and Plomin, 2011; Johnson, Martin, Brooks-Gunn, & Petrill, 2008), systems perspectives emphasize the effects of the collective whole on relational subsystems. It is reasonable to consider the possibility that disruptions in daily activities, a lack of control, and difficulty maintaining regular routines might result in greater disagreements between couples, less likelihood of effective resolution of those problems, or may simply be emotionally draining (Kamp Dush, 2011). When considering the impact of environmental chaos on relationships, it is important to recognize that chaos undermines social connections and emotional security (Weisner, 2010) and predicts relationship dissolution (Kamp Dush, 2011).

Couple conflict resolution

Conflict within close partnerships has negative effects on parenting which are often associated with child maladjustment (Cox, Paley, & Harter, 2001; Cummings & Davies, 1994, 2011). Some argue that it is not only the presence of interparental conflict that has such negative effects on their children, but the inability of the parents to adequately resolve conflicts in a way that returns a positive emotional tone to their relationship (Cummings & Davies, 2011; Kerig, 1996). In this case, the report of how parents resolve conflicts together also represents a Level 2, or between-family, dyadic construct.

Three conditions may also implicate couple conflict resolution as a mediator between family chaos and child behavior problems. First, family chaos makes it more challenging to resolve interparental conflict or results in more animosity between parents following attempts to resolve conflict. Second, family chaos also impacts child behavior. Third, interparental conflict also impacts child behavior problems. If these three conditions exist, couple conflict resolution may be mediating the association between family chaos and child behavior problems.

Substantive hypotheses

Based on theory and prior research, we first illustrate the value of the standard CFM to assess the impact of family chaos in the home environment on couple conflict resolution. We hypothesize that greater family chaos will result in couple conflict that is more difficult to resolve, leaving couples with lower positive emotionality following conflict. We then employ hybrid models of the CFM to assess (a) the impact of family chaos on child behavior problems, (b) the impact of couple conflict resolution on child behavior problems, (c) the potential mediating role of couple conflict resolution in the relationship between family chaos and child behavior problems, and (d) potential effects on adolescents' unique perceptions about their problem behaviors. Consistent with prior research, we hypothesize that higher levels of family chaos will be associated with more child behavior problems. We further hypothesize that lower positive emotionality following attempts to resolve interparental conflict will also be associated with child behavior problems. In the mediational model, we hypothesize that the association between family chaos and child behavior problems is likely mediated by interparental conflict resolution.

Method

Sample

Data for the illustrative example are from the *Eunice Kennedy Shriver* Study of Early Child Care and Youth Development (SECCYD; NICHD Early Child Care Research Network, 1997). Researchers recruited participants from 10 sites across the U.S, in 1991. Recruitment resulted in a sample of 1,364 healthy infants and their families. This study uses data from mothers and fathers, collected when the children were in third and sixth grades and age 15. By age 15, a total of 391 (34.8%) of the initial 1,123 partnered couples had separated or divorced. Thus, we use data from the 732 couples who remained partnered at the age 15 assessment.

The children in the sample were evenly divided by gender (373 males and 359 females). The majority were White, non-Hispanic (83%) with 7.4% African American, 5.2% Hispanic, and 4.4% "other" races. As would be expected for a subset of continuously coupled individuals, this subset is slightly better educated ($M_{\text{mother}} = 14.73$ years, $SD = 2.41$ years; $M_{\text{father}} = 14.97$ years, $SD = 2.68$ years) and has a higher income-to-needs ratio ($M = 5.33$, $SD = 4.56$) when compared with the entire SECCYD sample. The mean age of the mothers at 1 month ($M = 29.21$ years, $SD = 5.35$ years) in the subset was also approximately 13 months older than the mean for the entire SECCYD sample.

Measures

Demographic information. Demographic information was collected from participants and included as control variables in all models. Items included whether the mother's partner was the child's father (1 = *yes*; 81.83% of the sample), mother's education (in years), child's gender (1 = *male*), child's birth order (1 = *firstborn*, 0 otherwise; 45.36% of children were the first born), child ethnicity (1 = *minority*, 0 otherwise), and mother's age at the 1-month interview. Due to insufficient cell sizes, ethnicity was collapsed into two groups: White, non-Hispanic and other.

Average income-to-needs ratio. This ratio provides a view of a family's overall economic status and is calculated by dividing the total family income by the poverty threshold for each year based on family size. Given the high correlation between the income-to-needs ratio between third and sixth grades and age 15 (rs > .75), an average was computed and included as a covariate.

Chaos. The CHAOS (Matheny et al., 1995) was used to assess general levels of environmental chaos in the home. The scale consists of 15 items that assess routine, noise, and confusion. Participants rate items, such as *You can't hear yourself think in our home* and *We are usually able to "stay on top of things"*, as either 1 = *True* or 2 = *False*. Items are coded such that higher scores represent a more chaotic home environment. The scale showed adequate reliability ($\alpha = .78$ for fathers and $\alpha = .81$ for mothers). Data on chaos were only available at third grade in this data set.

Conflict resolution. As a measure of conflict resolution, each parent responded to the 13 items from Kerig's (1996) conflict resolution scale designed to assess "emotional tone" following conflict when the child was in sixth grade. Questions ask participants to indicate how conflict is resolved in their relationship. Items assess whether resolution is positive and leads to greater intimacy or negative and leads to animosity. Responses were given on a 4-point Likert-type scale ranging from 0 = *Never* to 3 = *Usually*. Consistent with Kerig's protocol, highly positive items (e.g., *We feel closer to one another than before the fight*) are multiplied by 2, highly negative items (e.g., *We don't resolve the issue; We continue to hold grudges*) are multiplied by –2, and slightly positive items (e.g., *We each give in a little bit to the other*) have a weight of 1. Thus, higher scores represent a more positive emotional tone following conflict. The scale showed adequate reliability (α = .87 for fathers and α = .89 for mothers). Data on conflict resolution were first collected at fifth grade in this data set.

Children's problem behavior. Mothers and fathers rated their child's behavior using the Child Behavior Checklist (CBCL; Achenbach, 1991). Adolescents also rated their own behavior on a modified form of the CBCL. The CBCL is a well-validated scale used to obtain standardized ratings of problem behaviors. Within the 118 items (the adolescent form had 101 items), are measures of 8 syndrome scales: withdrawn, somatic complaints, anxious/depressed, social problems, thought problems, attention problems, delinquent behavior, and aggressive behavior. Internalizing behavior is represented in the withdrawn, somatic complaints, and anxious/depressed items. Externalizing behavior is based upon the delinquent and aggressive behaviors. Total problem behaviors is derived from all eight syndromes. For each item, the respondent was asked to determine how well that item described the target child currently or within the last 6 months. Responses were given on a 3-point Likert-type scale: 0 = *Not True (as far as you know)*, 1 = *Somewhat or Sometimes True*, and 2 = *Very True or Often True*. Scores on the CBCL are standardized and reported as T-scores, with higher scores indicating more problem behavior. The CBCL showed good reliability (α = .95 for fathers; α = .94 for mothers; α = .94 for adolescents). Problem behavior was assessed at multiple time points. For simplicity in discussing the CFM, we selected the age 15 child problem behaviors assessment, as it was the only time point that included adolescents' report on their own behavior.

Analysis procedure

We constructed a series of structural equation models to illustrate how CFM and hybrid models can be applied to research with families. To account for missing data, we employed full information maximum likelihood (FIML) estimation. Because results are less biased and statistical power is retained, using FIML estimation to estimate missing data is preferred to listwise deletion or similar methods (Enders, 2010). To protect against any problems with multicollinearity, before constructing the models, we considered the correlations among the study variables. All of the correlation coefficients were less than Kline's (2010) recommended cutoff of .85 (see Table 1).

As shown in Figure 2, in the traditional CFM, each partner's score serves as an indicator to a latent couple score, with each indicator path fixed to unity (i.e., each path weight is set equal to 1). Indicator variable intercepts are freely estimated, and the latent means or intercepts for the family- or couple-level variables are fixed to 0 (Ledermann & Kenny, 2012). Alternate parameterizations allow for estimation of the latent variable means and intercepts but impose other constraints (Peugh, DiLillo, & Panuzio, 2013). As relations between family- or couple-level constructs may be inflated due to correlations between each partner's individual reports—an idea Peugh, DiLillo, and Panuzio refer to as intrapersonal dyadic dependence—error terms for each partner's report of one family- or couple-level variable are correlated with their own report of other family- or couple-level variables.

Models 2 through 4 (see Figures 3 and 4) illustrate a hybrid model approach. Family chaos (Models 2 and 4) and couple conflict resolution (Models 3 and 4) are treated as

Table 1. Descriptive statistics and correlations among study variables.

Variables	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.
1. CHAOS in the home (mother report)	—													
2. CHAOS in home (father report)	.50***	—												
3. Partner conflict resolution (mother report)	–.24***	–.12**	—											
4. Partner conflict resolution (father report)	–.14***	–.28***	.52***	—										
5. CBCL total problems T-score (mother report)	.24***	.18***	–.11**	–.11**	—									
6. CBCL total problems T-score (father report)	.18***	.27***	–.04	–.20***	.56***	—								
7 CBCL total problems T-score (youth report)	.06	.14***	–.11**	–.08*	.29***	.31***	—							
8. Spouse/partner is child's father (1 = *Yes*)	–.07†	–.13***	–.09*	–.07†	–.14***	–.23***	–.13***	—						
9. Average income-to-needs ratio (Grades 3, 6, & age 15)	–.16***	–.10*	.05	.03	–.19***	–.12**	–.12**	.19***	—					
10. Mother's education (years)	–.09*	–.06	–.04	–.03	–.18***	–.14***	–.09*	.31***	.48***	—				
11. Child's sex (1 = *Male*, 0 = *Female*)	.01	.04	.06	.02	–.01	.04	–.04	–.04	–.02	–.05	—			
12. Child is firstborn (1 = *Firstborn*, 0 = *Later born*)	–.11**	–.06	.00	–.03	.11**	.10**	.02	–.08*	.08*	.02	.00	—		
13. Ethnic minority (1 = *Minority*, 0 = *White, non-Hispanic*)	–.04	–.04	.02	–.03	–.04	–.01	.07+	–.16***	–.12***	–.18***	.02	.00	—	
14. Mother's age at child's birth (years)	–.02	–.05	–.11**	–.08*	–.17***	–.13***	–.07+	.38***	.29***	.48***	–.06	–.26***	–.24***	—
Mean	19.00	18.81	5.82	6.04	43.60	44.29	48.49	.82	5.32	14.73	.51	.45	.17	29.21
Standard Deviation	3.19	3.00	12.36	11.79	11.13	12.01	9.93	.39	4.56	2.41	.50	.50	.38	5.34

Note. $N = 732$.
†$p < .10$; ***$p < .001$; **$p < .01$; *$p < .05$.

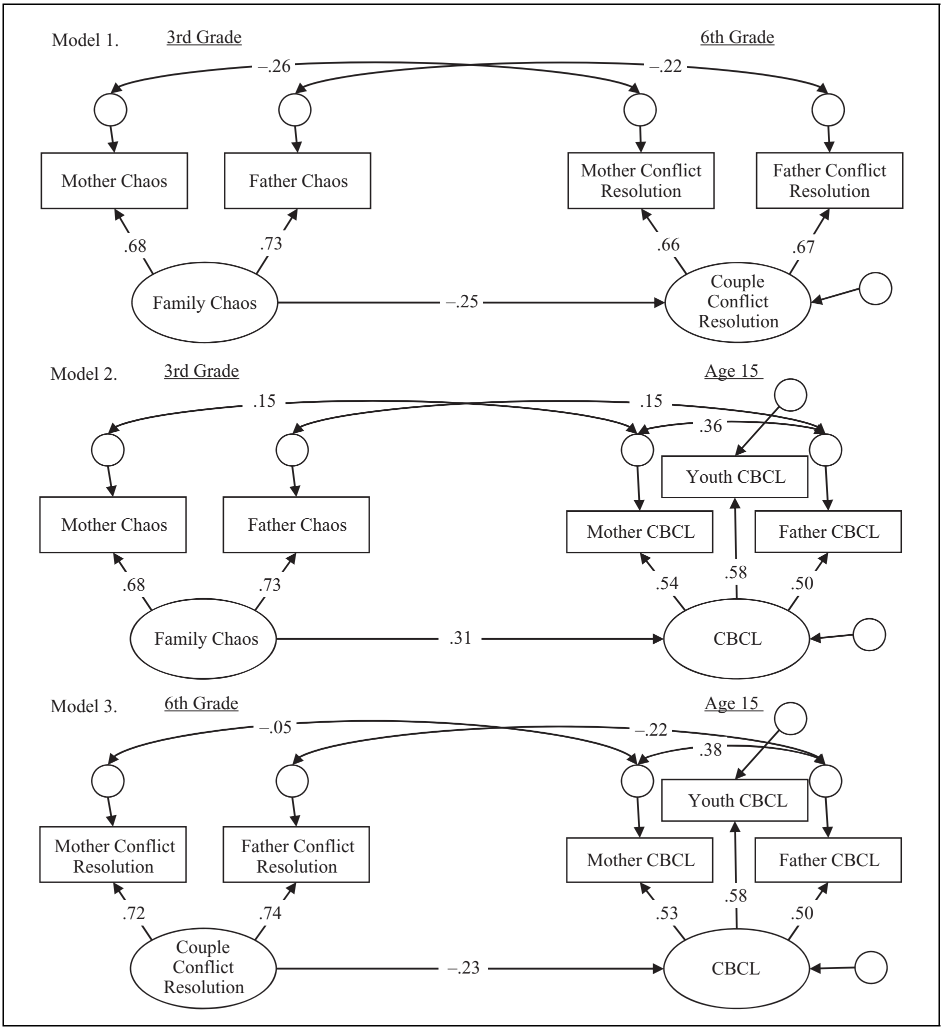

Figure 3. Common fate model and hybrid models. *Note*. $N = 732$. Control variables include partner is father, income-to-needs ratio, mother's education, child's sex, child is firstborn, child is ethnic minority, and mother's age. All coefficients are significant at $p < .05$. Model fit statistics: Model 1: $\chi^2(15) = 16.429$, *n.s.*; CFI = .999; TLI = .994; RMSEA = .011. Model 2: $\chi^2(25) = 55.579$, $p < .01$; CFI = .976; TLI = .924; RMSEA = .041. Model 3: $\chi^2(25) = 47.135$, $p < .01$; CFI = .982; TLI = .945; RMSEA = .035. CFI: comparative fit index; TLI: Tucker–Lewis Index; RMSEA: root mean square error of approximation.

common fate variables. Because the CBCL assesses the behavior of the child rather than a shared family- or couple-level construct, it is an individual-level outcome variable rather than a common fate variable. Furthermore, the wording of the CBCL does not use the family or couple wording that Ledermann and Kenny (2012) argue adds validity to a true CFM. With reports of child behavior from mothers, fathers, and children, we model

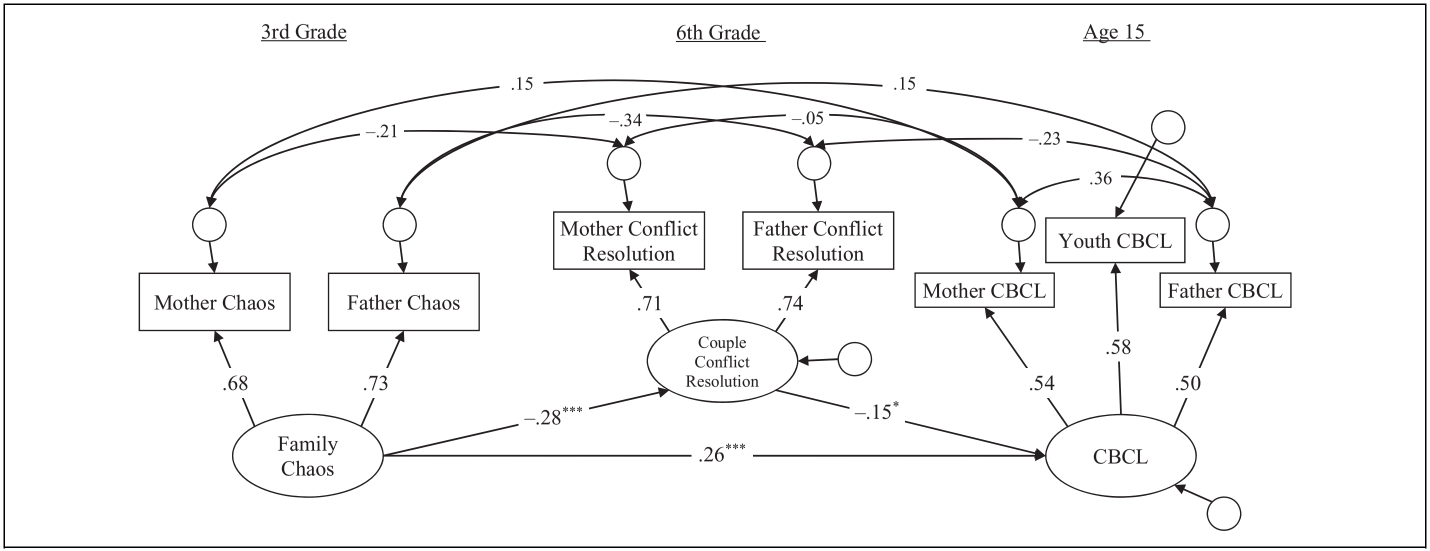

Figure 4. Hybrid mediation model with common fate chaos and conflict variables predicting a multi-informant Child Behavior Checklist variable (Model 4). *Note*. $N = 732$. β coefficient p values: $^{***}p < .001$; $^{*}p < .05$. Control variables include partner is father, income-to-needs ratio, mother's education, child's sex, child is firstborn, child is ethnic minority, and mother's age at child's birth. Model fit statistics: $\chi^2(36) = 64.180$, $p < .01$; CFI = .982; TLI = .947; RMSEA = .033. CFI: comparative fit index; TLI: Tucker–Lewis Index; RMSEA: root mean square error of approximation.

child problem behavior as a latent variable with multiple informants (Bauer et al., 2013; Byrne, 2010; Muschkin & Malone, 2007) and include error term covariances and reference indicators as one would with a common fate variable. Because mothers and fathers likely share variance above that shared within the parent–child triad, we also include the covariance between parents. Although we used a multi-informant variable in our example, a single-informant outcome would also be appropriate in a hybrid model. To test for mediation, we used maximum likelihood Monte Carlo bootstrapping to extract 5,000 bootstrap samples to obtain the bias-corrected significance levels for the mediated effect (Shrout & Bolger, 2002; Wu & Jia, 2013).

Finally, in Model 5, we employ an extension of the hybrid model approach to explore how mother's and father's shared and unique perceptions of family chaos and couple conflict resolution are related to the youth's unique (non-shared) report of his or her own behaviors. We use the youth's unique report of his or her behavior because, if adolescents withhold information from their parents, the parent reports may be less accurate (an assumption reflected in the higher factor loading and the higher total problems score for the youth report than either parent report; see Figure 4).

For Model 5, it is not possible to simultaneously estimate predictors of both individual and shared perceptions, as such models are unidentified. Dyer et al. (2014) resolved this issue by saving the factor scores for the individual perceptions (CFM error terms) and then separately estimating relations with these perceptions. Hoshino and Bentler (2013) note, however, that saving latent variable factor scores often results in decreased variance, which may lead to biased parameter estimates for analyses that use these parameters. Gustavson et al. (2012) modeled these associations in a latent variable model, but they did not indicate how they handled model identification issues. To allow for proper model identification, we propose a three-step process. First, a CFM model predicting the shared perceptions is estimated (see Model 4 in Figure 4). Next, parameter estimates for the paths predicting the endogenous CFM variable(s) are set to the (unstandardized) values obtained in Step 1, paths predicting individual perceptions are estimated, and error terms for the individual perceptions are added. Finally, to verify the stability of estimates, the paths predicting the individual perceptions are set to the values obtained in Step 2, and the paths predicting the shared perceptions are freely estimated. Excepting small rounding errors, the estimates for these freed paths should be identical to those obtained in Step 1. (Note if *both* shared and unique perceptions of one construct are to be included as predictors of *both* shared and unique perceptions of another construct, the three-step process should also be followed to avoid changes in the latent CFM construct.) This process essentially follows the procedure outlined by Dyer et al. but retains the advantage of latent variable models, as saving the residual scores and using them as dependent variables in later analyses assumes that the original regression paths predicting shared perceptions is constant.

Results

Common fate and hybrid model analyses

We first explored the value of a CFM framework by evaluating the association between family chaos and couple conflict resolution. In Model 1, we constructed a common fate structural equation model with family chaos at third grade predicting couple conflict resolution at sixth grade (see Figure 3). We included whether or not mother's partner is the child's biological father, the average income-to-needs ratio, mother's education, child's sex, child's birth order, child's ethnicity, and mother's age as control variables. After accounting for the demographic factors, higher family chaos scores predicted lower levels of positive conflict resolution ($\beta = -.25$). This model fit the data well: $\chi^2 = 16.429$, $df = 15$, *n.s.*; comparative fit index (CFI) = .999; Tucker–Lewis Index (TLI) = .994; root mean square error of approximation (RMSEA) = .011 (Byrne, 2010).

In Model 2, we evaluated how family chaos at third grade was associated with children's problem behavior at age 15. We constructed a hybrid CFM and multi-informant structural equation model with family chaos at third grade predicting children's problem behavior at age 15 (see Figure 3). We included the same control variables as before. Higher levels of family chaos in third grade were predictive of more problem behavior in children at age 15 ($\beta = .31$). Model fit: $\chi^2 = 55.579$, $df = 25$, $p < .01$; CFI = .976; TLI = .924; RMSEA = .041.

In Model 3, we considered the relation between couple conflict resolution in sixth grade and children's problem behavior at age 15. This hybrid CFM and multi-informant SEM included demographic variables and modeled couple conflict resolution as a predictor of children's problem behavior (see Figure 3). More positive conflict resolution was predictive of fewer problem behaviors ($\beta = -.23$). Model fit: $\chi^2 = 47.135$, $df = 25$, $p < .01$; CFI = .982; TLI = .945; RMSEA = .035.

In Model 4, we combined all elements from the first three CFM/hybrid models. We constructed a hybrid model with family chaos in third grade predicting couple conflict resolution in sixth grade and children's problem behavior at age 15. Couple conflict resolution also was entered as a predictor of children's problem behavior (see Figure 4). In this model, family chaos was predictive of lower levels of positive couple conflict resolution ($\beta = -.28$) and increased levels of children's problem behavior ($\beta = .26$), while positive couple conflict resolution was related to lower levels of children's problem behaviors ($\beta = -.15$). The bootstrap results suggested that the effect of family chaos on child behavior problems was partially mediated by couple conflict resolution (indirect $\beta = .04$). The same control variables as before were included in this model. The control variables effects for this final model are shown in Table 2. This model fit the data well: $\chi^2 = 64.180$, $df = 36$, $p < .01$; CFI = .982; TLI = .947; RMSEA = .033. To assess whether model fit was more due to the control variables than the substantive variables, we also assessed model fit for this model without covariates. This model did not have any substantive differences from the model with control variables and also fit the data well: $\chi^2 = 20.008$, $df = 8$, $p < .01$; CFI = .988; TLI = .969; RMSEA = .045.

Finally, in Model 5, using the three-step process outline above, we evaluated predictors of adolescents' unique (non-shared) perceptions of their own problem behaviors. We found that shared perceptions of family chaos negatively predicted adolescents' unique (unshared) perceptions of behavior problems ($\beta = -.12$), while, as noted above, shared perceptions of family chaos positively predicted shared perceptions of behavior problems ($\beta = .26$). Being a firstborn was associated with decreased scores for adolescents' unique perceptions of behavior problems ($\beta = -.12$) but increased scores for shared perceptions of behavior problems ($\beta = .19$). Finally, if the adolescent was an

Table 2. Control variable effects for Model 4.

Variables	Chaos	Conflict resolution	CBCL
1. Spouse/partner is child's father (1 = *Yes*)	–.12**	–.12*	–.19***
2. Average income-to-needs ratio (Grades 3, 5, & 6)	–.18***	.09	–.12*
3. Mother's education (in years)	–.10*	–.01	–.09
4. Child's sex (1 = *Male*, 0 = *Female*)	–.03	.05	.04
5. Child is firstborn (1 = *Firstborn*, 0 = *Otherwise*)	–.13**	–.11*	.14*
6. Ethnic minority	–.06	–.07	–.02
7. Mother's age at child's birth (in years)	–.04	–.16**	–.03

Note. $N = 732$. Values for control variable effects on chaos are correlation coefficients. Values for effects on conflict resolution and CBCL are standardized regression coefficients. CBCL = Child Behavior Checklist.
p value significance levels: $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$.

ethnic minority, scores for unique perceptions of behavior problems were higher ($\beta = .16$), while scores for shared perceptions of behavior problems were lower ($\beta = –.13$). These results were substantively similar compared to those obtained using Dyer et al.'s (2014) approach, which initially validates our three-step approach noted above. This final model also fit the data well: $\chi^2 = 31.733$, $df = 27$, *n.s.*; CFI = .997; TLI = .988; RMSEA = .015.

Discussion

This article answers Ledermann and Kenny's (2012) call to more carefully distinguish between levels of analysis in dyadic research. We build on Ledermann and Kenny's (2012) work in this article in four important ways. First, we offer a theoretical foundation for relationships researchers, family scholars, and human development scholars to consider the distinction between individual-level (i.e., Level 1 or within-family) dyadic phenomena and group-level (i.e., Level 2 or between-family) dyadic phenomena. Second, we offer illustrative examples of ways scholars can utilize the standard CFM to explore a family-level common fate variable, chaos in the home environment, and a couple-level common fate variable, interparental conflict resolution. Third, we offer illustrative examples of hybrid models such as a hybrid CFM and multi-informant SEM model, along with a hybrid mediational model combining elements of all three earlier models. Finally, we illustrate extensions of the CFM that allow researchers to explore distinctions between individual and shared perceptions.

First, we note the importance for scholars in our field to consider the theoretical foundations of research questions when choosing data analytic techniques. In the relationship science field, we often ask questions about processes at the family or dyad level. Such questions may often be answered more correctly with analytical techniques that assess dyadic or family variables and processes, such as the CFM approach. In the 30 years since the CFM was first proposed, only a limited number of studies have used this technique (Ledermann & Kenny, 2012). More often family and close relationships researchers use the APIM in studies with dyadic data. This "default" choice, however, may not be strongly connected to the theoretical perspective(s) they espouse, the measurement they use, or the research questions they consider.

Second, we offer theoretically driven examples for scholars whose research question, measurement, and/or data support Level 2 CFMs. In our examples, we also build the empirical literature on family chaos, conflict resolution, and child behavior problems. As family routines provide the backdrop for relationships in the family system, we hypothesized that family-level chaos would be associated with a decreased sense that couple conflicts are resolved and increased incidence of child behavioral problems. We confirm that family-level chaos is significantly associated with dyad-level conflict resolution—an empirical finding we have not seen explored elsewhere. We also provide empirical evidence in early adolescence consistent with prior research with preschoolers (Dumas et al., 2005) and late adolescents (Deater-Deckard et al., 2009) that family-level chaos is significantly associated with individual-level child behavior. In meeting our goal to illustrate another couple-level dyadic construct impacting an individual-level variable—and to illustrate mediational hybrid models with the CFM—we found that couple conflict resolution that leads to emotional animosity between parents was associated with child behavior problems. Thus, the association between family chaos and child behavior problems was partially mediated by couple conflict resolution. Given the longitudinal nature of our data, this could suggest that family environments influence parent interactions and that these interactions have an effect beyond that of the family environment. It is also possible that child perceptions of interparental conflict resolution would be more closely associated with actual child behavior problems than parental reports of conflict resolution (Cummings & Davies, 2002), that differing levels of interparental conflict have differential impacts on child behavior problems (Cummings & Davies, 2011), or that interparental conflict may matter more for other dyad-level processes like parent–child relationship quality (Cox et al., 2001). These are valuable areas for future research.

It is noteworthy that the dyad-level reports of chaos in third grade were associated with dyad-level reports of conflict resolution in sixth grade and individual-level reports of child problem behavior at age 15. According to family systems theory, once families establish patterns of interaction, these patterns are maintained by the system. Any effort to change these patterns would be met with resistance, concepts known as homeostasis and negative feedback (S. Minuchin, 1974). By the time a child is in third grade, family interaction patterns are well established. Thus, patterns of chaos would be established and likely to persist up through the later grades.

The additional findings in Model 5 further illustrate ideas from family systems theory and are consistent with systemic ideas regarding boundaries (Bowen, 1978) and prior research regarding parental monitoring and attention (Crouter, Bumpus, Davis, & McHale, 2005; Crouter, Helms-Erikson, Updegraff, & McHale, 1999; Findlay, Garner, & Kohen, 2013; Kerr & Stattin, 2000). Taken together, these results speak to the utility of the methods illustrated herein to explore important theoretical questions.

Extensions, limitations, and conclusion

Although we used manifest variables in our CFM analysis, it would be appropriate to conduct such analyses with latent variables. In such an analysis, the CFM variables would be modeled as a second-order latent variable (Byrne, 2010). As an alternative to using latent variables to model measurement error, researchers could also use factors scores as a proxy for the latent variables, though there are drawbacks to this approach (see Hoshino & Bentler, 2013). Additionally, Ledermann and Kenny (2012) also note that the CFM framework can be expanded to include more than two reporters. Although we used data from three reporters in our models, these were of an individual-level construct—child behavior problems. Consistent with the family systems argument and the cautions we stated in our theoretical foundations section, individual-level and group-level phenomena within the same system will likely increase the validity of couple and family models (Cook & Kenny, 2006) and help progress theoretical ideas. Within the CFM framework, family-level constructs could also be assessed by each parent and their children. Finally, longitudinal analysis techniques could also be used to explore change in dyadic- or family-level constructs over time, such as latent change analyses (McArdle, 2009), growth curve analyses (Ledermann & Macho, 2014), or analyses that consider prior levels of constructs as covariates (Laursen, Little, & Card, 2012). For simplicity in illustrating CFM methods herein, we did not employ these methods.

One of the challenges in using the CFM may be finding measures that conceptually assess dyadic- and family-level constructs. We used data from the NICHD SECCYD. This study includes measures of nearly 250 constructs across 15 years, with reports from fathers, mothers, children, teachers, friends, and independent observers. Even in such a comprehensive study, it was difficult to find measures that employed wording that denoted a dyadic- or family-level phenomenon. In some cases, it may be appropriate to modify existing measures to ask questions using plural pronouns (e.g., we, our) rather than singular pronouns (e.g., I, my). These measures may then better assess the dyadic or family construct rather than an individual's perception. In other cases, modifying pronoun usage may not be sufficient. Interdependence or systems frameworks may suggest that some constructs scholars have traditionally considered at the individual level deserve reconceptualization at the dyad- or family level. Indeed, Cook and Kenny (2006) have argued that an additional component of measurement validation is to consider unit of analysis and assess for level validity.

In some cases, it may be acceptable to use the CFM even when constructs are not assessed with plural language if the language seems to be clearly directed at assessing a dyadic- or family-level construct and the reporter scores are sufficiently correlated. For example, partners may report on their participation in housework by rating their relative contribution in comparison to their partner. Even though partners may be reporting their own contribution, they are reporting on how housework is shared—a dyadic-level construct—and thus each partner's score could be coded and used as a CFM indicator. However, if individuals reported their own absolute contribution to housework, partner reports may be negatively correlated and may be better modeled at the individual level. Ledermann and Kenny (2012) note that indicators of the CFM variables should be at least moderately positively correlated ($r > .20$), while Schumacker and Lomax (2004) advocate for a higher correlation between indicators ($r > .50$; cf. Ledermann & Macho, 2009). In cases where language is more individualized, we recommend the higher correlation threshold of $r > .50$. This higher correlation will provide greater assurance that despite the individualized wording the underlying construct seems to be dyadic in nature—though this should also be empirically validated (Cook & Kenny, 2006).

Furthermore, researchers should be cognizant of rater effects and the bias often introduced in using self-report measures (Orth, 2013).

To conclude, as a field focused on studying families and close relationships, we should more often assess constructs at the dyad- and family level and employ suitable methods for analyzing such data, such as the CFM or SRM. In many cases, the use of these methods will better align with our theoretical assumptions and add greater understanding to the base of research in many substantive areas of family and relationship research.

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Authors' note

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