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Growth Curve Models for Indistinguishable Dyads Using Multilevel Modeling and Structural Equation Modeling: The Case of Adolescent Twins' Conflict With Their Mothers

Deborah A. Kashy, M. Brent Donnellan, and S. Alexandra Burt
Michigan State University

Matt McGue
University of Minnesota

Growth modeling is a useful tool for studying change over time, and it is becoming increasingly popular with developmental researchers. There is a considerable methodological literature surrounding growth modeling for individuals; however, far less attention has been focused on growth models for pairs of related individuals (i.e., dyads). In this article, the authors consider dyadic growth models for those cases where there are no relevant variables that can empirically distinguish between dyad members (e.g., same-sex twins or best friends). The authors describe how researchers can estimate growth models for indistinguishable dyads using both multilevel modeling and structural equation modeling. Although both approaches can be used to estimate the same underlying models, the authors focus on practical similarities and differences between the two approaches. They illustrate modeling issues using an overtime study of adolescent twins' conflict with their mothers, a substantively important topic given the enduring interest in parent–child relationships during adolescence.

Keywords: dyadic growth models, indistinguishable dyads, adolescence, family conflict, puberty

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Developmental researchers need methods that can adequately model interpersonal dynamics that unfold over time. Indeed, nearly all contemporary models of social development emphasize the importance of social relationships (Elder & Shanahan, 2006; Lerner, 2006; Parke & Buriel, 2006), and therefore techniques that allow researchers to understand changes that occur both between and within dyads would seem to be an essential component of the developmental scientist's tool kit (Kashy & Donnellan, 2008). Important dyads are ubiquitous in developmental studies and include such staple "pairs" as parents and children, siblings, friends, and romantic partners. Accordingly, the goal of this article is to illustrate how researchers can use dyadic growth models to study change over time. Given the long-standing interest in parent–child relationships during adolescence (e.g., Collins & Laursen, 2004; Laursen, Coy, & Collins, 1998; Smetana, Campione-Barr, & Metzger, 2006; Steinberg, 2001), we demonstrate the usefulness of this approach by examining adolescent–parent conflict in a sample of twins.

Deborah A. Kashy, M. Brent Donnellan, and S. Alexandra Burt, Department of Psychology, Michigan State University; Matt McGue, Department of Psychology, University of Minnesota.

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Correspondence concerning this article should be addressed to Deborah A. Kashy, Department of Psychology, Michigan State University, East Lansing, MI 48824. E-mail: kashyd@msu.edu

Adolescent–Parent Conflict and Puberty: Substantive Considerations

Relationships between parents and children change during adolescence. For example, Laursen et al. (1998) concluded that the affective intensity of conflict between parents and adolescents increases from early to mid adolescence and then remains fairly constant. This broad trend appears to hold across a range of diverse types of American families (for a review, see Smetana et al., 2006). Thus, there are normative changes in parent–child conflict that seem to occur across the adolescent years. Nonetheless, there is also evidence of variability between families in patterns of change in conflict (Collins & Laursen, 2004).

The between-families variability in parent–adolescent conflict naturally leads to questions about the antecedents of conflict. For instance, what factors seem to exacerbate adolescent–parent conflict and conversely what factors seem to mitigate conflict? One potentially interesting possibility is puberty (e.g., Ge, Conger, & Elder, 1996; Paikoff & Brooks-Gunn, 1991). In particular, pubertal timing seems to be more important than pubertal status for predicting parent–child conflict, with early maturing daughters and sons demonstrating relatively more conflict with their parents than their on-time and late-maturing peers (Collins & Laursen, 2004). This line of research links biological changes with changes in family interactions and therefore addresses an integrative issue in the study of adolescence, namely the evaluation of the psychological and interpersonal impact of the pubertal transition (e.g., Compas, Hinden, & Gerhardt, 1995).

These substantive considerations raise particular analytic challenges. Specifically, there is a need for analytic techniques that can capture variability in conflict both over time and across families while also capturing normative developmental trends (i.e., average trends). Likewise, it would be ideal to have a method that flexibly incorporates predictors of change; fortunately, growth models are well suited for this challenge.

Applying Growth Models to the Dyadic Context

Growth models estimate whether a variable changes in systematic ways as a function of time and can be used to evaluate whether other factors, such as individual differences or contextual variables, moderate the degree of change over time. When two related individuals are observed over time, a dyadic growth model can be estimated, allowing researchers to examine how change over time is coordinated across the two individuals. Methods for estimating growth curve models for individuals have become increasingly important tools for applied researchers. (These models are sometimes called *latent growth curve models* in the structural equation modeling literature; Bollen & Curran, 2006; Duncan, Duncan, & Strycker, 2006.) However, the issues and complexities that occur when extending growth curve models to dyads are not as well known (e.g., Kashy & Donnellan, 2008; Kenny, Kashy, & Cook, 2006).

In this article, we consider methodological and data-analytic issues for a particular type of dyadic data—when the two dyad members are indistinguishable. It is perhaps easiest to understand the meaning of indistinguishability by considering first what constitutes a distinguishable dyad. Two members of a dyad are said to be distinguishable if there is an empirically meaningful way to classify the two members of the dyad. For example, consider a study of depressive symptoms in mother–daughter dyads. There are many reasons to expect that depression scores would differ systematically for mothers and daughters, and as a result, a variety of statistics (e.g., means, variances) are likely to differ by family role. In this case, mother–daughter dyads would be "distinguishable" with respect to family role.

Next consider the evaluation of depressive symptoms in sister–sister dyads. Here there might be some reason to expect that older sisters would differ in terms of mean levels of depression as compared to younger siblings, but these reasons might not be as strongly compelling as with the mother–daughter case. In short, there might be reasons to expect that members of sister–sister dyads could be distinguished by birth order, but this expectation might be worthy of empirical evaluation. Finally, consider dyads made up of identical twin sisters. Here there are very few reasons to expect systematic differences between the two twins. Thus, assigning the twins Sally and Jane to the designations of Twin A and Twin B, respectively, is arbitrary, and we could have alternatively assigned Jane to be Twin A and Sally to be Twin B. In other words, identical twins are indistinguishable for our purposes.

The issue of distinguishability involves both conceptual and empirical considerations. In conceptual terms, researchers must first identify a categorical variable that can be used to systematically classify dyad members. The empirical part of distinguishability is the evaluation of whether there are detectable differences between dyad members as a function of this classification variable. The empirical part of distinguishability can be tested using procedures presented in Kenny et al. (2006, pp. 129–131).[1] We recommend that researchers routinely evaluate the degree of empirical support for distinguishability. For example, although the older–younger distinction can potentially classify our nontwin sisters, if the means, variances, and covariances among the key variables do not differ across the older–younger distinction, then the sisters would be empirically indistinguishable. In this case, we believe that researchers should use methods that are appropriate for indistinguishable dyads. Indeed, indistinguishability is beneficial in statistical terms because it allows researchers to pool estimates both within and across dyad members, which ultimately increases the precision of estimates and statistical power.

We present two data-analytic approaches for estimating growth models for the indistinguishable case: multilevel modeling (MLM) and structural equation modeling (SEM). These two approaches are equivalent at a fundamental level (e.g., Bauer, 2003; Curran, 2003), and so estimates derived using SEM are equivalent to estimates derived using MLM when each method is used to estimate the parameters of an identical model. Because of space limitations, we assume that readers are familiar with SEM and MLM methods. An in-depth introduction to SEM can be found in Kline (2005), and an introduction to growth models in the SEM framework can be found in Duncan et al. (2006). A detailed introduction to MLM can be found in Bryk and Raudenbush (2002), Hox (2002), or Singer and Willet (2003). In addition, a discussion of growth modeling issues with distinguishable dyads is provided by Kashy and Donnellan (2008) and Kenny et al. (2006).

In the next sections, we first introduce the basic parameters of growth models for individuals. We then describe our example data set in which twin siblings (both monozygotic [MZ] and dizygotic [DZ]) each report on their own level of conflict with their mother at three time points during adolescence. Next, we broaden the individual growth model to include indistinguishable dyads. Subsequently, we present a detailed discussion of the MLM and SEM approaches for dyadic growth models. We then expand the example to consider predictors of growth and nonlinear trajectories. We close by considering how these methods can be used in genetically informed analyses.

Growth Models for Individuals

Prior to considering dyadic growth models, it is useful to first introduce growth models for independent individuals. Consider a hypothetical longitudinal study of adolescents' perceptions of conflict with their mothers in which data were collected at four occasions: when participants were 11, 13, 15, and 17 years of age. For the purposes of this example, we treat the initial assessment as Time 0, and we code the four occasions such that their values reflect the number of years since the initial assessment (i.e., 0, 2, 4, and 6 for the four occasions of measurement; see Biesanz, Deeb-Sossa, Papadakis, Bollen, & Curran, 2004, for a discussion of coding time in growth models).

From a multilevel perspective, the essential idea is that these data have a hierarchical structure in which repeated observations

[1] Kenny et al. (2006) described the omnibus test for distinguishability using structural equation modeling. A similar test can be conducted in multilevel modeling using maximum likelihood estimation by comparing the deviances of two models, one that specifies that dyad members are distinguishable and one that specifies that dyad members are not distinguishable.

across time are nested within individuals. Put another way, occasion is the Level 1 or lower-level unit and person is the Level 2 or upper-level unit. Conceptually, a multilevel analysis begins by conducting a within-person regression analysis for each child in the data set such that conflict scores serve as the dependent variable (Y_{ij}, with $i = 1$ to n denoting child, and $j = 1$ to 4 denoting the four levels of time) and time of measurement serves as the independent variable. This gives the following lower level equation:

$$Y_{ij} = b_{0i} + b_{1i}T_{ij} + e_{ij}$$

where T_{ij} is the time of measurement (taking on values 0, 2, 4, and 6) for child i at time j. Given that time is scaled to be zero at the initial assessment, the intercept from this equation, b_{0i}, is an estimate of child i's initial conflict score, and the slope, b_{1i}, measures the child's change in conflict over a 1-year period. A positive slope indicates an increase in conflict over time, and a negative slope indicates that conflict decreases over time. The error represents the part of child i's conflict score at time j that is not predicted by the time variable.

Continuing with the multilevel approach, in a basic growth model (i.e., one without any moderating person-level, or Z, variables) the lower level intercepts and slopes are aggregated across the sample as follows:

$$b_{0i} = a_0 + u_{0i}$$

$$b_{1i} = c_0 + u_{1i}.$$

These models result in two fixed-effect estimates: a_0, which measures the average intercept (i.e., the average conflict score at age 11 when time = 0) and c_0, which measures the average slope (i.e., the average change in conflict for 1 year). In addition to these two fixed effects, the multilevel framework yields two random effects. The variance for the intercept is based on the variance of u_{0i} and represents how much children vary in their conflict scores at age 11. The variance for the slope is based on the variance of u_{1i} and measures the degree to which children vary in their rate of linear change in conflict. Additionally, these two random effects may be correlated, and so there may be a covariance between the intercept and slope. This covariance measures the degree to which individuals who start with higher conflict scores at age 11 change more rapidly (or slowly) than those who start with lower conflict scores at age 11.

Figure 1 shows a typical linear growth model for these data from the perspective of a path diagram, a common starting point for SEM analyses. In this model, the four observations of conflict are treated as indicators of two latent variables, an intercept variable and a slope variable. To identify the intercept variable, we fixed the unstandardized path coefficients to each indicator to 1.0. To identify the slope variable, we fixed the unstandardized path coefficient for the age 11 observation to 0. This defines the intercept variable as the value of conflict at age 11. The remaining unstandardized slope paths to the age 13, 15, and 17 observations are fixed to 2, 4, and 6, respectively. This specification defines the slope variable as the change in conflict for each 1-year increase in time. In addition to the usual assumption that the errors have zero means, the intercepts of the observed variables are also set to 0 in order to identify the mean structure of the model.

As can be seen in Figure 1, the growth model in the SEM framework includes the same basic parameters as the growth model in the MLM framework: an average intercept and an average slope, a variance for the intercept and a variance for the slope, as well as a covariance between the intercept and slope. One difference between the MLM approach and the SEM approach is that the error structure for the residuals is an explicit feature of the model. In particular, as displayed in the figure, the residuals are allowed to have unequal variances across time. In contrast, the variances for the residuals are typically constrained to the same value in the MLM approach, although alternative specifications are possible. Likewise, it is very easy to constrain the variances for the residuals to the same value in SEM. Researchers who estimate models in any framework should be aware of the constraints that are imposed on the residuals because this is often where we see the

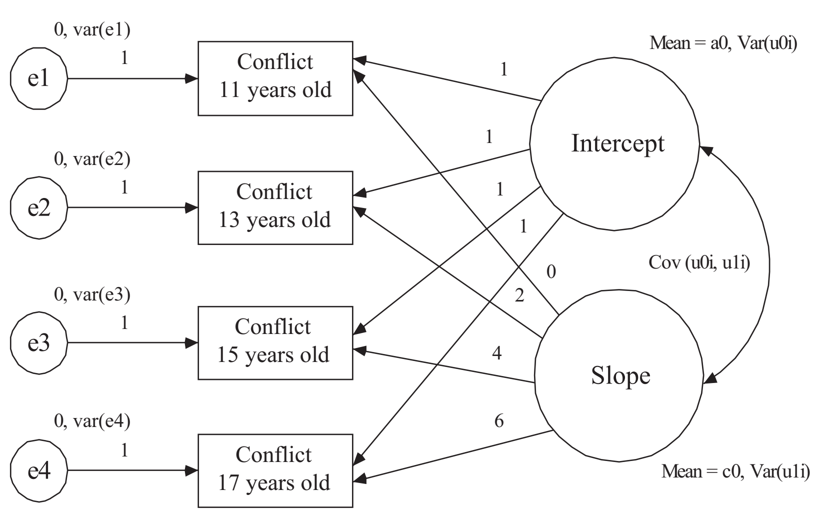

Figure 1. Basic growth model for individuals. a = average intercept; c = average slope; e = residual variance; u_{0i} = the random component for the intercepts; u_{1i} = the random component for the slopes.

most significant differences between the typical models estimated with MLM and SEM programs.

Example Data Set: Adolescent Twins' Conflict With Mothers

The sample was drawn from participants in the ongoing Minnesota Twin Family Study (MTFS). The MTFS is a population-based, longitudinal study of adolescent twins born in the state of Minnesota. More than 90% of twin births between 1971 and 1985 were located using public databases. Participating families were broadly representative of the population of Minnesota at the time the twins were born; approximately 98% are Caucasian. Further information regarding the design, recruitment procedures, participation rates, and zygosity determination procedures of the MTFS can be obtained from Iacono, Carlson, Taylor, Elkins, and McGue (1999). Family assessments took place when the twins were approximately 11 years old (range = 10.7–12.7, M = 11.73, SD = .43), 14 years old (range = 13.6–16.6, M = 14.77, SD = .51), and 17 years old (range = 16.6–20.3, M = 18.12, SD = .68). At the age 11 assessment, parents also completed some basic demographic information including occupational status using the Hollingshead two-factor system (Hollingshead, 1957). Mean occupational status for fathers was 4.1 (SD = 1.9) and 4.0 (SD = 2.0) for mothers on a scale for which 1 indicates a professional occupation, 7 indicates unskilled labor, and 8 indicates unemployment. In addition, 24.7% of the fathers and 28.0% of the mothers graduated from college. Analyses include 2,970 reports of conflict with mother from 566 same-sex twin pairs (367 MZ and 199 DZ; 314 female and 252 male twin pairs).[2]

Perceptions of Conflict

Twins completed the Parental Environment Questionnaire (Elkins, McGue, & Iacono, 1997), which has 12 items assessing conflict with mothers using a 4-point scale (1 = *definitely true* to 4 = *definitely false*). Example items include "My mother and I often get into arguments" and "I often seem to anger or annoy my mother." The overall conflict score is computed by reversing appropriate items and summing across the 12 items such that higher scores indicate greater perceived conflict. The means, standard deviations, and internal consistencies for the three assessment occasions are presented in Table 1.

Early Pubertal Development

Twins completed the Pubertal Development Scale (PDS; Petersen, Crockett, Richards, & Boxer, 1988) at both the 11- and 14-year old assessments. Adolescents were asked to report development on five aspects of pubertal growth including physical growth, body hair, and skin changes (especially pimples). Boys responded to questions concerning changes to voice and growth of facial hair, whereas girls were asked about breast development and menstruation. Response options vary from 1 (*not yet begun*) to 4 (*seems completed*). However, following logic outlined in Ge, Conger, and Elder (2001), we assessed early pubertal development using the PDS scores at the earliest available assessment to capture maturation in the initial years of adolescence (i.e., the age 11 assessment). Because there are substantial gender differences in pubertal development (with corresponding gender differences in PDS items), PDS scores at age 11 were standardized within gender. Using this procedure, higher scores reflect the degree to which a person's pubertal development is more advanced relative to his or her same-sex agemates in very early adolescence. The means, standard deviations, and reliability coefficients for the PDS at the 11-year-old assessment were M = 2.08, SD = 0.61, α = .74 for girls and M = 1.31, SD = 0.38, α = .67 for boys.

Table 1
Means, Standard Deviations, and Reliability Coefficients for Conflict With Mothers Assessed at Ages 11, 14, and 17

Age	M	SD	α
11	19.09	5.67	.83
14	20.86	6.41	.86
17	21.18	6.50	.88

Longitudinal analyses of the MTFS conflict data have been published previously. Most notably, McGue, Elkins, Walden, and Iacono (2005) used a mixed-model analysis of variance to assess whether conflict with parents changed across the 11-year-old to 14-year-old periods. In addition to an overall gender difference such that conflict was higher on average for boys than for girls, they also found moderate increases in parent–child conflict over time. These main effects were qualified by an interaction between time and gender such that perceptions of conflict from girls tended to increase more than boys. The analyses reported in this article extend McGue et al. (2005) to an additional wave and include pubertal timing as a predictor of conflict. In addition, the present analyses examine cross-dyad correlations in both levels of conflict and change in conflict. Thus, the substantive results reported here extend existing work from the MTFS.

Growth Models for Indistinguishable Dyads

Conceptually, growth modeling of dyadic data begins with growth functions for each individual. In our example, we coded the time variable such that a one-unit increase corresponds to a 1-year increase in time. We chose to set Time 0 as the study midpoint and so the 11-year-old assessment occasion was coded as –3, the 14-year-old assessment occasion was coded as 0, and the 17-year-old assessment occasion was coded as 3. As a result, the intercept of this growth model represents conflict at the study midpoint, and the slope coefficient represents the average change in conflict for each 1-year increase in time. Compared to individual growth models, there are two unique aspects of growth models for indistinguishable dyads: (a) Certain parameter estimates must be pooled across dyad members, and (b) there are additional parameters that capture the degree of correspondence between dyad members' outcomes.

To formally introduce these parameters, we develop equations using the MLM approach to dyadic growth models for our exam-

[2] We tested whether the twins were distinguishable with respect to delivery order because the Twin A label was always assigned to the firstborn twin. Our test indicated that there was no evidence of systematic differences in perceived conflict ratings between twins as a function of delivery order.

ple data set. If Y_{Ajk} is the conflict rating for Twin A in dyad j at time k and Y_{Bjk} is the conflict rating for Twin B in dyad j at time k, then we would have the following two equations for each dyad:

$$Y_{Ajk} = b_{0Aj} + b_{1Aj}T_{jk} + e_{Ajk}$$

$$Y_{Bjk} = b_{0Bj} + b_{1Bj}T_{jk} + e_{Bjk}.$$

Because the identical twins are indistinguishable in these data, assigning each child to be either *A* or *B* is arbitrary. It is important to note that if the assignment to *A* or *B* were switched for some dyads, estimates would change. This is the heart of the indistinguishablity issue, and therefore it would be technically more appropriate to use notation that does not categorically differentiate the two individuals. For example, we could use Y_{ijk} to represent the conflict score of child i in dyad j at time k, where $i = 1, 2$. In this case we could use a single individual-level or lower level equation to represent both children:

$$Y_{ijk} = b_{0ij} + b_{1ij}T_{ijk} + e_{ijk}.$$

As was true for the case of growth models for individuals, the lower level intercepts and slopes are aggregated across the sample. However, this aggregation now occurs both within dyads and across dyads:

$$b_{0ij} = a_0 + u_{0ij}$$

$$b_{1ij} = c_0 + u_{1ij}.$$

These equations show that the individual intercepts representing conflict scores for each twin at age 14 (i.e., when time is 0) are aggregated over individuals and dyads, resulting in a single estimate of the average intercept, a_0. Similarly, the individual slopes estimating the yearly change in conflict are aggregated across the entire sample into a single estimate, c_0.

There are three random effects whose variances can be estimated, as well as five covariances between these effects. The variance in the intercepts, $\mathrm{Var}(u_{0ij})$, measures the degree to which the adolescents vary in conflict with their mothers at the study midpoint. The variance in the slopes, $\mathrm{Var}(u_{1ij})$, measures the degree to which the adolescents vary in the increase (or decrease) of conflict over time. Finally, the specified model produces a single estimate of residual variance of e_{ijk} that measures the degree to which conflict varies from time point to time point after accounting for the other parameters in the model.

As previously mentioned, several covariances can be estimated in dyadic growth modeling. In discussing these covariances it is useful to distinguish between-persons covariances (sometimes called *interpersonal* covariances) from within-person covariances (sometimes called *intrapersonal* covariances). Often the between-persons covariances are the more substantively interesting parameters for dyadic growth models. First, there is the between-persons covariance of the intercepts, $\mathrm{Cov}(u_{01j}, u_{02j})$, which measures the degree to which the twins are similar in their conflict scores at the study midpoint. Second, there is the between-persons covariance of the slopes, $\mathrm{Cov}(u_{11j}, u_{12j})$, which measures the degree of similarity in the twins' change in conflict over time. That is, if one twin shows increasing conflict, does the other twin also show that pattern? In terms of within-person covariances, the dyadic growth model includes a parameter estimating the within-person covariance between the slope and intercept, $\mathrm{Cov}(u_{0ij}, u_{1i'j})$ where $i = i'$. This within-person covariance assesses whether adolescents who are higher at the study midpoint also have greater (or less) change in conflict with their mothers. The model also includes a between-persons covariance between the slope and intercept, $\mathrm{Cov}(u_{0ij}, u_{1i'j})$, where $i \neq i'$. This covariance measures the association between one twin's level of conflict at age 14 (Year = 0) and the other twin's rate of change. Finally, the between-persons covariance between the residuals captures the degree to which the twins' conflict scores at each measurement occasion are associated after controlling for the other parameters in the model (i.e., controlling for the effects of time). This covariance can be specified as constant over time for each measurement occasion, or it can be freely estimated at each occasion.

Figure 2 presents a path diagram representing the latent growth model for indistinguishable dyads assessed at three occasions. Like the path diagram presented in Figure 1, each person's observed variables are treated as indicators for a latent intercept variable and a latent slope variable. The intercept path coefficients are all fixed to 1, and the slope coefficients are fixed to –3, 0, and 3. These specifications define Time 0 as the study midpoint (i.e., age 14), and they define the slope to be the predicted change in conflict as time increases by 1 year. Three new parameters are depicted in Figure 2: The cross-twin intercept–intercept covariance, which is specified by the *ii* parameter; the slope–slope covariance, which is specified by the *ss* parameter; and the residual covariance, which is specified by the *ee* parameter.

One clearly evident aspect of this figure is that the two twins have been categorized as either Twin A or Twin B. Recall that such an assignment is arbitrary, and therefore models based on this designation must be adjusted. This adjustment requires two steps (see Olsen & Kenny, 2006). First, a series of equality constraints on the parameter estimates must be imposed. As depicted in the figure, the mean intercept values for Twin A and Twin B must be constrained to the same value (i.e., equality constraints must be placed on the intercept means for Twin A and Twin B), and the mean slope values for Twin A and Twin B must also be constrained to the same value. Likewise, the twins' intercept variances, slope variances, and residual variances must be set equal. In addition, the within-person covariance between the intercept and slope must be equated across twins. Finally, the between-persons covariance between the intercept and slope must also be equated across twins. In all there are seven equality constraints made in the model.[3]

The second adjustment to the model involves recomputing the goodness-of-fit indices (Olsen & Kenny, 2006) to account for the arbitrary assignment of individuals to the designation of Twin A or Twin B. The chi-square value generated by the model in Figure 2 includes two sources of model misfit: specification error (i.e., misfit because the specified model does not exactly reproduce the given data) and arbitrary misfit due to the assignment of twins to be As or Bs. The former source of error is the principal source of concern when researchers are evaluating the adequacy of a particular model, whereas the second source of misfit is simply a nuisance. Fortunately, this second source of misfit can be esti-

[3] If the residual variances are allowed to vary at each occasion, then the number of equality constraints increases to 9.

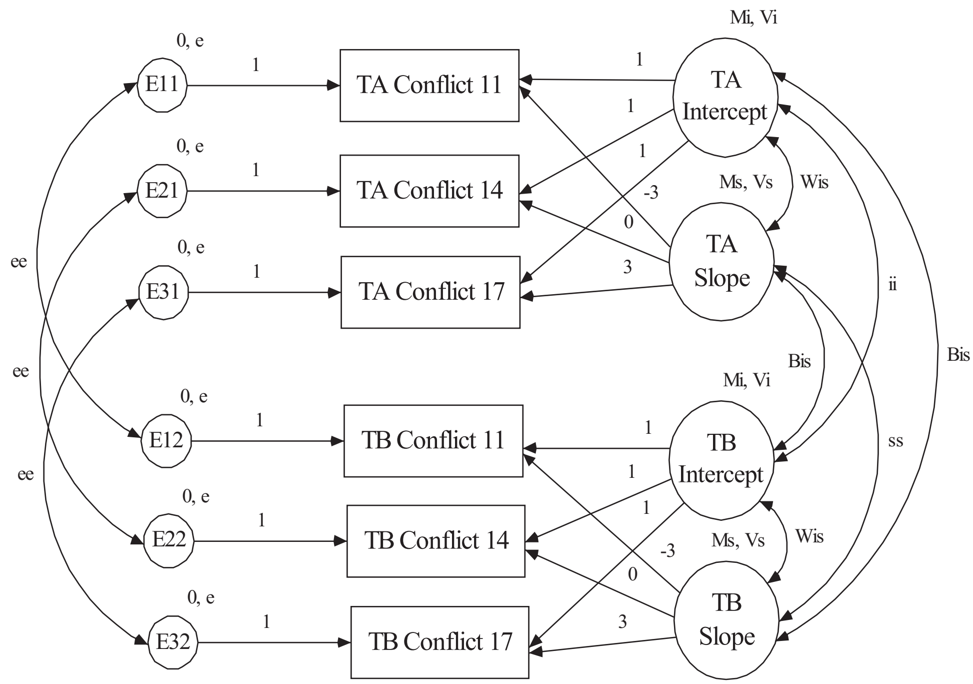

Figure 2. Basic dyadic growth model for indistinguishable dyads. TA = Twin A; TB = Twin B; Mi = mean intercept value; Ms = mean slope; Vi = intercept variance; Vs = slope variance; Wis = within-person covariance between the intercept and slope; Bis = between-persons covariance; ii = intercept–intercept covariance; ss = slope-slope covariance; E = error or residual component for the ratings; e = variance of the residuals; ee = covariance of the residuals at a specific time point across the two twins.

mated using what Olsen and Kenny (2006) called the saturated model for indistinguishable dyads (I-SAT) model, which is depicted in Figure 3. As is evident in Figure 3, the defining feature of the I-SAT model is that a series of equality constraints are made on the means, variances, and covariances for the two indistinguishable dyad members. If the number of observed variables in the model for each dyad member is q (e.g., in our example $q = 3$), then the I-SAT model has $q(q + 1)$ constraints, and so there are 12 constraints for the example. Given that there are a total of $2q$ (i.e., 6) observed variables, the number of available pieces of information equals 27, the number of estimated parameters equals 15, and so the I-SAT model has 12 degrees of freedom.[4]

The chi-square value generated by the I-SAT model estimates the degree of arbitrary model misfit. This value should be subtracted from the chi-square value generated by estimating the latent growth model (i.e., Figure 2) before evaluating the overall fit of the dyadic growth model. Thus, the appropriate test of exact fit for the latent growth model with indistinguishable dyads is a chi-square difference test, subtracting off the chi-square from the I-SAT model, with a corresponding subtraction of the degrees of freedom. Olsen and Kenny (2006) provided formulas for computing other measures of model fit (e.g., the root-mean-square error of approximation [RMSEA]) for indistinguishable dyads based on the I-SAT correction.

Growth Models of Twins' Conflict With Mothers Using MLM

Although there are a number of statistical packages that can be used for MLM (e.g., HLM 6.0, Raudenbush, Bryk, Cheong, & Congdon, 2004; MLwiN, Rasbash, Steele, Browne, & Prosser, 2004; SAS's PROC MIXED and SPSS MIXED), to the best of our knowledge, a growth model with indistinguishable dyads that includes all of the required equality constraints can most directly be estimated using SAS's PROC MIXED or MLwiN.[5] Our discussion and our online Appendix uses PROC MIXED in SAS because it is more readily available.

MLM with overtime dyadic data requires that the data be organized in what is called a *person-period structure* (Singer & Willett, 2003; see Table 2). A person-period data set has one record for each person at each time point. Thus, with our example data, each twin pair would have six records in the data set—three for each individual representing his or her conflict with mother at ages 11, 14, and 17. There should also be a variable representing dyad membership (Dyad ID), along with a variable denoting which of the two persons generated the conflict score for that record (Person ID). Two dummy variables (P1 and P2) need to be created on the basis of the Person ID variable: P1 = 1 if the conflict score

[4] As an aside, the evaluation of the fit of the I-SAT model is equivalent to the omnibus test of distinguishability, which tests whether twins who are classified as As are statistically different from twins who are classified as Bs. A significant chi-square test statistic for the I-SAT model means that there is evidence of empirical distinguishability. In such a case, researchers should not use the methods outlined in this article and instead should use methods described in Kashy and Donnellan (2008).

[5] Duncan et al. (2006, chap. 7) presented a three-level parameterization of the dyadic growth model that could be estimated using other MLM programs such as SPSS MIXED and Stata.

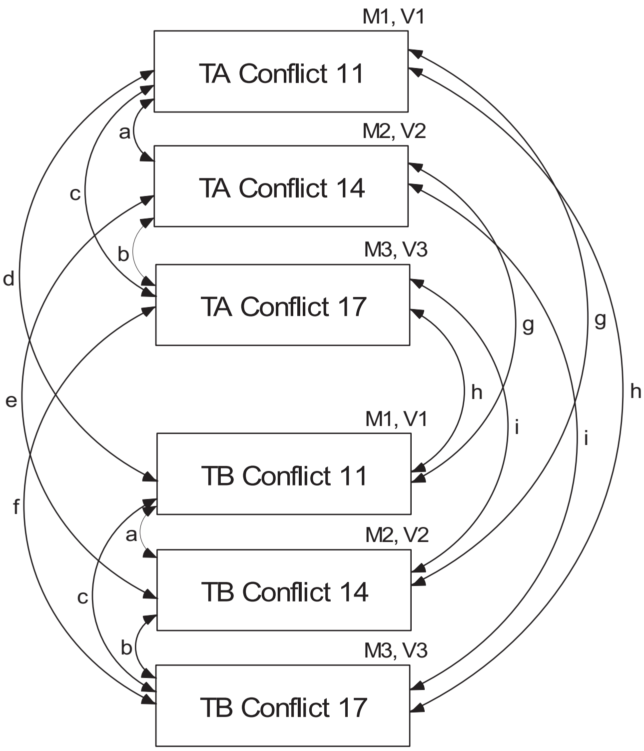

Figure 3. The saturated model for indistinguishable dyads model. TA = Twin A; TB = Twin B; M = mean of the variable; V = variance of the variable; a, b, and c = within-person covariances measuring the similarity of conflict scores across time but within person; d, e, and f = cross-person covariances that measure how similar the two twins' conflict scores are at a particular time point; g, h, and i = cross-person/cross-time covariances between the twins' conflict scores.

is from Twin 1 and P1 = 0 otherwise, and P2 = 1 if the conflict score is from Twin 2 and P2 = 0 otherwise. These obviously redundant dummy variables are needed to specify the set of equality constraints required because the dyad members are indistinguishable. Finally, there needs to be a variable representing the time of measurement. In the present data set, we have two key variables that reflect time (Year and Age), and a redundant third variable (Time) is included to make the output easier to read. Year takes on three values, –3, 0, and 3, representing wave of data collection. Age is the adolescent's actual age at the time of each measurement. This exact age variable can be used in place of Year to estimate the dyadic growth curve model in the MLM framework (indeed we use it to specify a nonlinear model using MLM), but it is more cumbersome to use when estimating the model with most SEM packages (but see Mehta & West, 2000).

As we have discussed (and as is specified using SAS in the online Appendix) an adolescent's perceived conflict with his or her mother is a function of an intercept (given the coding for year, this is the predicted conflict at the study midpoint or approximate age 14) and a slope (again, given the coding, this is the change in conflict as the child ages 1 year). The model further specifies that there are four random effects (two random intercepts that are represented by the two dummy variables, P1 and P2, and two random slopes, P1 × Year and P2 × Year). The two random intercepts are constrained to the same value, and the two random slopes are similarly constrained to be equal. The model further specifies that the intercepts and slopes can covary both within and between twin dyads. Finally, the residual error structure is specified as compound symmetry. This means that the variances of the residuals at each time point for both twins are set to be equal and that the covariances between the twins' residuals at the three time points are also equal.

Results from this analysis using the syntax provided in the online Appendix are presented in Table 3. Looking first at the fixed-effect estimates at the bottom section of the table, we see that the intercept for conflict scores is 20.45 (this is the mean intercept value in Figure 2), the slope is 0.34 (denoted as *Ms* in Figure 2), and both are statistically significant. Thus, the average perceived conflict score was 20.45 at the study midpoint, and perceptions of conflict scores increase by approximately one third of a point each year across ages 11 to 17.

The top section of Table 3 presents the variance–covariance matrix of the intercepts and slopes, and the second section provides significance tests for each of the parameters in the matrix. P1 in the G matrix represents the intercept for Twin 1, and P2 represents the intercept for Twin 2. Similarly, P1 × Year and P2 × Year represent the slopes. The identical values in the matrix make the specified equality constraints readily apparent.

The diagonal of the G matrix includes the variance of the intercepts (both 16.14; denoted as *Vi* in Figure 2) and the variance of the slopes (both 0.41; denoted as *Vs* in Figure 2). Both of these values represent significant variance according to the z tests provided in the covariance parameter section of the table. The variance of the intercepts suggests that although the average conflict score at the study midpoint was 20.45, there was considerable variation. For example, an adolescent whose perceived conflict at the study midpoint is one standard deviation below the average intercept for the sample would have an intercept of 16.43, whereas an adolescent whose conflict at the study midpoint is one standard deviation above average would have an intercept of 24.46. Similarly, there was considerable variance in the slopes, such that adolescents whose slopes were one standard deviation above and below the average slope, respectively, would be 0.99 and –0.30. Thus, although perceptions of conflict with mothers tend to increase over time, there is considerable variation in those trajectories.

The P1-P2 covariance, Cov(u_{01j}, u_{02j}) = 10.20, represents the covariance between the two twins' intercepts, and dividing that covariance by the intercept variance of 16.14 results in a correlation of r_{ii} = .63, z = 8.27, p < .001. This correlation indicates that twins were quite similar in their reports of conflict with their mothers at the study midpoint. The correlation between the slopes, r_{ss}, can similarly be computed by dividing the covariance between the two slopes, Cov(u_{11j}, u_{12j}) = .20, by the variance of the slopes, which was .41. This results in a correlation of r_{ss} = .48, z = 2.07, p = .039. Thus, twins were similar in the degree to which conflict with their mothers changed over time. The within-person covariance between the intercept and slope, Cov(u_{0ij}, $u_{1i'j}$), where $i = i'$, is .906, and dividing this covariance by the square-root of the product of the variance for the intercepts and the variance for the slopes gives a correlation of r_{Wis} = .35, z = 4.44, p < .001. Twins who were higher in conflict at age 14 also tended to be increasing in

Table 2
Example of the Person-Period Data Structure Required for Dyadic Growth Models Using Multilevel Modeling

Dyad ID	Person ID	P1	P2	Time	Year	Age	Gender	Conflict	Actor PDS	Partner PDS
001	1	1	0	1	−3	12.10	−1	18	−.124	.700
001	1	1	0	2	0	15.40	−1	12	−.124	.700
001	1	1	0	3	3	18.51	−1	14	−.124	.700
001	2	0	1	1	−3	12.10	−1	12	.700	−.124
001	2	0	1	2	0	15.40	−1	20	.700	−.124
001	2	0	1	3	3	18.51	−1	25	.700	−.124
002	1	1	0	1	−3	12.10	1	16	−.454	.864
002	1	1	0	2	0	15.00	1	19	−.454	.864
002	1	1	0	3	3	18.19	1	21	−.454	.864
002	2	0	1	1	−3	12.10	1	12	.864	−.454
002	2	0	1	2	0	15.00	1	15	.864	−.454
002	2	0	1	3	3	18.19	1	24	.864	−.454

Note. Dyad ID is an identification number for families, Person ID is an identification number for individuals within families (i.e., Twin 1 or Twin 2), P1 and P2 are dummy coded variables denoting which person provided the Conflict score. Gender is coded boys = 1, girls = −1. Actor PDS is the adolescent's standardized-within-gender pubertal timing score, and Partner PDS is the adolescent twin's pubertal timing score.

conflict more rapidly over time. Finally, the between-persons covariance between the intercept and slope, Cov(u_{0ij}, $u_{1i'j}$), where $i \neq i'$, is .37, and this value corresponds to a marginally significant correlation of r_{Bis} = 14, z = 1.72, p = .08: If one twin was relatively high in conflict at the study midpoint, there is a trend suggesting that the other twin's conflict increased more rapidly.

Table 3
Partial SAS Output for the Basic Indistinguishable Growth Model Examining Twins' Conflict With Their Mother

Estimated G matrix

P1	16.136	10.200	.906	.372
P2	10.200	16.136	.372	.906
P1 × Year	.906	.372	.412	.199
P2 × Year	.372	.906	.199	.412

Covariance parameter estimates

Covariance parameter	Subject	Estimate	*SE*	*Z*	Pr *Z*
LIN(1)	Dyad ID	16.136	1.183	13.64	<.001
LIN(2)	Dyad ID	10.200	1.233	8.27	<.001
LIN(3)	Dyad ID	.412	.089	4.64	<.001
LIN(4)	Dyad ID	.199	.096	2.07	.039
LIN(5)	Dyad ID	.906	.204	4.44	<.001
LIN(6)	Dyad ID	.372	.216	1.72	.085
Compound symmetry	Dyad ID × Time	5.631	1.009	5.58	<.001
Residual		14.483	.986	14.70	<.001

Solution for fixed effects

Effect	Estimate	*SE*	*df*	*t*	Pr > |*t*|
Intercept	20.447	.181	554	112.93	<.001
Year	.344	.044	536	7.76	<.001

Note. P1 = dummy code for Person 1; P2 = dummy code for Person 2; LIN = linear structure.

Two other elements in Table 3 remain to be discussed. The residual variance at the bottom of the *Covariance parameter estimates* section (14.483, z = 14.70, p < .001) indicates that there was considerable variation in conflict scores at the specific time points that was not explained by linear yearly changes. In addition, the significant compound symmetry covariance of 5.631 indicates that the residuals were correlated across twins at the specific time points (r_{ee} = .39, z = 5.58, p < .001). This suggests that the unique part of perceived conflict with mothers that is not explained by yearly changes is also similar across the two twins. In other words, if one twin experienced an exceptionally high or low level of conflict with his or her mother on a particular year, it was likely that the other twin did so as well.

Growth Models of Twins' Conflict With Mothers Using SEM

Although there are fundamental equivalencies between SEM and MLM, the two methods have some practical differences. One important difference is in the data structure used for the analyses. Whereas MLM typically requires a person-period data structure, SEM packages typically use a dyad data structure in which there is a single record for each dyad (i.e., one row for each family of twin pairs). In our example there are six variables for each row that record the three conflict scores for Twin A and the three conflict scores for Twin B. Table 4 presents a small subset of the data in dyad format.

We used the statistical package AMOS (Arbuckle, 2006) for our example SEM analyses. AMOS has both command-language and path-diagram input capabilities, but we focus on path diagram input because there is a graphical relationship between the models depicted in our figures and the input model for AMOS. However, we also estimated models using the Mplus (Muthén & Muthén, 2006) package and the results were

Table 4
Example of the Dyad Data Structure Required for Dyadic Growth Models Using SEM

	Twin A			Twin B		
Dyad ID	Age 11 conflict	Age 14 conflict	Age 17 conflict	Age 11 conflict	Age 14 conflict	Age 17 conflict
1	18	12	14	12	20	25
2	16	19	21	12	15	24
3	22	16	20	23	17	14

identical.[6] Figure 2 displays the path diagram depicting our dyadic growth model for twins. Although they are not presented, the parameter estimates for this model are identical to those from the MLM analyses with one rather trivial exception: The residual variance in the AMOS output is the sum of the residual variance and the residual covariance from the MLM analysis.

As was done in the multilevel analysis, the model depicted in Figure 2 specifies 10 parameters to be estimated from the data (one average intercept, one average slope, a variance of the intercepts and a variance for the slopes, a covariance between the two twins' intercepts and a covariance between the twins' slopes, a within-person intercept–slope covariance, a between-persons intercept–slope covariance, a residual variance, and a covariance between the residuals). This model is based on 6 manifest variables (p) for which we have means, variances, and covariances totaling 27 pieces of information (i.e., $p[p + 1]/2$ or 21 variances and covariances, plus 6 means). Because we are estimating 10 parameters, the unadjusted chi-square test of model fit has 17 degrees of freedom and was 43.96. The next step is to estimate the I-SAT model, which is depicted in Figure 3. This model involves estimating 15 parameters using the same 27 pieces of information, resulting in 12 degrees of freedom. The chi-square value from the I-SAT model was 10.30. This chi-square value is quite small relative to its degrees of freedom, indicating that misfit due to the arbitrary assignment of indistinguishable individuals to different roles is small.[7] Following through with the I-SAT adjustment to the test of overall model fit, our adjusted test is $\chi^2 = 43.96 - 10.30 = 33.66$ with $df = 17 - 12 = 5$, $p < .001$ (the adjusted RMSEA = .101; see Olsen & Kenny, 2006). Thus, there is considerable misfit in this dyadic growth model both in terms of the RMSEA and the chi-square goodness-of-fit test even after we remove the arbitrary misfit.

Given the relatively poor fit of the model in Figure 2, a second linear growth model, freeing up some of the constraints on the residuals, was estimated. In this model the variances of the three residuals were allowed to vary over time (but were constrained to the same value for the two twins). This added two parameters to the model. In addition, the covariances between the residuals were also allowed to vary over time, again adding two parameters. The resulting model had a $\chi^2(13) = 24.55$, $p = .026$, which represents a significant improvement relative to the previous model; however, adjusting the modified model for the I-SAT model still results in a rejectable model from the exact fit perspective ($\Delta\chi^2 = 24.55 - 10.30 = 14.25$ with $df = 13 - 12 = 1$, $p < .001$; RMSEA = .15).

In sum, SEM programs and MLM provide the same parameter estimates when used to estimate the same growth model. One difference is that SEM packages provide omnibus indices of fit, which indicate how well the specified model exactly reproduces the input matrix of means and covariances. In our example, model fit was not adequate by conventional SEM standards. One possibility for improving our model fit is the specification of nonlinear patterns of growth (see below). Needless to say, the focus on omnibus model fit in SEM is a potentially useful way to diagnose limitations in candidate models. Indeed, this is perhaps the biggest difference between the SEM and MLM approaches for estimating growth models (for an expanded discussion, see Kashy & Donnellan, 2008).

Extensions: Incorporating Predictors of Change into the Model

Gender

Basic growth models are often just the starting point for substantive analyses of the factors that moderate change. For instance, it may be that growth in perceptions of conflict with mothers differs for male versus female adolescents. To test this possibility, we conducted an analysis in which both the fixed effects (i.e., the average intercept and average slope) and random effects (i.e., the variances and covariances for the intercepts, slopes, and residuals) were allowed to vary by gender, and significant differences emerged for both types of effects. The SAS syntax for these analyses is included in the online Appendix, and the results are displayed in Table 5.

As is evident in Table 5, both the intercept and slope values differed for boys and girls. Boys reported higher levels of conflict with their mothers than did girls at the study midpoint; however, the rate of increase in perceptions of conflict was larger for girls than for boys. Projecting back to age 11 (i.e., when Year = –3), the difference in predicted conflict scores for boys and girls is relatively large, 20.78 versus 18.36, respectively, whereas by age 17 the difference in predicted conflict scores for boys and girls is quite small (21.62 and 21.36, respectively, for boys and girls).

Before interpreting the separate random effects for boys and girls, we conducted an omnibus test to determine whether separate random effects were necessary. MLM allows for such tests when the parameters in question are estimated using maximum likelihood estimation. The default for PROC MIXED and many other packages is restricted maximum likelihood, which uses general-

[6] Mplus input scripts are available from M. Brent Donnellan.

[7] It should be noted that the chi-square value of the I-SAT model is specific to the particular assignment of individuals to roles A and B, and if some such assignments are switched, a different I-SAT chi-square would result.

Table 5
Gender Differences in Growth of Conflict With Mothers During Adolescence

Fixed effects	*b*	*t*		
Intercept	20.53	112.59**		
Gender	.67	3.67**		
Year	.32	7.35**		
Gender × Year	−.18	4.12**		
Growth equations				
Boys	$\hat{Y} = 21.20 + .14 \times$ Year			
Girls	$\hat{Y} = 19.86 + .50 \times$ Year			

Random effects	Boys		Girls	
	Estimate	95% CI	Estimate	95% CI
Variances				
Intercept	18.22**	14.52–21.93	13.78**	10.93–16.63
Slope	.47**	0.23–0.72	.30*	0.07–0.54
Residual	14.87**	11.86–17.88	14.23**	11.71–16.74
Correlations				
Intercept–intercept	.71**	.65–.92	.54**	.33–.76
Slope–slope	.64*	.05–1.0	.18	−.65–1.0
Within intercept–slope	.18	−.03–.38	.69**	.44–.94
Between intercept–slope	.06	−.16–.29	.35**	.09–.61
Between residual	.20*	.02–.38	.54**	.34–.74

Note. Gender was coded as boys = 1, girls = −1. CI = confidence interval.
* $p < .05$. ** $p < .01$.

ized least squares methods to estimate the fixed effect parameters and maximum likelihood methods to estimate the random effect parameters. In our examples, we used maximum likelihood to estimate all of the parameters in the model so that the MLM estimates would be equivalent to the SEM estimates.

Our constrained model forced the variances and covariances of the random effects to be the same across gender, while still allowing the fixed effects to differ by gender. The unconstrained model estimated separate values for the random effects as well as the fixed effects. Thus, the unconstrained model estimated 8 additional parameters (3 variances and 5 covariances). We conducted a chi-square difference test using the –2 log likelihood values and found that $\chi^2(8) = 16.7$, $p < .05$. Thus, there was evidence that constraining the entire set of random effects across gender significantly worsened the model fit.

To assist in determining which random effects differed significantly across gender, we computed the 95% confidence intervals for each of the variances and covariances. These confidence intervals indicate that there was more variance in the intercepts for boys such that adolescent boys varied in their conflict with mothers more at the study midpoint than did girls. It also appeared that the within-person and between-twins correlations varied by gender. The correlation between male twins' intercepts was somewhat larger than that for female twins, indicating that boys were more similar to one another in perceived conflict at the study midpoint than were girls. Male twins were also more similar to one another in their yearly change in conflict than were female twins. In contrast, the rates of change for girls were more strongly related to the level of both their own and their twin's conflict at the study midpoint. Thus, if a girl or her twin was relatively high in conflict at the study midpoint, she also tended to show more of an increase in levels of conflict over time. Finally, the time-specific or residual correlations across twins were larger for girls relative to boys, such that twin girls were more similar in their unique levels of perceived conflict with their mothers at the three measurement occasions than were twin boys.

Collectively these results suggest that average trajectories of perceived conflict differ by gender. In analysis of variance terms, there is evidence of a Time × Gender interaction. In addition and perhaps of more interest, there are gender differences in the cross-twin developmental trajectories for female versus male twin pairs. For example, it appears that male twins are more similar in rates of change and in the levels of conflict at the midpoint than female twins. These results suggest that processes of mutual influence in twin relationships differ by gender. Such findings would be overlooked if we had not used dyadic growth models to examine change over time in perceptions of conflict and thus illustrate the utility of dyadic growth modeling.

Early Puberty

Early puberty is another potentially important moderating factor of change in conflict with mothers during the adolescent years. Unlike gender, our measure of pubertal development—the PDS scale—is a continuous measure that varies both within twin pairs as well as across twin pairs.[8] Kenny et al. (2006) referred to variables of this type as *mixed* variables, and they noted that such variables are particularly interesting in dyadic research because

[8] For girls the cross-twin correlation for PDS scores was $r = .56$, $p < .001$, and for boys this correlation was $r = .54$, $p < .001$.

they can be used to estimate actor and partner effects.[9] An *actor effect* is the effect of a person's predictor variable (i.e., early puberty) on that same person's outcomes (i.e., perceptions of conflict), and a *partner effect* is the effect of a person's predictors on his or her partner's (i.e., twin's) outcomes. Partner effects are cross-dyad effects that reflect the interdependence between dyad members; moreover, partner effects would be particularly interesting in this case because they would suggest that early maturation in one twin influences the other twins' perception of conflict.

We used MLM to assess the degree to which an adolescent's perceived conflict at the study midpoint (i.e., intercept), and his or her change in conflict (i.e., slope) was predicted by both that adolescent's early puberty (i.e., actor effect) and his or her twin's early puberty (i.e., partner effect). Because we found evidence of gender differences for both the intercept and slope, we first estimated a model (using maximum likelihood estimation for both the fixed effects and random effects) that included gender, early pubertal development, as well as their interaction, as moderators of the intercept and slope.[10] In this initial model, the only significant gender effects were those for the intercept and slope, and gender showed no interactions involving early pubertal development. We subsequently ran a second model (again using maximum likelihood estimation) dropping the four gender interactions with actor and partner's pubertal status (two for the intercept and two for the slope), and a chi-square difference test indicated that removing these interactions did not significantly worsen model fit, $\chi^2(4) = 2.8$, *ns*. Thus, the fixed effects components of our model include an intercept, a coefficient estimating the gender difference on the intercept, an effect of year and a coefficient estimating the gender difference on the effect of year, the actor effect for early puberty (i.e., the person's own standardized-within-gender PDS score at the earliest assessment), the partner effect for early puberty (i.e., the person's twin's standardized-within-gender PDS at the earliest assessment), an interaction between year and the actor's early puberty, and an interaction between year and the partner's early puberty. Although they are not discussed, the random effects specified in this model are the same as those specified in the basic linear growth model described earlier. The syntax for this analysis is presented in the online Appendix.

Results from this analysis suggest that when puberty is early in either twin, conflict with mothers was relatively high at the study midpoint (i.e., the effect of early pubertal timing on the intercept). The actor effect, specifying the effect of the adolescent's own early puberty on his or her conflict with mother, was $b = .38$, $t(939) = 2.32$, $p = .02$, and the partner effect, specifying the effect of the person's twin's early puberty on that person's conflict with mother, was similar in size, $b = .42$, $t(913) = 2.52$, $p = .01$. Because the actor and partner effects are estimated simultaneously, they represent the unique effects of each person's early puberty, controlling for the twin's early puberty. Thus, adolescents who themselves were early maturers and adolescents whose twins were early maturers tended to have higher levels of conflict with their mothers at age 14. If both twins were early maturers such that both were one standard deviation above average on the PDS at the earliest assessment, their predicted conflict score at age 14 would be 0.8 points higher than it would be if their PDS scores were both at the sample mean.

Finally, there was also evidence that the person's early puberty moderates the effect of time, with the Time × Actor interaction yielding a negative coefficient of $b = -0.11$, $t(922) = 2.31$, $p = .02$. Thus, although early maturers were relatively high in conflict at the study midpoint, there is evidence that their rate of increase in conflict over time is diminished. There was no parallel effect for the Time × Partner interaction, $b = -0.01$, $t(895) = 0.23$, *ns*.

All and all, these results suggest that trajectories of perceived conflict with mothers are associated with early puberty in interesting ways that potentially extend existing knowledge on the correlates of early puberty. Specifically, early puberty in both girls and boys is associated with increased conflict in middle adolescence, consistent with the existing literature about the relation between early puberty and parent–child conflict (e.g., Collins & Laursen, 2004). A second and even more interesting finding is that early puberty has partner effects such that early maturation in one twin is associated with perceptions of increased maternal conflict in middle adolescence by the other twin. This suggests that the impact of early puberty extends beyond the individual experiencing the biological transition and hints at the possibility that early puberty might broadly alter family dynamics. This intriguing finding would not have been as easily illuminated with other longitudinal analytic techniques, thereby highlighting the value of dyadic growth modeling for developmental studies.

Extensions: Estimating a Nonlinear Growth Model

Thus far, we have discussed only linear growth functions, but nonlinear models are also possible. In the present data, it may be that conflict with mothers is curvilinear such that it grows very quickly during early adolescence but then levels off after puberty. Such a pattern would be consistent with the existing literature (e.g., Laursen et al., 1998). On the one hand, nonlinear models can be difficult to estimate with only three waves of data; however, both SEM and MLM offer possibilities. In SEM it is possible to freely estimate some of the slope factor loadings to capture nonlinear growth (see Duncan et al., 2006, pp. 31–35). For example, the loading for the initial assessment could be fixed to 0 and loading for the third assessment could be fixed to 1. The loading for the second assessment point is then freely estimated from the data, and if the unstandardized loading turns out to be close to .5, the growth is approximately linear. If, on the other hand, the unstandardized loading is larger than .5, then it suggests that more growth occurs between the first and second measurement occasions than between the second and third occasions. For the example data, the unstandardized loading was 0.79, which indicates that perceptions of conflict increase more rapidly during early to mid adolescence than from middle to late adolescence. This finding fits nicely with the existing literature (e.g., Laursen et al., 1998).

[9] If our example data set had included mixed-gender twin pairs, gender would have also been a mixed variable in that it would have varied both within and between dyads. Had that been the case, we could have estimated both actor and partner effects for gender.

[10] In these analyses, we examined moderation of the fixed effects only. The random effects were not allowed to vary with pubertal status or gender and instead were specified in the same manner as those in the basic model described previously. We estimated a model that also allowed gender differences in the random effects, and the estimates, tests, and conclusions did not change.

MLM offers another alternative that takes advantage of the fact that the adolescents were assessed approximately, but not exactly, at ages 11, 14, and 17. Because there is variation in the actual ages of the participants at the three assessments, and because MLM can readily use the actual age as a marker of time, it is possible to estimate both a linear and a quadratic component in the growth model. (This modeling strategy is possible in SEM, although it can be very difficult to implement in some popular programs such as AMOS.) We estimated a quadratic model in which actual age (measured in years and grand mean centered) rather than the time variable was used to estimate the growth function. Our model specified both linear and quadratic fixed effects for age, and allowed for gender differences in both of these components.[11] Results indicated significant nonlinearity in overall growth with the quadratic effect being $b = -0.08$, $t(752) = 4.79$, $p < .001$. There was also evidence of a gender difference in the quadratic effect with $b = 0.047$, $t(752) = 2.78$, $p = .006$. The results of the full model are depicted in Figure 4. As is apparent in the figure, and as we saw with the gender-moderated linear growth model, girls' conflict with their mothers is relatively low at age 11 but increases steeply over time. The estimated nonlinear growth model for girls was

$$\text{Predicted Conflict} = 20.79 + .49(\text{Age}) - .13(\text{Age})^2$$

And the corresponding model for boys was

$$\text{Predicted Conflict} = 21.43 + .14(\text{Age}) - .04(\text{Age})^2$$

Given that the grand mean for age is 14.87, these equations suggest that perceptions of conflict with mothers peak for girls at age 16.76 and peak for boys at age 16.59. It is interesting to note that the predicted levels of conflict for girls never exceed predicted levels for boys. Indeed, these results are especially interesting given that many parents perceive that girls are particularly argumentative during adolescence. It might be the case that parents are responding to a contrast effect driven by the more pronounced increases in conflict during adolescence for girls rather than boys. This assumes, of course, that adolescent perceptions of conflict reasonably correspond with parental perceptions. Nonetheless, these nonlinear modeling extensions further illustrate the flexibility of growth models, even when only three data points are available.

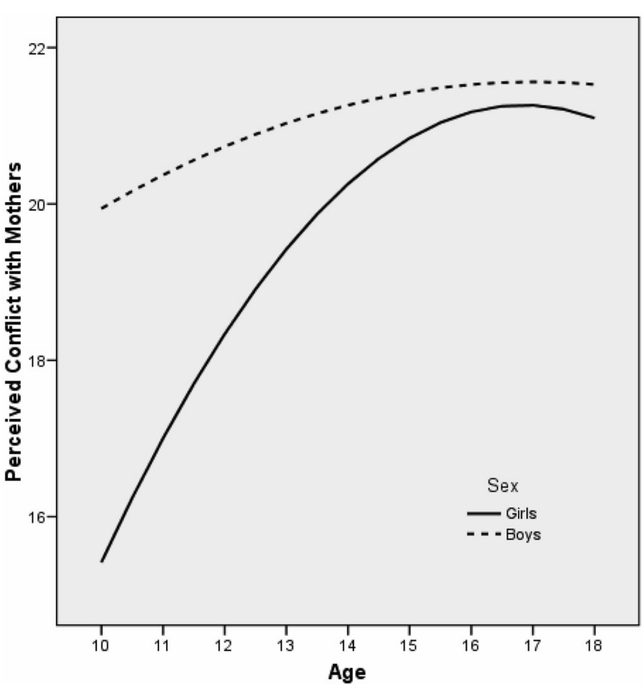

Figure 4. Nonlinear growth in conflict with mothers for adolescent boys and girls using both linear and quadratic components for time.

A Conceptual Introduction to Behavioral Genetic Approaches to Dyadic Growth Models

Because these are twin data comprised of both MZ and DZ twins, they naturally bring to mind questions of the degree to which growth in perceptions of conflict with mothers is associated with genetic and environmental factors. However, a complete discussion of the behavioral genetic approach to growth modeling is beyond the scope of this article, and readers interested in more technical details should see McArdle and Hamagami (2003) and Neale and McArdle (2000). Nevertheless, the underlying logic of the models follows directly from the data analytic strategies we have presented.

Behavioral genetic analyses have the goal of estimating three unobserved sources of variability: genetic influences, shared-environmental influences, and nonshared environmental influences. The most common strategy is to compare the similarities of reared-together MZ and DZ twins. Genetic influences are inferred when MZ twins are more similar to one another than are DZ twins. Shared environmental influences are factors that create similarity between siblings and are inferred when MZ and DZ twins are roughly identical in their similarity. Nonshared environmental influences are factors that result in dissimilarity between siblings and are inferred when MZ twins are not perfectly similar for a given attribute.

From an SEM perspective, the genetically informative latent growth model begins with a multiple group analysis in which MZ and DZ twins are treated as separate groups. A series of cross-group equality constraints then specify that the fixed effects for intercepts and slopes; the variances for the intercepts, slopes, and residuals; and the within-person intercept–slope covariances are the same across groups. Thus, several important descriptive components of the dyadic growth model—the means and variances of the intercepts and slopes—are the same across twin type. The key differences between the MZ and DZ groups are specified in parameters that cross twins: the intercept–intercept covariance, the slope–slope covariance, the between-persons intercept–slope covariance, and the cross-twin residual covariance(s). These parameters are freely estimated (i.e., allowed to differ) for MZ and DZ twins.

In these data, the intercept–intercept correlation across MZ twins was $r = .73$, $z = 8.94$, $p < .01$, and the same correlation for

[11] This model included separate linear random effects for men and women, but we were not able to treat the quadratic component of the model as a random effect because such a specification was not supported by the data.

DZ twins was $r = .44$, $z = 4.04$, $p < .01$. The correspondence between the two twins' slopes was $r = .69$, $z = 2.66$, $p < .01$, for MZ twins, but for DZ twins this correlation was only $r = .17$, $z = .48$, *ns*. The between-twins intercept–slope correlation (i.e., the correspondence between one person's intercept and the other person's slope) was $r = .20$, $z = 2.25$, $p = .02$, for MZ twins and $r = .03$, $z = .22$, *ns*, for DZ twins. These correlations suggest that genetic factors underlie individual trajectories of perceptions of conflict. By contrast, the correspondence between the time-specific conflict scores was quite similar for MZ ($r = .27$, $z = 4.65$, $p < .01$) and DZ ($r = .29$, $z = 3.74$, $p < .01$) twins, highlighting the possibility of shared environmental factors. These estimated correlations are the foundation for the behavior genetic variance decomposition; however, the actual modeling is more sophisticated.

Conclusion

We hope that our discussion provides researchers with the basic understanding needed for estimating and evaluating the results of indistinguishable dyadic growth models. We have illustrated how researchers can estimate models using twin data, but we believe that indistinguishable pairs might be more common than many researchers suspect. Accordingly, we urge researchers to empirically test for distinguishablity before conducting additional analyses with their dyadic data. For instance, following Kenny et al. (2006), we believe that research on male–female romantic dyads should routinely test whether these romantic couples really are distinguishable by gender before estimating growth models for heterosexual couples. It may be the case that the indistinguishable growth model is the appropriate model for couple data of this sort and thus our discussion may have additional relevance to developmentalists who study couple dynamics over time.

Needless to say, dyadic growth models for both indistinguishable and distinguishable dyads have a great deal of promise as a tool for advancing developmental science. The fixed effects from these models provide insights into normative developmental trends, such as how average levels of conflict change over adolescence. The random effects point to individual differences in change that can be predicted by theoretical interesting factors such as the early onset of puberty. Moreover, dyadic growth models allow researchers to study the impact that related individuals have on one another's developmental trajectories. This last feature is particularly important given that much of social and personal development is done within the context of dyadic relationships. All told, we hope that the widespread use of dyadic growth models may help bring the statistical tools of developmental psychology in closer accord with the reality that lives unfold in the context of significant relationships.

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