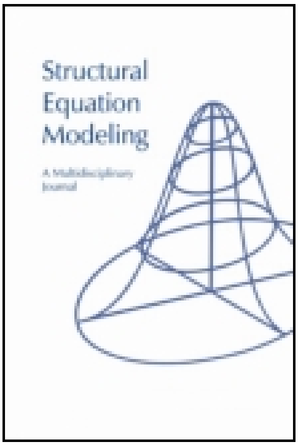


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# Analyzing Mixed-Dyadic Data Using Structural Equation Models

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Mixed-dyadic data, collected from distinguishable (nonexchangeable) or indistinguishable (exchangeable) dyads, require statistical analysis techniques that model the variation within dyads and between dyads appropriately. The purpose of this article is to provide a tutorial for performing structural equation modeling analyses of cross-sectional and longitudinal models for mixed independent variable dyadic data, and to clarify questions regarding various dyadic data analysis specifications that have not been addressed elsewhere. Artificially generated data similar to the Newlywed Project and the Swedish Adoption Twin Study on Aging were used to illustrate analysis models for distinguishable and indistinguishable dyads, respectively. Due to their widespread use among applied researchers, the AMOS and M*plus* statistical analysis software packages were used to analyze the dyadic data structural equation models illustrated here. These analysis models are presented in sufficient detail to allow researchers to perform these analyses using their preferred statistical analysis software package.

*Keywords*: distinguishable, dyadic, exchangeable, indistinguishable, mixed

Applied researchers often pose empirical questions designed to test theories regarding individuals, and subsequent data are typically analyzed assuming the responses from one participant are independent of responses from all other participants. As such, applied researchers typically identify the correct statistical analytic technique needed to answer such individualistic research questions by considering (a) the type of research question posed (e.g., descriptive, comparative,

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or relationship), (b) the number of independent and dependent variables under consideration, (c) the measurement scale of these variables, and (d) the sampling strategy used to obtain the data. However, researchers also investigate questions designed to clarify how individuals interact, and a dyad is defined as an interactive relationship between a pair of individuals (e.g., dating or married couples, monozygotic or dizygotic twins, or employer–employee, doctor–patient, or parent–child relationships). If data were collected from dyadic relationships, three additional considerations need to be addressed before the correct statistical analysis technique can be identified and applied: dependence, distinguishability, and the type of dyadic variables to be analyzed.

Dyadic dependence refers to the fact that the variable scores collected from individuals interacting within dyads are not independent, but are likely to be more correlated than scores from individuals in different dyads (cf. Gonzalez & Griffin, 1999; Kenny, Kashy, & Bolger, 1998). Further, dependence in dyadic data takes two forms. Similar to traditional analysis models (e.g., ordinary least squares [OLS] regression) that specify shared predictor and response variable variation, intrapersonal (relationships of variable scores from the same person) dyadic dependence refers to the variation in an individual's predictor or covariate score that is shared with the variance of his or her own response variable score. However, interpersonal (relationships of variables from different persons) dyadic dependence refers to the variation in an individual's predictor or covariate score that is shared with the variation of the other dyad member's response variable score (cf. Kenny, 1996). Dependence is an important issue because traditional analysis approaches that assume independence of individual scores, such as analysis of variance and OLS regression, can produce biased parameter estimates and standard errors if applied incorrectly to dyadic data. A number of analytic techniques are available that estimate the degree of dependence in dyadic data. Perhaps the most widely used approach is the intraclass correlation (Gonzalez & Griffin, 2002; Kenny & Judd, 1996; McGraw & Wong, 1996), which quantifies the proportion of response variable variability that is due to mean differences across dyads. Dyadic dependence assessment is not reviewed here because researchers collect dyadic data to answer dyadic research questions, the presence of dyadic dependence is to be expected, and quantifying the amount of dependence present typically does not inform the research question. Interested readers can consult Kenny, Kashy, and Cook (2006) for additional details on assessing dependence. However, as shown in the analysis examples that follow, properly specifying and modeling both the intrapersonal and interpersonal dependence is crucial to dyadic data structural equation modeling (SEM) analysis.

This article illustrates the SEM analysis steps necessary to analyze mixed dyadic data (i.e., data that vary both within a dyad and across dyads) sampled cross-sectionally and longitudinally from either distinguishable or indistinguishable dyads. Dyadic distinguishability refers to whether the two individuals comprising a dyad possess a distinctive characteristic that can differentiate them in a manner that is relevant to the research question under investigation (e.g., Kenny & Ledermann, 2010). For example, individuals making up a traditional marital dyad could be identified by their designated gender value (e.g., gender: 1 = wives, 2 = husbands) and could be considered distinguishable. By contrast, same-sex identical twins are an example of dyads whose members could be considered indistinguishable because the designation of "Person 1" and "Person 2" within each dyad would be arbitrary. Although an empirical test of distinguishability is available (see Griffin & Gonzalez, 1995; Kenny & Cook, 1999; Kenny et al., 2006), that test is not reviewed here. This article proceeds from the assumption that it is the research question under investigation, not the results of a statistical test, that drives all research design and statistical analysis decisions involving dyad distinguishability. To further clarify the distinguishability issue, consider an example of identical brother-sister twins. If the research question under investigation was genetic in nature, this would suggest the twins be treated as indistinguishable in the data analysis. However, several research questions could be posed (e.g., skill level) that would suggest the twins be treated as distinguishable in the data analysis. The key point to be made regarding the issue of dyad distinguishability is that the question is not whether any variable exists on which dyads under consideration could be rendered distinguishable or indistinguishable, but whether the variables that are crucial to the theory being tested by the research question under investigation suggest the dyads be treated as distinguishable or indistinguishable in the data analysis.

## GOALS OF THIS ARTICLE

Artificially generated data consistent with the mean structures and covariance matrices of both the Newlywed Project (DiLillo et al., 2009) and the Swedish Adoption Twin Study on Aging (SATSA; Pedersen, 2004) were used to illustrate hypothetical analysis models for distinguishable and indistinguishable dyads, respectively. The Newlywed Project involved data collected from newlywed couples in 3 consecutive years to investigate the relationships between various psychological phenomena and their subsequent impact on marital functioning. The SATSA project involved data collected from twin pairs in 1987, 1990, and 1993 that examined the relationships between measures of psychological functioning and quality of life. As described later, it is further assumed that the research questions under investigation suggest that the Newlywed marital couples be treated as distinguishable and the SATSA twins be treated as indistinguishable in all of the dyadic data analysis examples.

The purpose of this article is to (a) show that several dyadic structural equation models are available to model the intrapersonal and interpersonal dependence in mixed dyadic data sampled from distinguishable or indistinguishable dyads; (b) provide specific analysis details and explanations regarding how mixed dyadic data structural equation models are specified and why certain modifications are needed for indistinguishable dyad structural equation models that have not been addressed in other publications; (c) provide AMOS (Version 16) and M*plus* (Version 6.11; Muthén & Muthén, 1998–2010) examples for all dyadic analysis models described here, as well as supplemental Microsoft Excel files designed to assist in the computation of additional fit indexes for the indistinguishable dyad analysis models, in an Appendix available at https://bmixythos.cchmc.org/xythoswfs/webui/_xy-476611_1-t_AXKarXYG; and (d) provide descriptions of the analysis models used here in sufficient detail to allow researchers to apply these models using the statistical analysis software package of their choice. For all dyadic data analysis models shown here, the distinguishable dyad analysis models are described first so that the model specification alterations needed to analyze data from indistinguishable dyads with the same analysis model are more clearly presented. Further, Table 1 presents an overview of the dyadic data analysis model examples presented, their respective linear model equations, the research questions addressed, and the parameter estimate constraints involved with each. Finally, as demonstrated in all example analyses, the research question under investigation and the distinguishability decision together dictate the dyadic structural equation model needed

TABLE 1
Dyadic Data Analysis Model Organizational Schematic

| | | *Actor-Partner Interdependence Model (APIM)* | *Common Fate (CF) Mediation Model* | *Dyadic Latent Growth Curve Model (DLGCM)* |
|---|---|---|---|---|
| Equations | Distinguishable | $Y_i = (v_i +) b_i(Actor) + b_i(Partner) + \varepsilon_i$ | $Y_i = (v_i +)\Lambda_Y \eta + \varepsilon_i$<br>$M_i = (v_i +)\Lambda_M \eta + \varepsilon_i$<br>$X_i = (v_i) + \Lambda_X \xi + \varepsilon_i$<br>$\eta = \tau' \xi + (\alpha\beta)\xi + \zeta_\eta$ | $Y_{tid} = \Lambda \eta_{i(INTERCEPT)} + \Lambda_t \eta_{i(SLOPE)} + \varepsilon_{tid}$<br>$\eta_{i(INTERCEPT)} = \alpha_{i(INTERCEPT)} + \gamma_i(X_i) + \zeta_{i(INTERCEPT)}$<br>$\eta_{i(SLOPE)} = \alpha_{i(SLOPE)} + \gamma_i(X_i) + \zeta_{i(SLOPE)}$ |
| | Indistinguishable | $Y_i = v_i + b(Actor \,\&\, Partner) + \varepsilon_i$ | $Y_i = v + \Lambda_Y \eta + \varepsilon$<br>$M_i = v + \Lambda_M \eta + \varepsilon$<br>$X_i = v + \Lambda_X \xi + \varepsilon$<br>$\eta = \tau' \xi + (\alpha\beta)\xi + \zeta_\eta$ | $Y_{tid} = \Lambda \eta_{(INTERCEPT)} + \Lambda_t \eta_{(SLOPE)} + \varepsilon_i$<br>$\eta_{(INTERCEPT)} = \alpha_{(INTERCEPT)} + \gamma(X_i) + \zeta_{(INTERCEPT)}$<br>$\eta_{(SLOPE)} = \alpha_{(SLOPE)} + \gamma(X_i) + \zeta_{(SLOPE)}$ |
| Unit of Analysis | Distinguishable<br>Indistinguishable | individuals within dyads<br>dyads | dyads<br>dyads | individuals within dyads<br>dyads |
| Parameter Estimate Constraints | | Distinguishable dyads<br>$b_1(Actor) = b_2(Actor); b_1(Partner) = b_2(Partner)$<br>Indistinguishable dyads<br>$b_1(Actor) = b_2(Actor) = b_1(Partner) = b_2(Partner)$ | $v \sim [v_X = v_X, v_M = v_M, v_Y = v_Y]$<br>$\varepsilon_{\text{indistinguishable}} \sim \begin{bmatrix} \sigma^2_X \\ 0 & \sigma^2_X \\ \sigma_{X,M} & 0 & \sigma^2_M \\ 0 & \sigma_{X,M} & 0 & \sigma^2_M \\ \sigma_{X,Y} & 0 & \sigma_{M,Y} & 0 & \sigma^2_Y \\ 0 & \sigma_{X,Y} & 0 & \sigma_{M,Y} & 0 & \sigma^2_Y \end{bmatrix}$ | $\varepsilon_{\text{indistinguishable}} \sim \begin{bmatrix} \sigma^2_Y \\ 0 & \sigma^2_Y \\ 0 & 0 & \sigma^2_Y \\ \sigma & 0 & 0 & \sigma^2_Y \\ 0 & \sigma & 0 & 0 & \sigma^2_Y \\ 0 & 0 & \sigma & 0 & 0 & \sigma^2_Y \end{bmatrix}$<br>$\eta_{indistinguishable} \sim [\alpha_{\text{Intercept}} = \alpha_{\text{Intercept}}, \alpha_{\text{Slope}} = \alpha_{\text{Slope}}$ $\begin{bmatrix} \psi_{\text{Intercept}} \\ \psi_1 & \psi_{\text{Slope}} \\ 0 & \psi_2 & \psi_{\text{Intercept}} \\ \psi_2 & 0 & \psi_1 & \psi_{\text{Slope}} \end{bmatrix}$ |

*Note.* $i$, $_1$, and $_2$ subscripts refer to individuals within dyads; symbols lacking an $i$ subscript, or symbols with the same subscript(s), indicate parameter estimates constrained to equality between individuals within dyads. $(v_i +)$ indicates response variable intercepts that can be estimated in distinguishable dyad analyses to test for significant differences between individuals within dyads as a function of the distinguishing factor.

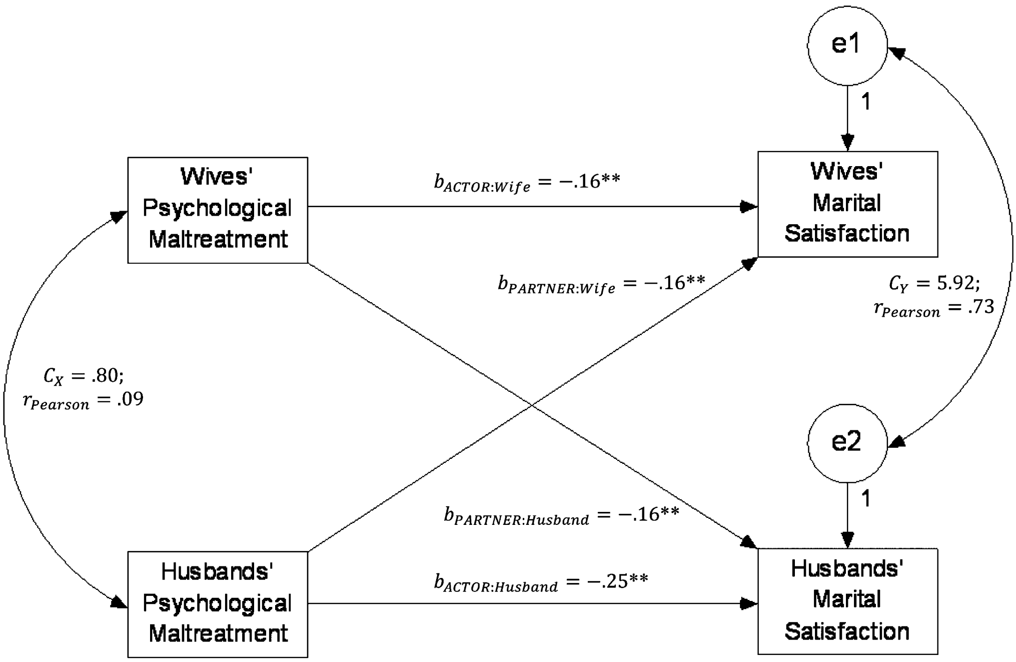


FIGURE 1 Distinguishable dyad actor–partner interdependence (APIM) analysis model. $^{**}p < .01$.

and how the intrapersonal and interpersonal dyadic dependence should be specified within the model.

## CROSS-SECTIONAL DYADIC DATA ANALYSES

Researchers collect cross-sectional data from dyads to answer research questions involving interpersonal dynamics, such as whether the predictor variable score of the first dyad member ($X_1$) is significantly related to their own response variable ($Y_1$) score (i.e., $X_1 \rightarrow Y_1$; an intrapersonal or "actor" effect), and if the predictor variable score of the first dyad member is significantly related to the response variable score of the second dyad member (i.e., $X_1 \rightarrow Y_2$; an interpersonal or "partner" effect; Cook & Kenny, 2005; Furman & Simon, 2006; Kenny, 1996). A traditional SEM analysis model used to answer research questions involving dyadic intrapersonal and interpersonal relationship patterns is the actor–partner interdependence model (APIM; cf. Kenny, 1996). An example APIM that investigates the intrapersonal and interpersonal relationships between childhood psychological maltreatment and subsequent marital satisfaction among newlywed couples is shown in Figure 1.

### Distinguishable Dyads

The APIM shown in Figure 1 estimates (a) predictor variable (psychological maltreatment)

TABLE 2
Actor–Partner Interdependence Model Fit Statistics

| | *Distinguishable Dyads* | | | | *Indistinguishable Dyads* | | |
|---|---|---|---|---|---|---|---|
| | *Null Model* | *Analysis Model, Initial* | *Analysis Model, Final* | *Saturated Model* | *Null Model* | *Analysis Model* | *Saturated Model* |
| $\chi^2$ | 387.38 | 13.66 | 4.91 | 0 | 65.97 | 10.97 | 9.99 |
| *df* | 6 | 3 | 2 | 0 | 10 | 3 | 6 |
| LogL | −4,028.83 | −3,841.97 | −3,837.60 | −3,835.14 | −3,831.02 | −3,803.52 | −3,803.03 |

means, (b) response variable (marital satisfaction) intercepts, (c) predictor variable variances, (d) response variable residual ($e$) variances, (e) a predictor variable covariance ($Cx$), (f) a residuals covariance ($Cy$), (g) actor ($b_{ACTOR}$) effects, and (h) partner ($b_{PARTNER}$) effects. Intrapersonal dyadic dependence is modeled through the estimation of actor effects ($b_{ACTOR}$); interpersonal dyadic dependence is modeled through the estimation of partner effects ($b_{PARTNER}$) and covariances ($Cx$ and $Cy$). Estimating each of these parameters separately for the two dyad members results in a saturated model (in more complex analyses, the unconstrained model might not be saturated). The goal of an APIM analysis in the distinguishable dyad case is to test the fit of more parsimonious models that constrain actor and partner effect estimates. For example, two of the more common constraint patterns in the distinguishable case involve a model that constrains actor effects (e.g., $b_{ACTOR,Wives} = b_{ACTOR,Husbands}$) and partner effects (e.g., $b_{PARTNER,Wives} = b_{PARTNER,Husbands}$) separately to equality (i.e., where $b_{ACTOR} \neq b_{PARTNER}$), and a model constraining all four effects (e.g., $b_{ACTOR,Wives} = b_{ACTOR,Husbands} = b_{PARTNER,Wives} = b_{PARTNER,Husbands}$) to equality. These equality constraints allow testing for significant differences in actor and partner effects between distinguishable dyad members (Gonzalez & Griffin, 2001). It is important to note that the standard null and saturated structural equation models are the appropriate models with which to test the fit of an APIM with distinguishable dyads. However, the definition and specification of the appropriate null and saturated models will differ for indistinguishable dyad analyses, as shown in the subsequent sections.

*Distinguishable APIM example.* As an example, the APIM shown in Figure 1 was estimated using the Newlywed Project data to quantify childhood psychological maltreatment and subsequent marital satisfaction actor and partner effects, and to test for possible differences in these effects between newlywed husbands and wives. As shown in the left panel of Table 2, estimating an initial analysis model that constrained all four regression paths to equality resulted in the following chi-square model fit index value: $\chi^2_3 = 13.66$, $p < .01$ (not shown in Table 1: comparative fit index [CFI] = .97, Tucker–Lewis Index [TLI] = .95, root mean square error of approximation [RMSEA] = .09).[1] Modification indexes showed that the husband actor effect

[1]This article used generated hypothetical data to demonstrate the procedures involved in various dyadic data analyses using SEM, not to evaluate dyadic data analysis models. Model fit statistic values are presented "as is"; no judgments as to the quality of the fit of the model to the data are made and no theoretical conclusions should be drawn from the hypothetical results presented.

path ($b_{\text{ACTOR:Husband}}$) should be freed; estimating that final analysis model resulted in the following chi-square model fit index value: $\chi^2_2 = 4.91$, $p > .05$ (CFI = .99, TLI = .98, RMSEA = .06). The final model parameter estimates are shown in Figure 1. As childhood psychological maltreatment for either spouse increased, marital satisfaction significantly decreased for both spouses, but this decrease was significantly greater for the relationship between husbands' childhood maltreatment experiences and husbands' marital satisfaction.

## Indistinguishable Dyads

Fitting the APIM to distinguishable dyadic data is a fairly straightforward process. However, analyzing indistinguishable dyadic data is a more involved process that requires additional steps. From the SATSA data, twins' self-reported fear and life satisfaction scores will be used to illustrate the steps in an APIM analysis with indistinguishable dyads. The analysis model used in the example is shown in Figure 2. However, before introducing the analysis steps, a brief review of structural equation model fit is needed.

In SEM, model fit is determined by estimating three models: the substantive analysis model of interest, a null model, and a saturated model. The null (or baseline) model estimates only

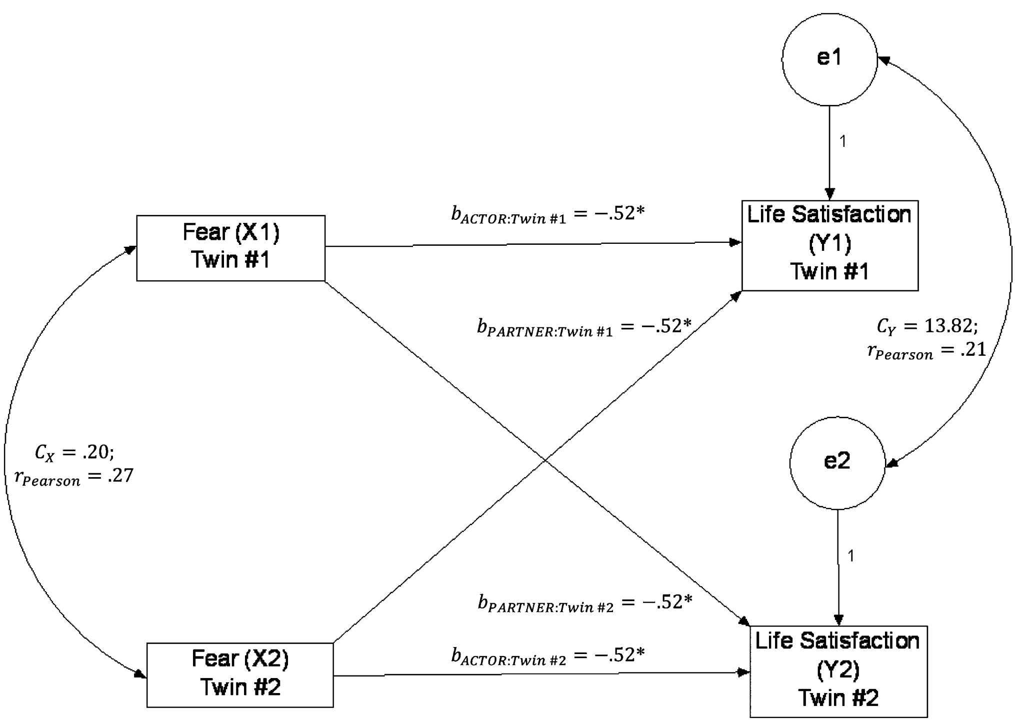


FIGURE 2 Indistinguishable dyad analysis actor–partner interdependence model (APIM). $^*p < .05$.

means and variances for each analysis variable, constrains all possible analysis variable covariances to zero, and is considered the worst possible model to fit to a set of sample data.[2] A saturated model is defined as a model that freely estimates all analysis variable means, variances, and covariances. The saturated model is considered the best fitting model possible, but is not parsimonious and is seldom of interest to researchers. Together the null (worst fitting model possible) and saturated (best fitting model possible) models provide a continuum within which to evaluate the fit of the analysis model.

The proper chi-square model fit statistic for a substantive structural equation model is obtained by subtracting the chi-square statistic for the saturated model from the chi-square statistic for the analysis model. This chi-square difference value is then tested by referencing it to a chi-square distribution at degrees of freedom equal to the difference in the number of estimated parameters between the analysis and saturated models. However, the chi-square statistic for a typical structural equation model is tested directly by referencing it to a chi-square distribution at degrees of freedom equal to the degrees of freedom for the analysis model because a typical saturated structural equation model has a chi-square statistic and degrees of freedom that are both zero. This chi-square model fit statistic quantifies misspecification, or the lack of fit of the analysis model to the sample data.

In addition to theoretical misspecification, indistinguishable dyad structural equation models contain a second source of model misfit: arbitrary designation. Specifically, the designation of Person 1 and Person 2 within each indistinguishable dyad would be arbitrary, but not inconsequential. As demonstrated elsewhere (Woody & Sadler, 2005), reversing this arbitrary Person 1/Person 2 designation for some, but not all, of the dyads in the sample data set can notably alter the relationships among analysis variables. A method of removing this arbitrary misfit, leaving only a quantification of analysis model misspecification, is needed to accurately evaluate the fit of an APIM for indistinguishable dyads. As shown later, removing arbitrary designation misfit involves the estimation of chi-square statistics and degrees of freedom for null and analysis structural equation models in the usual fashion, but it also involves the estimation of a special saturated model with a chi-square statistic and degrees of freedom that are both nonzero. The term *saturated* is used throughout the article to maintain a consistency with the dyadic literature even though the indistinguishable dyad saturated models shown here are not saturated from the usual SEM perspective.

Specifically, in a typical structural equation model, estimating a saturated model involves estimating all possible parameters for a set of data, which uses all available degrees of freedom and results in a chi-square fit statistic value of zero. However, the appropriate saturated model for indistinguishable dyads involves estimating all parameters that make logical sense, but would not exhaust all degrees of freedom. Specifically, for APIMs, separate parameter estimates for the two dyad members would not be needed for indistinguishable dyads because there would be no theoretical reason to expect differences, and any observed differences would be due to arbitrary designation. As a result, an indistinguishable dyad saturated (or I-SAT; Olsen & Kenny, 2006) model is defined as a model that constrains the following six pairs of

[2]No consensus currently exists, either in the empirical literature or across statistical analysis software packages, as to whether exogenous variable covariances should be estimated in a null model (see Widaman & Thompson, 2003). For all null models used here (e.g., Figures 4, 8, and 11), all analysis variable covariances were manually fixed to zero in M*plus* and AMOS.

parameter estimates (i.e., each element of the sample mean vector and covariance matrix) to equality between Person 1 and Person 2: (a) predictor variable means, (b) predictor variable variances, (c) intrapersonal covariances, (d) interpersonal covariances, (e) response variable means, and (f) response variable variances, as shown in Figure 3. Notice in Figure 3 that the model is saturated in the traditional sense; the model estimates all possible associations among analysis variables. However, the degrees of freedom value for this model is not zero due to the equality constraints imposed as a result of the arbitrary Person 1/Person 2 designation of indistinguishable dyad members.

Several properties of the I-SAT model are noteworthy. If dyad members were perfectly indistinguishable (i.e., if predictor and response variable means, variances, and covariances each were equivalent between both dyad members), the I-SAT model chi-square fit statistic would equal zero, the model would have six degrees of freedom due to the equality constraints, and the model-reproduced covariance matrix would match the sample data covariance matrix (Carey, 2005). Assuming that the dyads under investigation are not perfectly indistinguishable,



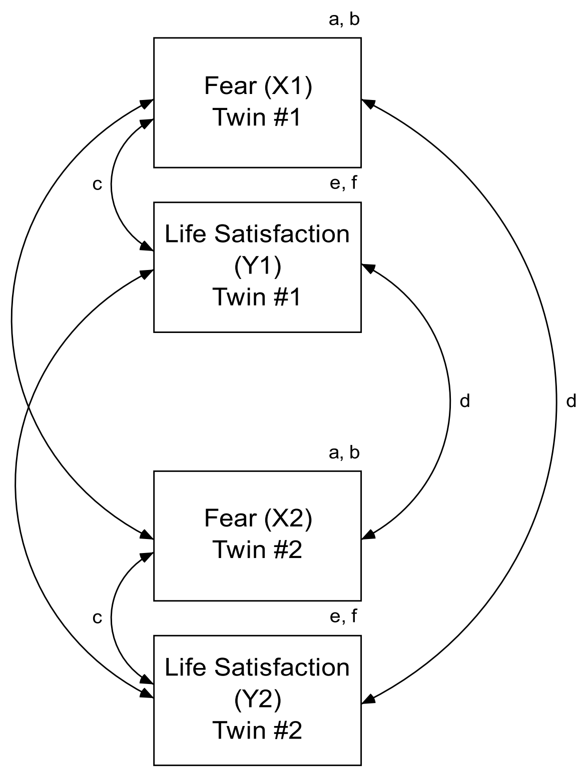


FIGURE 3 Indistinguishable dyad actor–partner interdependence model (APIM) saturated model: (a) predictor variable means, (b) predictor variable variances, (c) intrapersonal covariances, (d) interpersonal covariances, (e) response variable means, and (f) response variable variances constrained to equality. The two unlabeled covariances on the left side of the model are freely estimated (i.e., not given a letter label) to model interpersonal dyadic dependence.

reversing the Person 1/Person 2 designation for some, but not all, of the dyads in the sample data set would change the I-SAT model chi-square fit statistic value, but the model parameter estimates would not change. This means that the I-SAT's nonzero chi-square statistic value quantifies arbitrary designation misfit only (Kenny et al., 2006; Olsen & Kenny, 2006).

Computing the proper chi-square model fit statistic for an indistinguishable dyad APIM requires subtracting the chi-square fit statistic for the indistinguishable dyad saturated model (Figure 3, which contains only arbitrary designation misfit) from the chi-square fit statistic for the indistinguishable dyad analysis model (Figure 2, which contains both model misspecification and arbitrary designation misfit), and testing the resulting chi-square difference value (which now quantifies model misspecification only) by referencing a chi-square distribution with degrees of freedom equal to the difference in the number of estimated parameters between the analysis and saturated models. (Alternatively, the chi-square difference test can also be implemented by subtracting the log-likelihood values of the two models rather than the chi-square statistics.) Conceptually, the I-SAT model is the correct saturated model for indistinguishable dyads just as an unconstrained APIM is the correct saturated model for distinguishable dyads (Olsen & Kenny, 2006). Further, the I-SAT model serves as the best fitting indistinguishable model against which to test substantive APIMs that contain additional parameter estimate constraints.

Although most SEM analysis software packages provide analysis model and null model chi-square statistics and degrees of freedom by default, neither are the appropriate statistics for the purposes of computing additional SEM fit indexes, such as the CFI, TLI, and the RMSEA, for indistinguishable dyad APIMs. Computing the correct fit indexes begins by estimating the appropriate indistinguishable dyad baseline or null model, which can be done by fixing all covariances in the indistinguishable dyad saturated model to zero. This results in a model that estimates means and variances only, as shown in Figure 4. For fit index computation purposes, the correct analysis model chi-square statistic and degrees of freedom are obtained by subtracting the indistinguishable dyad saturated model (Figure 3) chi-square statistic and degrees of freedom from the indistinguishable dyad analysis model (Figure 2) chi-square statistic and degrees of freedom. Similarly, the appropriate chi-square statistic and degrees of freedom for the null (or baseline) model for fit index computation purposes involves subtracting the indistinguishable dyad saturated model (Figure 3) chi-square statistic and degrees of freedom from the indistinguishable dyad null or baseline model (Figure 4) chi-square statistic and degrees of freedom.

*Indistinguishable APIM example.* The APIM shown in Figure 2 was used to test for differences in the actor and partner effects relating self-reported fear to life satisfaction among pairs of twins. The right panel of Table 2 shows that estimating an analysis model that constrained all four regression paths to equality resulted in the following chi-square model fit index value: $\chi^2_3 = 10.97$, $p < .05$ (not shown in Table 2: CFI = .74, TLI = .57, RMSEA = .08). However, recall that this chi-square fit statistic contains both misspecification and arbitrary designation misfit. Arbitrary designation misfit is removed by subtracting the chi-square fit statistic of the saturated model from the chi-square fit statistic of the analysis model ($10.97 - 9.99 = 0.98$). This chi-square difference value is then tested at a chi-square distribution equal to the difference in the number of parameters estimated between the two models ($6 - 3 = 3$). After arbitrary designation was removed, the analysis model showed

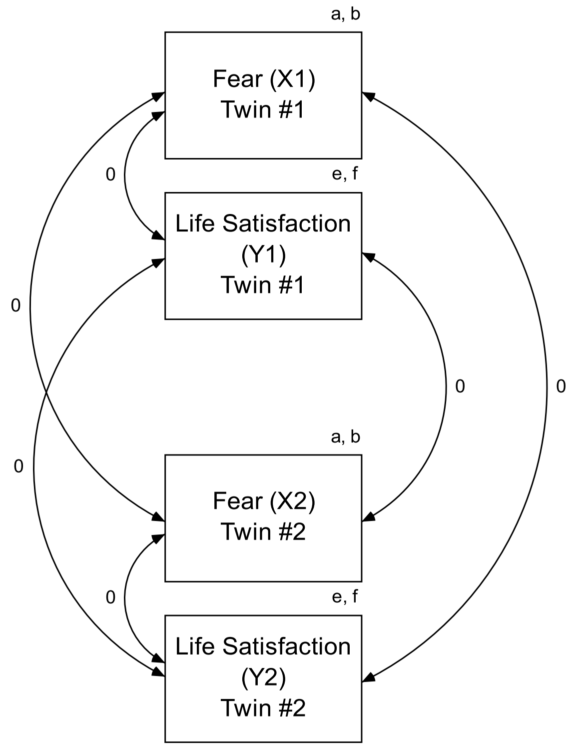


FIGURE 4 Indistinguishable dyad actor–partner interdependence model (APIM) null model: (a) predictor variable means, (b) predictor variable variances, (e) response variable means, and (f) response variable variances constrained to equality.

the following chi-square model fit index value: $\chi^2_3 = .98$, $p > .05$ (CFI = .96, TLI > 1, RMSEA = .04). Figure 2 shows the parameter estimates from the analysis model; as either twin's fear increased, life satisfaction significantly and equally decreased for both twins.

## Common Fate Model: Distinguishable Dyads

The APIM is well-suited to test theoretical relationships among variables at the individual level; the actor effects quantify intraindividual influences, and the partner effects quantify the interindividual influences within dyads. However, certain phenomena of interest to dyadic researchers, such as marital discord or family crises, tend to impact the relationship between the dyad members and might be better assessed at the dyad level. For example, if a research question involved traditional married couples rating their marital satisfaction, the APIM is needed to quantify possible individual differences in satisfaction within the dyad. However, if the research question involved the impact of life stressors on couples' cohesion, a dyad-level analysis model would be needed to assess the impact on the relationships, not the individuals.

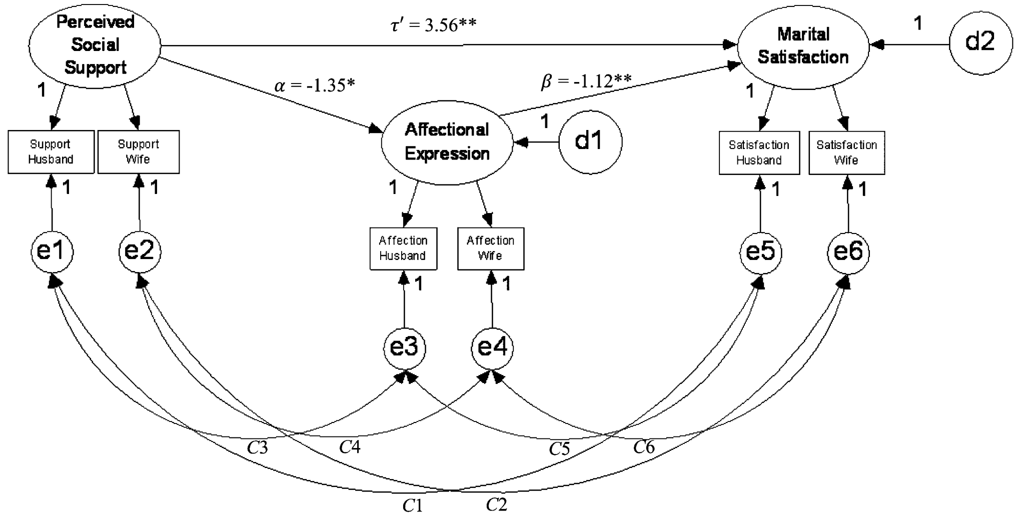


FIGURE 5 Distinguishable dyad common fate mediation analysis model. $*p < .05$. $**p < .01$.



The common fate model (cf. Gonzalez & Griffin, 1999, 2001; Griffin & Gonzalez, 1995; Kenny, 1996; Kenny & LaVoie, 1985) is a structural equation model that uses variable scores collected from both individuals as indicators of a dyad-level phenomenon to test research questions regarding the dyadic relationship. An example of a common fate mediation model (e.g., Ledermann & Macho, 2009) is shown in Figure 5. Measurements of perceived social support, affectional expression, and marital satisfaction taken from husbands and wives are used to test whether affectional expression mediates the relationship between perceived social support and marital satisfaction at the relationship or dyad level. The methods described here to test for the presence of a significant indirect or mediated effect, as well as the regression path notation ($\alpha, \beta, \tau'$) shown in Figure 5, are consistent with the mediation studies of MacKinnon and colleagues (see Fritz & MacKinnon, 2007; MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002; MacKinnon, Lockwood, & Williams, 2004) and are described further later.

Several features of the common fate model shown in Figure 5 are noteworthy. Intrapersonal dyadic dependence is modeled through estimating the observed variable unique covariances (C) for each dyad member (i.e., Husbands: C1, C3, and C5; Wives: C2, C4, and C6). Although typically not estimated in SEM, these unique covariances are needed to model specific intrapersonal dyadic phenomena such as a common method variance, individual perceptual tendencies, or a response set, among others (Gonzalez & Griffin, 1999; Ledermann & Macho, 2009; Woody & Sadler, 2005). Interpersonal dyadic dependence is modeled by using confirmatory factor analysis (CFA) methods to combine the perceived social support, affectional expression, and marital satisfaction scores of both husbands and wives into three latent and shared dyadic variables. As also shown in Figure 5, the first factor loading for each of the three CFA models is fixed to unity (Bollen, 1989; Griffin & Gonzalez, 1995). The second factor loading for each

TABLE 3
Common Fate Model Fit Statistics

| | *Distinguishable Dyads* | | | *Indistinguishable Dyads* | | |
|---|---|---|---|---|---|---|
| | *Null Model* | *Hypothetical Model* | *Saturated Model* | *Null Model* | *Hypothetical Model* | *Saturated Model* |
| $\chi^2$ | 583.28 | 2.89 | 0 | 660.61 | 13.69 | 13.69 |
| *df* | 15 | 3 | 0 | 21 | 9 | 12 |
| LogL | −3,825.44 | −3,535.241 | −3,533.79 | −7,044.93 | −6,721.47 | −6,721.47 |

CFA is freely estimated (i.e., allowed to differ) consistent with distinguishable dyads (Ledermann & Macho, 2009).[3]

For both the distinguishable and indistinguishable common fate model analysis examples, significant mediation was present if the bias-corrected bootstrap 95% confidence interval (e.g., Efron & Tibshirani, 1993) for the combined indirect or mediated path ($\alpha\beta$) did not include zero (MacKinnon, 2008). If the confidence interval did not contain zero and the direct effect path ($\tau'$) was significant, partial mediation was present. If the confidence interval did not contain zero and direct effect path ($\tau'$) was nonsignificant, full mediation was present (Fritz & MacKinnon, 2007).

*Distinguishable common fate example.* As an example, the common fate mediation model shown in Figure 5 was estimated using the Newlywed Project data to test whether affectional expression mediated the relationship between perceived social support and marital satisfaction at the dyad level. As shown in the left panel of Table 3, estimating the analysis model resulted in the following chi-square model fit index value: $\chi^2_3 = 2.89$, $p > .05$ (not shown in Table 3: CFI = 1, TLI > 1, RMSEA = 0). As shown in Figure 5, all three regression paths ($\alpha, \beta, \tau'$) were statistically significant, which suggested the possibility of partial mediation. However, the joint indirect path estimate ($\alpha\beta = 1.51$) showed a 95% confidence interval (based on 5,000 bias-corrected bootstrap samples) that contained zero [−.16, 3.25]; affectional expression did not significantly mediate the relationship between perceived social support and marital satisfaction.

## Common Fate Model: Indistinguishable Dyads

Figure 6 shows the analysis model used in the example of a common fate mediation model for indistinguishable dyads. That model uses twins' socioeconomic status (SES), desire for personal growth (Growth), and attitudes toward education (ATE) scores to test whether a desire for personal growth mediates the relationship between SES and attitudes toward education. Similar to the APIM example, the indistinguishable dyad common fate analysis model also differs from the common fate model for distinguishable dyads by the parameter estimate constraints needed due to arbitrary designation. Specifically, as shown in Figure 6, the indistinguishable dyad

[3]Depending on the statistical analysis software package used, researchers might need to take additional steps to avoid estimation errors. See the Additional Caveats.docx file in the online Appendix materials.

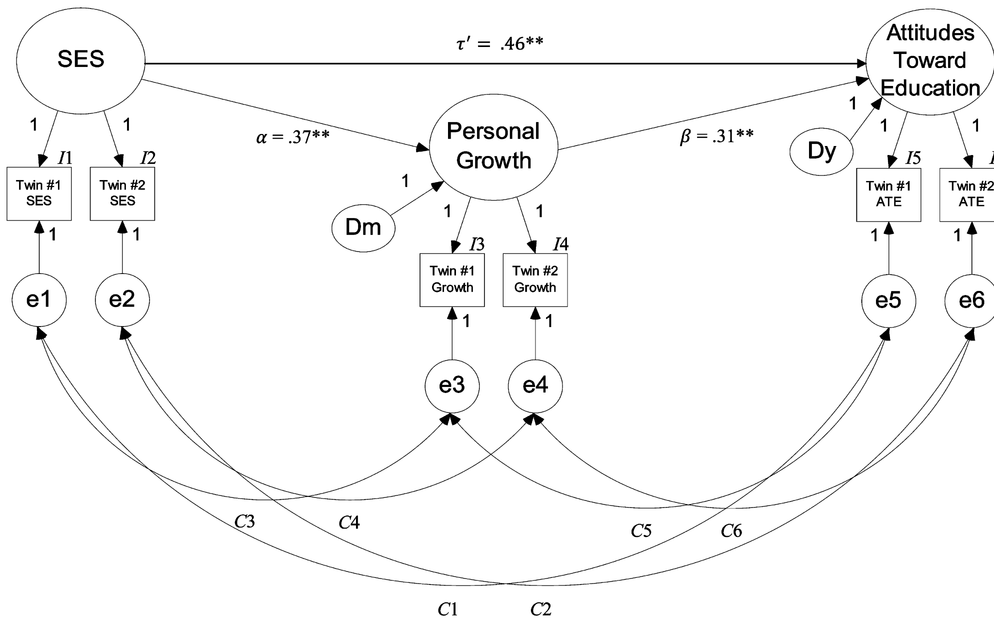


FIGURE 6 Indistinguishable dyad common fate mediation analysis model: factor loadings fixed to unity; measurement intercepts ($I1 = I2$; $I3 = I4$; $I5 = I6$), unique variances ($e1 = e2$; $e3 = e4$; $e5 = e6$), and unique covariances ($C1 = C2$; $C3 = C4$; $C5 = C6$) each constrained to equality. $^{**}p < .01$.



common fate analysis model fixes all six factor loadings for the three CFA models to unity (Bollen, 1989; Griffin & Gonzalez, 1995), and constrains measurement intercepts ($I1 = I2$; $I3 = I4$; $I5 = I6$), unique variances (i.e., $VAR_{e1} = VAR_{e2}$; $VAR_{e3} = VAR_{e4}$; $VAR_{e5} = VAR_{e6}$), and unique covariances (i.e., $C1 = C2$; $C3 = C4$, $C5 = C6$) to equality (Ledermann & Macho, 2009).

Unlike the APIM example, the I-SAT and null (I-NULL) models for a common fate mediation model analysis with indistinguishable dyads are not estimated because the indistinguishable dyad common fate mediation model and the appropriate I-SAT model are equivalent models. As shown in the right panel of Table 3, the chi-square and log-likelihood model fit statistics for both the indistinguishable dyad common fate mediation model (Figure 6) and the appropriate saturated (I-SAT) model for a common fate mediation model (not shown, but included in the online Appendix) are identical. Further, although not shown here, the model-reproduced mean structures and covariances matrices for both models are also identical even though the two models differ by $(12 - 9 = 3)3df$.

Both the indistinguishable dyad common fate model in Figure 6 and its appropriate I-SAT model constrain response variable means and response variable variances to equality between dyad members. The reason for the 3 *df* difference between these two equivalent models can best be explained in terms of differences between interpersonal covariances that are explicitly versus implicitly estimated and constrained to equality. Specifically, three pairs of same-variable interpersonal covariances (i.e., cov[Twin 1 SES, Twin 2 SES], cov[Twin 1 Growth, Twin 2 Growth], cov[Twin 1 ATE Twin 2 ATE]) that would be freely estimated in the appropriate I-SAT model are not included or estimated in the common fate model (i.e., cov[$e1, e2$], cov[$e3, e4$], and cov[$e5, e6$], respectively, are not estimated in Figure 6). The common fate model addresses this interpersonal dyadic dependence by estimating three shared latent variable variances rather than three interpersonal covariances, as described earlier. The 3 *df* difference between the two models comes from the remaining three interpersonal covariances (i.e., cov[Twin 1 SES, Twin 2 ATE] = cov[Twin 1 ATE, Twin 2 SES]; cov[Twin 1 SES, Twin 2 Growth] = cov[Twin 2 SES, Twin 1 Growth; cov[Twin 1 Growth, Twin 2 ATE] = cov[Twin 2 Growth, Twin 1 ATE]) that (a) would be explicitly estimated and constrained to equality (using 3 *df*) in the I-SAT model, (b) are not explicitly included or estimated in Figure 6, but (c) are implicitly constrained to equality (using 0 *df*) in the indistinguishable dyad common fate model-reproduced covariance matrix as a direct result of the equality constraints ($e1 = e2$, $e3 = e4$, $e5 = e6$ and $C1 = C2$, $C3 = C4$, $C5 = C6$) already included in the model.

As mentioned previously, if dyads were perfectly indistinguishable, the chi-square model fit statistic would equal zero. The nonzero chi-square value shown in Table 3 (13.69) indicates the SATSA twins are not perfectly indistinguishable. As also mentioned previously, saturated models in general are not parsimonious and are seldom of interest to researchers. The indistinguishable dyad common fate mediation model is an example of a model that, although essentially saturated in the indistinguishable dyad sense discussed previously, can still be used to test a substantive research question involving mediation. However, similar to a model that is saturated in the typical SEM sense, the question of fit for an indistinguishable dyad common fate mediation model is a moot point; all fit indexes will show ideal values by definition.

*Indistinguishable common fate example.* To illustrate, the indistinguishable dyad common fate mediation model was used with the SATSA data to test whether a desire for personal growth mediated the relationship between SES and attitudes toward education. As shown in Figure 6, both regression path ($\alpha$ & $\beta$) coefficients were statistically significant, which suggested the possibility of mediation. The joint indirect path estimate ($\alpha\beta = .12$) showed a 95% confidence interval (based on 5,000 bias-corrected bootstrap samples) that did not contain zero [.05, .23]. A desire for personal growth partially mediated (as shown in Figure 6, the $\tau'$ path coefficient was also statistically significant) the relationship between SES and attitudes toward education.

## LONGITUDINAL DYADIC DATA ANALYSES

The actor–partner interdependence and common fate analysis models shown in the previous sections can model dyadic data intrapersonal and interpersonal dependence and can quantify dyadic relationship dynamics from data sampled cross-sectionally, but they cannot assess dyadic response variable changes over time. However, the same intrapersonal and interpersonal dyadic dependence can be modeled longitudinally to quantify separate, but related, changes in dyad members' response variable scores over time. An example of a latent growth curve structural equation model (cf. Meredith & Tisak, 1990) that has been modified to accommodate longitudinal dyadic data with covariates (e.g., DiLillo et al., 2009; Kashy, Donnellan, Burt, & McGue, 2008) is shown in Figure 7. Recall that the Newlywed Project involved psychological

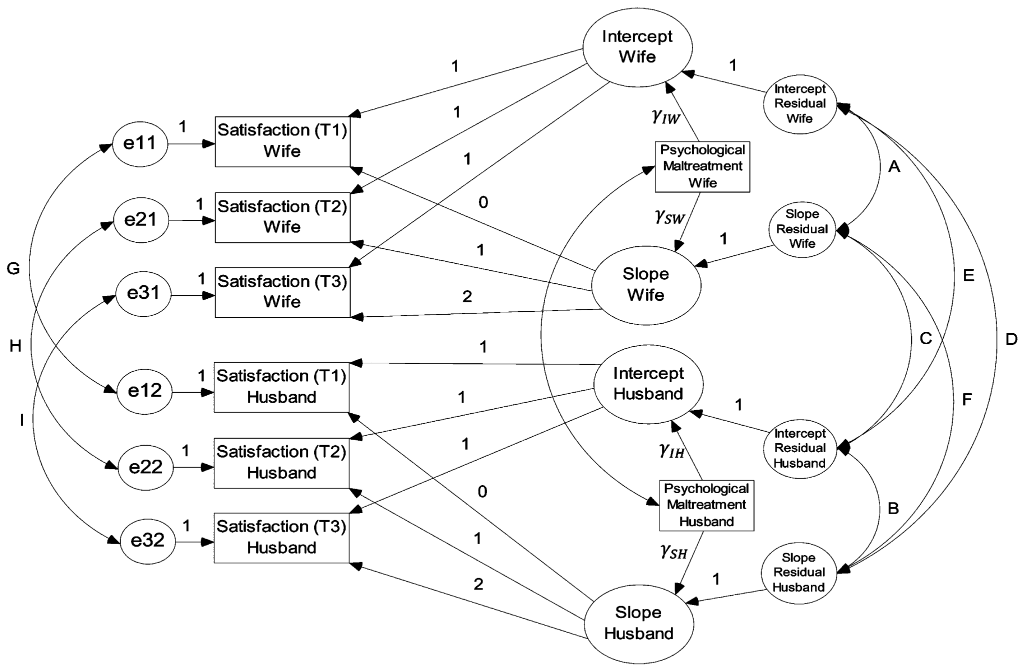


FIGURE 7 Distinguishable dyad longitudinal analysis model: (a) intrapersonal intercept-slope covariances (labeled A&B), (b) inter-personal growth trajectory covariances (labeled C–F), (c) interpersonal unique covariances (labeled G–I), (d) unique variances (labeled $e11, e21, \ldots e32$), and (e) covariate effects ($\gamma_{IW}$, $\gamma_{SW}$, $\gamma_{IH}$, $\gamma_{SH}$) all freely estimated.

functioning and marital satisfaction data collected over 3 consecutive years. As shown in Figure 7, the slope loadings (0, 1, 2) for both husbands and wives define the intercepts as the expected marital satisfaction score for husbands and wives at the first year of data collection, and allows the slope estimates to be interpreted as the expected linear change in husbands' and wives' marital satisfaction per year.

## Distinguishable Dyads

For both dyad members, the dyadic growth curve model shown in Figure 7 freely estimates (a) intercept fixed effects (average response variable score at Time 1), (b) slope fixed effects (average rate of response variable change over time), (c) intercept random effects (individual response variable variation at Time 1), (d) slope random effects (variation in individual response variable change over time), (e) intrapersonal intercept–slope covariances (labeled A and B), (f) intrapersonal unique variances ($e11, e21, \ldots, e32$), (g) interpersonal intercept–slope covariances (labeled C–F), and (h) interpersonal unique covariances (labeled G–I). In addition to research questions involving the form of the mean response variable growth trajectory and the presence of significant variation in intercepts and slopes for husbands and wives, the dyadic latent growth curves model shown in Figure 7 can be used to answer research questions

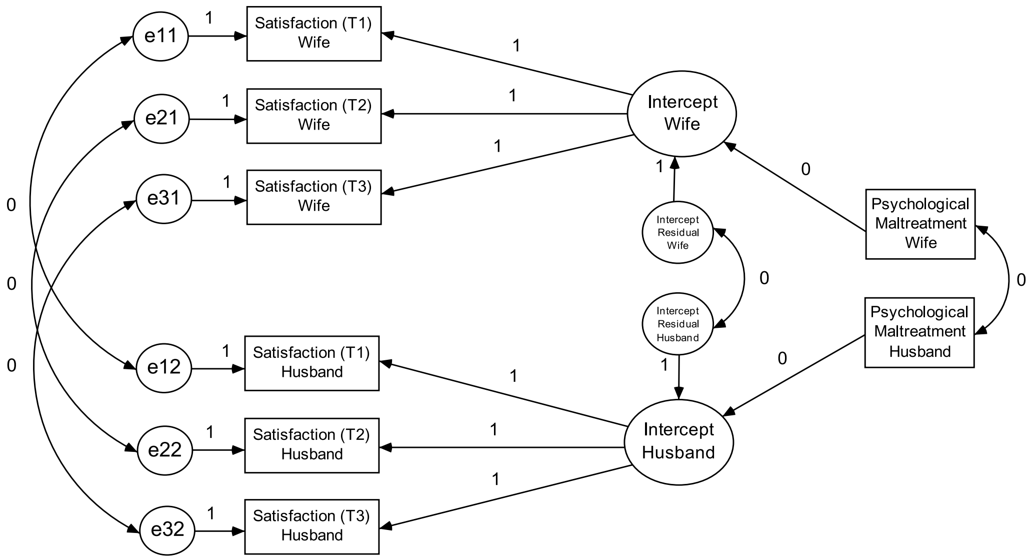


FIGURE 8 Distinguishable dyad longitudinal null model: unique variances (*es*) freely estimated, unique covariances, intercepts covariance, covariate regressions, and covariate covariance all fixed to zero.

regarding whether differences exist in the average growth trajectories between husbands and wives in the sample and the effects of covariates on husbands' and wives' growth trajectories. Specifically, as shown in Figure 7, the effect of childhood psychological maltreatment on marital satisfaction intercepts and slopes can be estimated separately for husbands ($\gamma_{IH}$ and $\gamma_{SH}$) and wives ($\gamma_{IW}$ and $\gamma_{SW}$).

In the previous actor–partner interdependence and common fate models for distinguishable dyads, the standard null and saturated models were the appropriate models for assessing the fit of those models to the data. However, for a longitudinal dyadic growth model, the standard saturated model remains the appropriate model, but the correct null model is shown in Figure 8. The correct null model for a latent growth curve model is an intercept-only model that fixes unique covariances, covariate regressions, the intercepts covariance, and the covariates covariance to zero. Notice also in Figure 8 that the unique variances ($e11, e21, \ldots, e32$) that were freely estimated in the analysis model are also freely estimated in the null model (Widaman & Thompson, 2003).

*Distinguishable longitudinal example.* The conditional longitudinal dyadic growth curve model shown in Figure 7 was fit to the Newlywed Project data to test for possible differences in marital satisfaction changes over time between husbands and wives.[4] As shown in the left

[4]Many researchers consider the estimation of an unconditional model (i.e., omitting the psychological maltreatment covariates from Figure 7) prior to a conditional model a prudent testing step. An unconditional model was fit to the Newlywed data; that model showed the following fit indexes ($\chi^2_4 = 4.95$, $p > .05$; CFI & TLI = 1, RMSEA = .02). The intercept and slope variance estimates for both husbands ($\psi_{IH} = 7.69$, $p < .01$; $\psi_{SH} = 2.35$, $p < .01$) and wives ($\psi_{IW} = 11.00$, $p < .01$; $\psi_{SH} = 1.59$, $p < .01$) were statistically significant.

TABLE 4
Longitudinal Dyadic Growth Model Fit Statistics

| | *Distinguishable Dyads* | | | | *Indistinguishable Dyads* | | |
|---|---|---|---|---|---|---|---|
| | *Null Model* | *Conditional Model* | *Constrained Model* | *Saturated Model* | *Null Model* | *Conditional Model* | *Saturated Model* |
| $\chi^2$ | 300.70 | 35.76 | 35.77 | 0 | 331.19 | 72.44 | 54.91 |
| *df* | 30 | 12 | 14 | 0 | 39 | 29 | 20 |
| LogL | −8,282.86 | −6,137.98 | −6,137.98 | −8,132.51 | −8,412.74 | −8,283.37 | −8,274.60 |

panel of Table 4, estimating the conditional analysis model resulted in the following chi-square model fit index value: $\chi^2_{12} - 35.76$, $p < .05$ (not shown in Table 4: CFI $= .98$, TLI $= .95$, RMSEA $= .07$). Consistent with the previous APIM example, researchers could test the fit of additional longitudinal models that constrain parameter estimates between husbands and wives to equality. In this example, a model that constrained intercept ($\text{intercept}_{\text{husbands}} = \text{intercept}_{\text{wives}}$) and slope ($\text{slope}_{\text{husbands}} = \text{slope}_{\text{wives}}$) fixed effect estimates separately to equality was estimated. As also shown in the left panel of Table 4, estimating the constrained analysis model resulted in the following chi-square model fit index value: $\chi^2_{14} = 35.77$, $p < .05$ (CFI $= .98$, TLI $= .96$, RMSEA $= .06$). A nested model test comparing the conditional model ($\chi^2_{12} = 35.76$) to the constrained model ($\chi^2_{14} = 35.77$) showed a statistically nonsignificant result ($35.77 - 35.76 = .01$; $14 - 12 = 2$; $\Delta\chi^2_2 = .01$, $p > .05$), indicating that the conditional model should be rejected in favor of the more parsimonious constrained model. Additional results showed no significant relationship between wives' psychological maltreatment and marital satisfaction. However, husbands' psychological maltreatment was significantly related to both intercept ($\gamma_{\text{IH}} = -.24$, $p < .01$) and slope ($\gamma_{\text{SH}} = -.07$, $p < .05$). For husbands, increased childhood psychological maltreatment was related to significantly lower baseline marital satisfaction and significantly decreased marital satisfaction over time.

## Indistinguishable Dyads

From the SATSA data, twins' life satisfaction scores assessed over time and their self-reported fear scores will be used to illustrate the longitudinal growth model for indistinguishable dyads. The analysis model used for this example is shown in Figure 9. However, similar to the APIM, a longitudinal growth model analysis with indistinguishable dyads also begins by specifying the appropriate null and saturated models. Identical to the logic used to specify the saturated models for the APIM, the appropriate longitudinal I-SAT model is shown in Figure 10. The indistinguishable dyad longitudinal saturated model contains interpersonal equality constraints on mean (labeled A–D), variance (labeled E–H), and covariance estimates (labeled O–T), as well as intrapersonal covariance equality constraints (labeled I–N).[5] Further, similar to the

[5]For both distinguishable and indistinguishable dyadic longitudinal models, the issue of whether unique variances and covariances should be freely estimated (e.g., distinguishable) or constrained to equality (e.g., indistinguishable) between dyad members should be treated as a hypothesis to be tested rather than viewed as a dyadic methodological requirement (e.g., Kashy et al., 2008).

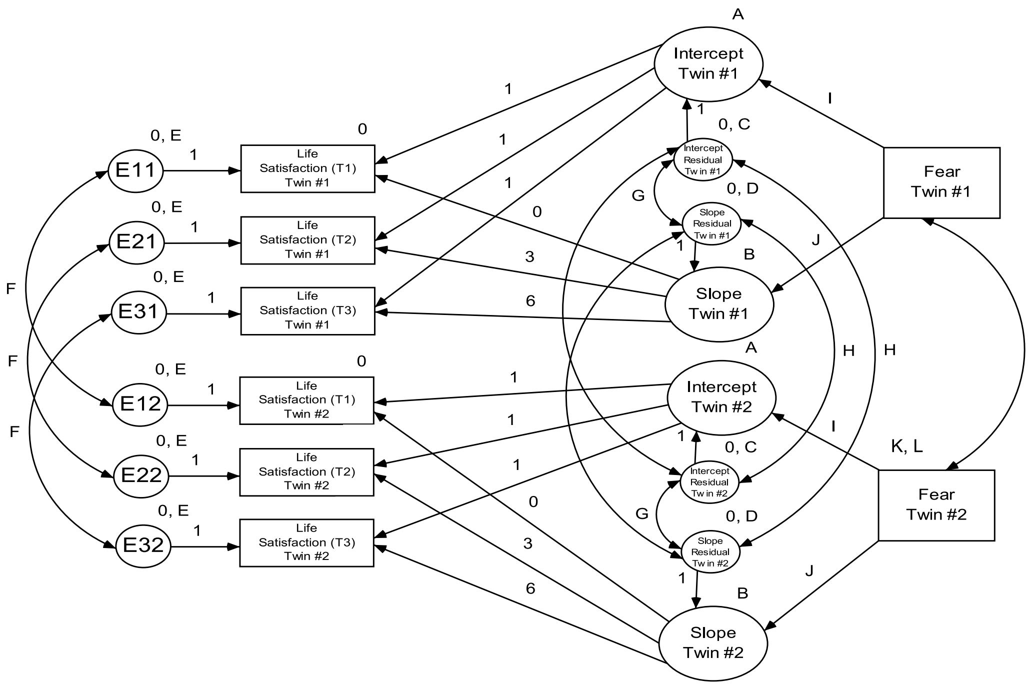


FIGURE 9 Indistinguishable dyad longitudinal model: intercept and slope means (A & B) and variances (C & D), unique variances (E), unique covariances (F), intrapersonal intercept-slope covariances (G), interpersonal growth trajectory covariances (H), covariate influences on intercept (I) and slope (J), and covariate means and variances (K & L) each constrained to equality.

longitudinal dyadic model for distinguishable dyads, the appropriate null model for a dyadic growth curve model for indistinguishable dyads is also an intercept-only model, as shown in Figure 11. Notice in Figure 11 that, consistent with indistinguishable dyads, the latent intercept variable means (labeled A) and variances (labeled B), covariate means (labeled C) and variances (labeled D), and unique variances (labeled E) are each constrained to equality, whereas unique covariances (labeled F in Figure 9), covariate regression paths, and the covariance between the two covariates, are all fixed to zero in the null model.

The indistinguishable dyad longitudinal saturated and null models again provide a continuum within which to evaluate the fit of a longitudinal analysis model. As shown in Figure 9, the indistinguishable dyad longitudinal analysis model differs from the longitudinal analysis model for distinguishable dyads by the parameter estimate constraints needed due to arbitrary designation. Specifically, as shown in Figure 9, the parameter estimates previously freely estimated for distinguishable dyads are constrained to equality between indistinguishable dyad members: (a) intercept means (labeled A), (b) slope means (labeled B), (c) intercept variances (labeled C), (d) slope variances (labeled D), (e) unique variances (labeled E), (f) unique covariances (labeled F), (g) intrapersonal intercept–slope covariances (labeled G), (h) interpersonal intercept–slope covariances (labeled H), (i) covariate influences on intercepts (labeled I), and (j) covariate influences on slopes (labeled J). Also, recall that the SATSA data were collected from twin

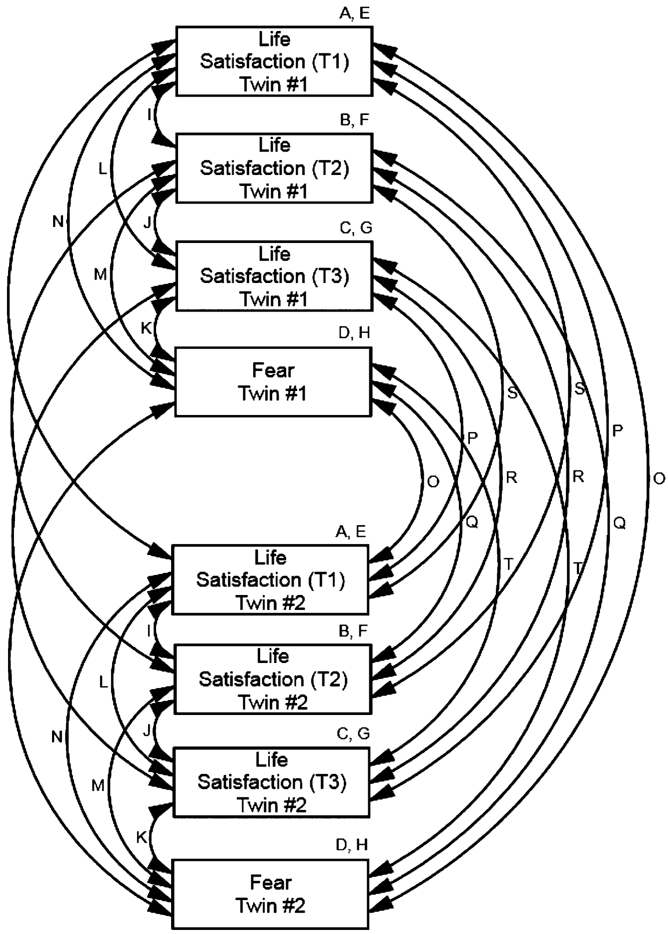


FIGURE 10 Indistinguishable dyad longitudinal saturated model: interpersonal means (labeled A–D) and variances (labeled E–H), intrapersonal covariances (I–N), and interpersonal covariances (O–T) each constrained to equality. The four unlabeled covariances on the left side of the model are freely estimated (i.e., not given a letter label) to model interpersonal dyadic dependence.



pairs in 1987, 1990, and 1993. The slope loadings (0, 3, 6) define the intercept as the expected life satisfaction score for a twin pair in 1987, and enable the slope estimate to be interpreted as the expected change in life satisfaction for every 1 year increase in time. Similar to the indistinguishable dyad actor–partner and common fate analysis models, arbitrary designation is again a source of misfit for an indistinguishable dyad longitudinal SEM analysis. However, identical to the actor–partner and common fate analysis models, arbitrary designation misfit can again be removed and corrected model fit indexes (CFI, TLI, and RMSEA) computed for the indistinguishable dyadic longitudinal analysis model (e.g., see Kashy et al., 2008).

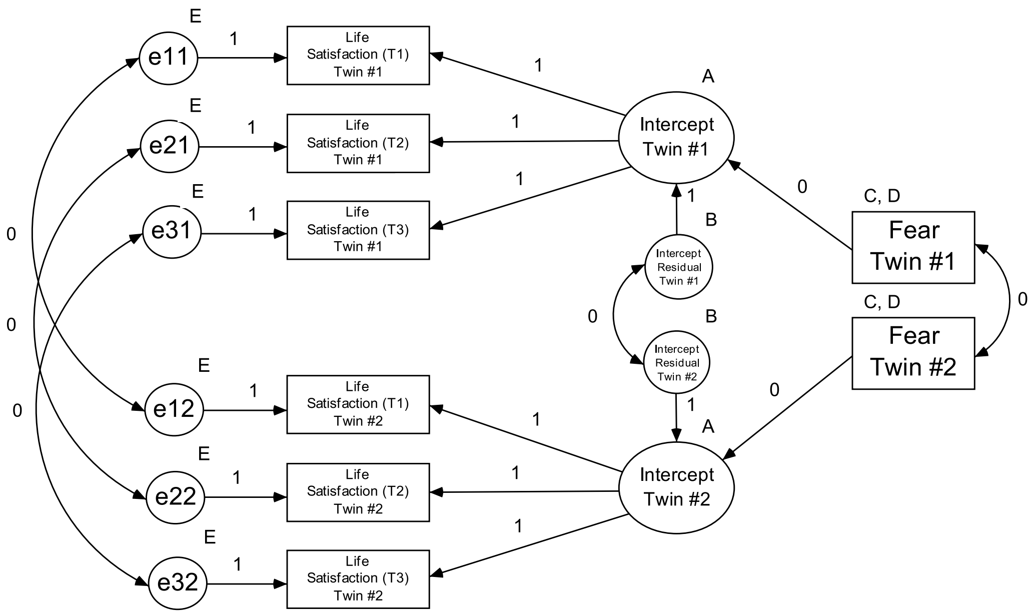


FIGURE 11 Indistinguishable dyad longitudinal null model: Intercept means (A) and variances (B), covariate means (C) and variances (D), and unique variances (E) each constrained to equality. Unique covariances (F), intercepts covariance, covariate regressions, and covariate covariance all fixed to zero.

*Longitudinal indistinguishable example.* As an example analysis, the conditional analysis model shown in Figure 9 was fit to the SATSA data.[6] As shown in the right panel of Table 4, after removing arbitrary designation misfit ($72.44-54.91 = 17.53$; $29-20 = 9$), the following chi-square model fit index value was observed for the conditional model: $\chi^2_9 = 17.53$, $p < .05$ (not shown in Table 4: CFI = .97, TLI = .93, RMSEA = .05). Results from the conditional model showed that self-reported fear was significantly related to twins' intercepts (labeled I in Figure 13; $\gamma_{\text{intercept}} = -.96$, $p < .01$) but not slopes; higher self-reported fear was significantly related to lower initial status life satisfaction.

## ADDITIONAL RESOURCES

The goals of this article were to illustrate the steps involved in estimating popular cross-sectional (i.e., APIM and common fate) and longitudinal (i.e., dyadic longitudinal growth) models used

[6]An unconditional model (i.e., omitting the self-reported fear covariates from Figure 9) was also fit to the SATSA data. After removing arbitrary designation misfit ($49.43 - 42.85 = 6.58$; $17 - 12 = 5$; $\chi^2_5 = 6.58$, $p > .05$), the unconditional model showed the following fit indexes: CFI = .99, TLI = .98, RMSEA = .03. Results also showed twins had an expected life satisfaction that differed significantly from zero in 1987 (45.96, $p < .01$), but decreased significantly per year ($-.30$, $p < .01$). Results further showed twins' intercept variance ($\psi_T = 42.76$, $p < .01$) and slope variance ($\psi_S = .33$, $p < .01$) estimates were statistically significant.

to analyze mixed-dyadic data collected from indistinguishable or distinguishable dyads, and to clarify why certain additional steps and modifications are needed to analyze indistinguishable dyad data using structural equation models. The AMOS and M*plus* statistical analysis software packages were used in all analysis models presented in this article; all examples are available in an appendix online at https://bmixythos.cchmc.org/xythoswfs/webui/_xy-476611_1-t_AXKarXYG. However, a secondary goal of this article was to provide sufficient detail to allow researchers to analyze these models in the analysis software package of their choice.

In addition to the models illustrated here, several authors have proposed additional cross-sectional and longitudinal dyadic data analysis models. For example, Newsom (2002) showed how a CFA model could also be used to test for significant differences among distinguishable dyad members. Also, Laurenceau and Bolger (2005) showed how diary methods can be used to quantify relationship process changes over time in marital data. Further, although most dyadic data analysis models assume a response variable measured on a continuous scale, each of these models can be used to analyze cross-sectional and longitudinal response variables measured on a categorical scale (e.g., see Kenny et al., 2006). In addition, many of the SEM models shown here and elsewhere can also be equivalently estimated as hierarchical linear models (e.g., see Atkins, 2005; Campbell & Kashy, 2002; Gonzalez & Griffin, 2002; Kashy, Campbell, & Harris, 2006; Wendorf, 2002; Whisman, Uebelacker, & Weinstock, 2004; Zhang & Willson, 2006).

The dyadic models demonstrated in this article have also been combined and expanded on in several ways. Kenny and Ledermann (2010) showed how the APIM can be modified so that the individual-level actor and partner effects can be used to identify dyad-level relationship patterns (e.g., actor only, partner only, couple, and contrast patterns). Several researchers have also shown how the APIM can be expanded to address dyadic research questions involving moderated mediation and mediated moderation possibilities (e.g., Bodenmann, Ledermann, & Bradbury, 2007; Campbell, Simpson, Kashy, & Fletcher, 2001; Ledermann & Bodenmann, 2006; Srivastava, McGonigal, Richards, Butler, & Gross, 2006). In addition, Matthews, Conger, and Wickrama (1996) showed how the common fate and actor partner interdependence models can be combined, and more than one mediating variable added, to answer complex dyadic research questions involving how mediated dynamics at the individual level can impact the relationship at the dyad level. Needless to say, applied researchers seeking to answer research questions involving cross-sectional or longitudinal mixed dyadic data collected from dyads considered to be distinguishable or indistinguishable can choose from among several SEM analysis options.

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