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The Common Fate Model for Dyadic Data: Variations of a Theoretically Important but Underutilized Model

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Studying dyads, very often there is a theoretical construct that has an effect on both members, such as relationship harmony or shared environment. To model such influences, the common fate model (CFM) is often the most appropriate approach. In this article, we address conceptual and statistical issues in the use of the standard CFM and present a series of variations, all of which are estimated by structural equation modeling (SEM). For indistinguishable dyad members (e.g., gay couples), we describe the use of a multilevel SEM method. Throughout the paper, we draw connections to the actor–partner interdependence model (APIM). We also discuss the analysis of hybrid models that combines both the CFM and the APIM. The models are illustrated using data from heterosexual couples.

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Keywords: dyadic data, common fate, SEM, MSEM, APIM

In the last decade, there has been an explosion of interest in dyadic data analysis. Researchers studying marriage, dating, coworkers, parent and child, siblings, friends, coworkers, adversaries, patients and caretakers, athletes and coaches, and therapists and clients have begun to use dyadic methods of data analysis. The hallmarks of such analyses are measuring the same variables in both members of each dyad and allowing for interdependence. To study causal relationships among such variables, the actor–partner interdependence model (APIM; Kenny & Cook, 1999; Kenny, Kashy, & Cook, 2006) has almost become the default. In this model, one variable measured from both members causes or predicts both dyad members' responses on a second variable. So for example, a person's depression affects both his or her own satisfaction and the satisfaction of the partner. As of October 2011, the APIM has been used over 300 times with more than 130 publications in the last three years (Kenny & Ledermann, 2011). Clearly, the APIM has dominated dyadic data analysis.

There are alternatives to the APIM, which have been underutilized in the analysis of dyadic data. The focus of this paper is on
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one of those models, the common-fate model, or CFM.[1] It can be used for variables that have an effect on both dyad members. Very often within dyads, there exists such a variable. Examples of such variables affecting both members of a couple include quality of housing and quality of the neighborhood, which can be considered shared external factors (Woody & Sadler, 2005). In addition, group members can be influenced by common relational variables, such as relationship harmony, relationship tension, the length of relationship, and household income. The key feature of these variables is that a single variable leads to responses from both members. Such variables have been called level-two or between-person variables in the multilevel modeling literature, or between-dyads variables in the dyadic literature. In dyadic data, the unit for these variables is the dyad, not the individual.

Sometimes these variables can be directly measured. For instance, it is a relatively simple matter to ascertain how long a couple has been married. However, at other times, a direct assessment of dyad-level variables is difficult, and so it may be necessary to obtain measures from both members. For example, if the interest is relational harmony, we might ask both members of the couple about that variable. That is, both members have some idea about the variable, but their two assessments may not exactly agree. What is often done in this case is to average the two responses, and treat it as a dyad-level (between-dyads) variable and keep the individual measures, but subtract out the dyad mean (i.e., group-center the measure). This strategy is sometimes called *between-within* (Curran & Bauer, 2011). However, such a strategy presumes that the construct is the sum of the two member's views, a formative construct (Bollen & Lennox, 1991). An alternative is to assume that the construct explains both members' perceptions, a reflective construct. Variables that evoke both members' responses presume the reflective model, as this model assumes that each member can access the construct, but not perfectly. The decision of whether the variable is formative or reflective depends on conceptual, measurement, and statistical factors.

To analyze such reflective, between-dyads variables measured from both members, the CFM, originally introduced by Kenny and La Voie (1985), is the most appropriate model. Although this approach has been discussed in the methodological literature in several subsequent papers (e.g., Gonzalez & Griffin, 1997, 1999; Griffin & Gonzalez, 1995; Ledermann & Macho, 2009; Woody &

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Computer setups to estimate the models can be downloaded from www.thomasledermann.com/cfm.php.

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[1] The other major alternative is the mutual-feedback model, which enables the assessment of reciprocal effects between dyad members (Kenny, 1996; Woody & Sadler, 2005).

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Sadler, 2005), the model has not yet found wide application. We are aware of just five substantive papers using that model. Three papers use it to study heterosexual couples (Conger, Rueter, & Elder, 1999; Ledermann, Bodenmann, Rudaz, & Bradbury, 2010; Matthews, Conger, & Wickrama, 1996), another to study siblings (Teachman, Carver, & Day, 1995), and one to study mother–child dyads (Burk & Laursen, 2010).

The current paper has two overarching purposes. The first is to encourage researchers to consider adopting the CFM for the analysis of dyadic data. Although the APIM is a key tool for dyadic researchers, we think it has been used in some cases in which the CFM is more theoretically appropriate. The second purpose is to discuss different variations of that model. For each variation, we address conceptual and statistical issues. We begin with a description of the CFM and a discussion of how it relates to the APIM. We then present different variations of the standard CFM and show how they can be estimated using structural equation modeling (SEM) and multilevel SEM (MSEM). Finally, we discuss the analysis of hybrid models incorporating both the CFM and APIM framework. To illustrate the models, we use data from heterosexual couples.

The Standard Common Fate Model

The standard CFM, sometimes called *latent group model* (Gonzalez & Griffin, 2002), was proposed by Kenny (Kenny, 1996; Kenny & La Voie, 1985) and Griffin and Gonzalez (1995; Gonzalez & Griffin, 2002) and is presented in Figure 1. The model
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consists of two latent variables (represented by ellipses), each measured by two indicators (represented by rectangles), reflecting the scores of Dyad Member A and Member B (e.g., husband and wife) on the underlying latent construct. The latent variables, which reflect the common-fate factors, are connected to each other by a direct effect. In addition, typically covariances between the error terms of the two persons are allowed. This model setup enables a decomposition of the relationships between the variables into a dyad-level relation (represented by the direct effect between X and Y) and two individual-level relations (represented by the error covariances), which reflect the systematic measurement bias (or the method variance in the context of multitrait-multimethod matrix models), or individual-level variances.

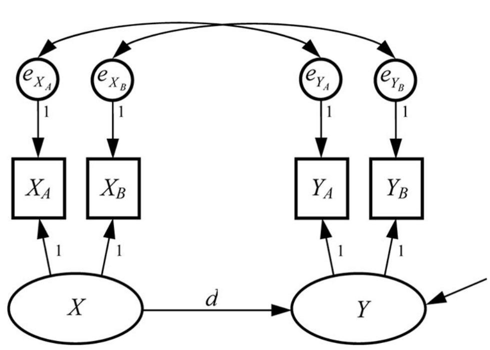

Figure 1. The standard common fate model. X_A and X_B indicate manifest variables measured in Person A and Person B; X and Y denote latent variables.

Conceptual Considerations

The CFM as presented in Figure 1 posits that dyad members are influenced by a latent common Y variable that depends on a latent common X variable. The common-fate conception implies that two dyad members are similar to one another on a given variable due to the influence of a shared or dyadic latent variable. In contrast, the APIM implies that nonindependence in dyads is due to the direct effect of a person's causal variable on the outcome variable of the partner (partner effect), adjusted for the effect on his or her own outcome variable (actor effect).

There are two different kinds of common forces that can affect dyad members: forces external to the relationship and characteristics of relationship itself (Woody & Sadler, 2005). Common external influences are forces that affect both members of a dyad but are external to the relationship. Examples include shared contextual and environmental influences, the quality of the home environment, and shared life events. Characteristics of a relationship itself can also have an effect on its members. Relationship cohesion is a typical example of such a characteristic (Cook, 1998; Cook & Kenny, 2006). Other examples are relationship harmony/disharmony, relationship closeness, relationship climate, and relationship adaptation.

In practice, the answer to the question of whether a particular variable measured in both members should be considered to reflect a common-fate (level-two) variable, or whether that variable represents an intrapersonal (level-one) variable, depends on measurement issues of the theoretical construct and the research objective. One major consideration is the wording of the question. Variables such as "I tell my partner how I feel" or "My partner tells me how he or she feels" refer to the individuals and so can be regarded as a measure of the individual communication behavior. In contrast, items such as "We both tell each other how we feel" or "In our relationship, we talk about things that make us angry" have the relationship as object. That is, both members of a dyad rate the same object (Cook & Kenny, 2006). The key question that follows for the use of the common-fate conception is whether the two dyad members are reporting on the *same* variable. If the answer is "yes", then the variable pair in question is best modeled as common-fate variable. Moreover, a construct expected to represent a common-fate variable underlies the assumption that the construct exists at the level of the dyad rather than at the individual level. This is not true for self-referential or partner-referential measures that are expected to represent individual behaviors or attitudes, which are more suitable for the APIM. In contrast, relationship-referential or shared-environment-referential measures are more suitable for modeling common variables at the dyad level. However, if the research objective is to study dyad members' perception on a relationship-referential or shared external variable in relation to other individual-level variables, one can use the variables in an APIM. In relationship research, for example, marital quality has been treated as a common relationship variable modeled in a CFM (Matthews et al., 1996), as well as an individual variable modeled in the APIM (Campbell, Simpson, Kashy, & Fletcher, 2001).

We might wonder what pattern of APIM results would suggest consideration of the CFM. If the actor and partner effects are both present and have the same sign, and when there is positive non-

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independence in both variable pairs, the CFM is expected to yield reliable estimates.[2]

Statistical Considerations

The standard CFM, as shown in Figure 1, consists of one exogenous and one endogenous measurement model, each of which describes how the indicators (observed variables) are related to the latent variables. Each measurement model take into account measurement errors and allow the modeling of systematic variance among error terms of different measurement models. The model in Figure 1 has 13 free parameters: One intercept for each indicator, one variance for each error term, one variance for the exogenous latent variable and one for the disturbance variance for the endogenous latent variable, two covariances between the error terms, and one direct path at the dyad-level. In the CFM, and as shown in Figure 1, normally all factor loadings of the measurement models are fixed to one to statistically identify the model (e.g., Cook, 1998; Gonzalez & Griffin, 2002; Ledermann & Macho, 2009). This setup yields a CFM with one degree of freedom (*df*).

The squared standardized factor loading represents the proportion of variance in an indicator explained by the latent variable, which is an estimate of the reliability of that indicator. The higher this reliability, the smaller the error variance and, thus, the better the indicator represents the latent construct. In measurement models with two indicators the product of the two standardized factor loadings equals the correlation. In measurement models with two indicators, the product of the two standardized factor loadings equals the correlation between the two indicators. Consequently, to be reliable indicators, the intradyadic correlation needs to be moderate to high. If this correlation is weak, there will be serious estimation difficulties as well as not much evidence of a common latent variable. Thus, before estimating the CFM, the researcher should check to see that correlations between the two members' X and between the two Y variables are robust (i.e., at least .20). We note that if loadings (correlations) are weak, we typically cannot compensate by obtaining more indicators because here the indicators are persons, and dyads by definition are limited to two.[3]

Sometimes dyad members are indistinguishable (e.g., gay or lesbian couples). In this case, additional constraints and adjustments on the fit statistic need to be made (Olsen & Kenny, 2006): In the CFM, the two intercepts and the two error variances terms for both measures are constrained to equality across members, and the two error covariances are set equal. With theoretically indistinguishable members the CFM is a saturated model with zero *df*.[4]

In addition to SEM, multilevel modeling (MLM) can be used for the analysis of the CFM for indistinguishable members. The CFM itself can be viewed as a two-level model with a between-cluster (dyad) and a within-cluster (individual) component. Gonzalez and Griffin (2002) presented a MLM approach to the estimation of a version of the standard CFM with the common-fate variables conceptualized as random intercepts. However, this approach estimates the correlation between the two latent variables, but does not constitute a path. The MSEM framework (Muthén & Asparouhov, 2008), also known as the multilevel-latent-covariate approach (Lüdtke et al., 2008), is a flexible alternative that separates between-and within level-effects and enables the assessment of relations in the form of covariances or direct effects. It has recently been used for the analysis of correlations with indistinguishable dyad members (Rhemtulla, Schoemann, & Preacher, 2011). We note that the fit statistic is correct for theoretically indistinguishable members and so does not require any adjustments, but,consequently, MSEM does not enable the testing of whether theoretically distinguishable members can be treated as indistinguishable.

Illustrative Example

To illustrate the application of the CFM, we use data from heterosexual couples and the variables *understanding each other* and *relationship success,* which both can be considered common-fate constructs having an effect on both husband and wife. We use complete data from 333 couples that are part of *The 500 Family Study* (Schneider & Waite, 2008). Understanding each other and relationship success are variables measured by the items "My partner and I understand each other perfectly" and "Our relationship is a perfect success", could range from 1 (*strongly disagree*) to 5 (*strongly agree*). In addition, they can be conceived of as two facets of relationship quality. We used the SEM software Amos (Arbuckle, 1995–2009) and Mplus (L. K. Muthén & Muthén, 1998-2010) to estimate the models. Computer setups are available online at www.thomasledermann.com/cfm.php.

Before estimating the CFM, we first checked to see that the intradyadic correlations were robust. As they were .462 for understanding each other and .499 for relationship success, they were both large enough to warrant the estimation of two separate common-fate variables.

For comparison purposes, we fitted an APIM with understanding each other and relationship success as causal and outcome variables, respectively. We obtained positive-actor effects for husband, 0.615 (standard error, SE = 0.049), and for wife, 0.639 (0.051), and positive-partner effects from wife to husband, 0.182 (0.047), and from husband to wife, 0.170 (0.053), which were all statistically significant. That is, one's own perception of relationship success is positively associated with both one's own and the partner's perception of understanding each other. The ratio of the partner effect to the actor effect, which has been termed k (Kenny & Ledermann, 2010), was 0.296 for husband (partner effect from wife to husband to husband's actor effect) and 0.267 for wife, indicating that the partner effects were less than 0.30 of the actor effects, or the actor effects were more than three times as big as the partner effects. The bias-corrected bootstrap-interval estimates based on 5000 bootstrap samples ranged from 0.123 to 0.532 for husband and from 0.071 to 0.534 for wife. We note that the ratios and their confidence intervals (CI) were somewhere between zero

[2] In general, using the k parameter as in Kenny and Lederman (2010), k must be positive and statistically greater than zero to estimate the CFM. If k is one, the error covariances are zero, if k is less than one, the error covariances are the same sign as the actor and partner effects, and if k is greater than one, the error covariances are the opposite sign as the actor and partner effects.

[3] It might be possible to improve the reliability of each informant by aggregating measures or even by creating a latent variable, in which case the common-fate variable would be a second-order latent factor.

[4] Actually, the standard CFM has 6 *df* which equals the *df* of a saturated indistinguishable model with two variable pairs. So, in this case, the standard chi-square statistic is not interpreted and is not meaningful, as it just represents the nonrandom assignment of persons to A and B.

and one and so do not support a specific pattern as discussed by Kenny and Cook (1999).

Standard CFM. We present the parameter estimates and
T1 chi-square fit statistic for the standard CFM or Model 1 in Table 1. The model showed a good fit, and the reliabilities reflected by the squared standardized factor loadings were reasonable. The dyad-level effect from understanding each other to relationship success was positive and statistically significant, indicating that an increase of understanding each other by one point is associated with an increase of husband's and wife's perception of relationship success of 1.010 point. Given the results of the APIM analysis, an increase of both husband's and wife's understanding each other by one point is associated with an increase of spouses' perception of relationship success of about 0.810. The error covariances in the standard CFM for husband and wife (individual-level effects in Table 1) were both positive and statistically significant, indicating some error covariation between understanding and relationship success at the individual level.

Standard CFM for indistinguishable members. There are cases in which dyad members are not distinguishable by a theoretically meaningful variable. Moreover, even when dyad members are theoretically distinguishable, it can sometimes be more parsimonious to treat them as if they were indistinguishable (Kenny et al., 2006). To illustrate the CFM for indistinguishable dyad members, we reanalyzed the sample data, but we treat husband and wife as if they were indistinguishable.

In the standard CFM setup for indistinguishable members (Model 1i), the reliabilities of the indicators understanding each other and relationship success were about the average of husband and wife reliabilities in the distinguishable models. The dyad-level effect was similar to that of the standard CFM for distinguishable members. The individual effect was about the average of husband's and wife's individual effect in the CFM for distinguishable members. The equality constraints lead to a smaller standard error (*SE*) of that effect relative to those in the CFM for distinguishable members. Using MSEM, we obtained the same estimates but with
Fn5 zero *df*.[5]

Alternative Common-Fate Models

We propose three alternative variations of the standard CFM,
F2 each of which is illustrated in Figure 2. The first variation, shown in Figure 2A, is a model with no covariances between the error terms. We call it the *pure CFM*, which is an idealized CFM in which all of the covariances between the two variables are at the dyadic level. The pure CFM is a restricted or nested version of the standard CFM and so the chi-square difference test with two *df* can be used to evaluate the constraints of this simpler model. We note that Conger et al. (1999) estimated a version of this model. In terms of the APIM, the pure CFM would imply that actor and partner effects are exactly equal, a couple-level model (Kenny & Cook, 1999).

A second variation, presented in Figure 2B, is a model in which each individual-level covariance is replaced by an individual-level latent variable that relates to the indicators for each dyad member. We call it the two-factor CFM, as it has two types of variables: common fate and individual-level latent variables. With all loadings fixed to one, Model 2B and the standard CFM are statistically
Fn6 equivalent (Lee & Hershberger, 1990; Stelzl, 1986).[6] That is, the overall fit statistic is the same for the two-factor CFM and the standard CFM. The two-factor CFM presumes that each manifest variable acts as an indicator of a common-fate variable and an individual-level latent variable that represents a more general aspect. That is, within each class, the indicators represent an aspect of an overall construct. So for instance, measuring relationship communication and relationship harmony in couples, we could set up a CFM with relationship harmony regressed on relationship communication and two individual latent variables representing husband's and wife's relationship quality. The two individual latent variables render the covariances between the error terms unnecessary. In fact, the variances of the latent variables equal the error covariances. This type of CFM is especially interesting when including additional variables not modeled as common fate variables. Continuing the above example, personality traits could be added to predict husband's and wife's relationship quality, which could further be used as predictors for husband's and wife's individual well-being. Alternatively, we can treat the individual-level latent variables as not having a substantive meaning but rather represent systematic measurement biases of each member.[7] Fn7

A third variation of a CFM is given in Figure 2C, and a variant of this model is presented in Kenny et al. (2006; see also Teachman et al., 1995). We call it the multilevel CFM because it has paths between X and Y at the dyad and individual level. Along with the path from the latent variables to the indicators, these direct effects make up four simple indirect effects connecting X with Y_A through Y and X_A and connecting X with Y_B through Y and X_B. That is, one simple indirect effect is the dyad-level effect times the factor loading, whereas the other simple indirect effect is the factor loading times the individual-level direct effect. These simple indirect effects constitute two total effects, which here are the sum of two indirect effects that connect an initial variable with an outcome: $X \rightarrow Y \rightarrow Y_A + X \rightarrow X_A \rightarrow Y_A$ and $X \rightarrow Y \rightarrow Y_B + X \rightarrow X_B \rightarrow Y_B$. Because the factor loadings are constrained to equal one, the parameter estimates of each given simple indirect effect equal the parameter estimates of the free-estimated direct effect of that simple indirect effect. This has two consequences. First, the simple indirect effects $X \rightarrow Y \rightarrow Y_A$ and $X \rightarrow Y \rightarrow Y_B$ are equal to each other. Second, each total effect is the sum of the dyad-level effect and one of the two individual-level direct effects (e.g., $d + i_A$). In contrast to the standard CFM, the inclusion of the direct effects between indicators commonly leads to an attenuation of (a) the dyad-level effect and (b) the standardized factor loadings of the endogenous common-fate variable, which, thus, reduces its variance.

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[5] To be consistent with the models estimated within the SEM framework, we used the maximum-likelihood method instead of restricted maximum likelihood, which is the preferred estimation method for small samples.

[6] This equivalence, however, does not hold for models with more than two CF variables (e.g., Ledermann & Macho, 2009).

[7] A prerequisite of the two-factor CFM is that the associations between the measured constructs are positive. However, if X and Y are negatively associated, a negative association is also expected to occur at the individual and dyadic level. If so, for each individual-level latent variable, one of the effects from that variable to the indicators is set to -1 in lieu of 1.

Table 1
Parameter Estimates and Model Fit for the Sample Dataset

	Treating Members as Distinguishable				Treating Members as Indistinguishable	
	Model 1	Model 2A	Model 2B	Model 2C	Model 1i	Model 2Ci
Standardized loadings						
X husband	.692	.688	.692	.690	.677	.677
X wife	.667	.670	.667	.668	.677	.677
Y husband	.727	.722	.727	.485	.705	.470
Y wife	.685	.689	.685	.459	.705	.470
Dyad-level effect (*SE*)	1.010 (0.080)	1.271 (0.104)	1.010 (0.080)	0.561 (0.111)	1.012 (0.081)	0.560 (0.111)
Individual-level effects						
Husband (*SE*)	0.237 (0.059)	—	0.237 (0.059)	0.438 (0.060)	0.278 (0.039)	0.451 (0.052)
Wife (*SE*)	0.315 (0.064)	—	0.315 (0.064)	0.461 (0.059)	0.278 (0.039)	0.451 (0.052)
Model fit						
χ^2	0.063	67.984	0.063	0.227	—	—
df	1	3	1	1	0	0
p	.802	<.001	.802	.634	—	—

Note. X = understanding each other; Y = relationship success; *SE* = standard error; Model 1 = standard CFM; Model 2B = two-factor CFM; Model 2C = multilevel CFM; Model 1i = Model 1 setup for indistinguishable dyad members; Model 2Ci = Model 2C setup for indistinguishable dyad members.

Using the multilevel CFM, we can test whether the dyad-level effect differs in size from the individual-level direct effects. We can compare the dyad-level effect with each individual-level effect and with the average of two individual-level direct effects. The *SE* for the difference between two effects, say the dyad-level effect (d) and the individual-level direct effect of member A (i_A), obtained by the first order delta method, is:

$$SE_{d-i_A} = \sqrt{s_d^2 + s_{i_A}^2 - 2s_{di_A}}$$

where s_d^2 and $s_{i_A}^2$ denote the variances of d and i_A, respectively, and s_{di_A} denotes the covariance between d and i_A.

The *SE* for the difference between the dyad-level effect and the average of the two individual-level direct effects is:

$$SE_{d-0.5(i_A+i_B)} = \sqrt{s_d^2 + 0.25(s_{i_A}^2 + s_{i_B}^2) + 0.5s_{i_Ai_B} - (s_{di_A} + s_{di_B})} \tag{2}$$

Having calculated the *SE*, a z score can be obtained by dividing each contrast to be tested by its *SE*. Alternative methods for testing contrasts are the standard chi-square difference statistic, or the phantom-variable method (Macho & Ledermann, 2011), which can be used to obtain point and bootstrap-interval estimates.

Illustrative Examples

We estimated the three models shown in Figure 2 using the data and variables from above and Amos and Mplus. In addition, we reestimated the multilevel CFM, treating husband and wife as indistinguishable. To test total indirect effects for statistical significance, we used the bootstrap method. The bootstrap bias-corrected 95% CI estimates reported here are based on 5000 bootstrap samples. The parameter estimates and chi-square fit statistic are given in Table 1.

Pure CFM. For the pure CFM (Model 2A), the fit was poor, and the chi-square difference test comparing it to the standard CFM was $X^2_{Diff}(2) = 67.921$, $p < .001$, which strongly suggests that the constraints of zero-error covariances are inadvisable. Although the model was inconsistent with the data, we report the parameter estimates in Table 1 for illustration purposes.

Two-factor CFM. This model (Model 2B) is statistically identical with the standard CFM. The direct effect between the latent variables and the four factor loadings for the common-fate variables were the same in this model as in the standard CFM. The individual-level latent variables can be thought to represent husband's and wife's unique view of relationship quality. The variances and *SE*s of those latent variables are identical with the error covariances from the standard CFM (see individual-level effects in Table 1).

Multilevel CFM. The model with direct effects at the individual and dyadic level (Model 2C) provided a good fit. The reliabilities reflected by the squared standardized factor loadings were reasonable for understanding each other. Because of the substantial individual-level direct effects, the reliabilities for relationship success were substantially lower than in the other models. The dyad-level effect and individual-level direct effects were all positive and statistically significant. In this model, husband's and wife's indicators of relationship success are each linked with understanding each other by two indirect effects: $X \rightarrow Y \rightarrow Y_h$, $X \rightarrow X_h \rightarrow Y_h$ for husband and $X \rightarrow Y \rightarrow Y_w$, and $X \rightarrow X_w \rightarrow Y_w$ for wife. With all factor loadings constrained to one, the estimated direct effects are a direct measure of the four simple indirect effects. The total effects from understanding each other to husband's and to wife's perception of relationship success were 0.998 and 1.022, respectively. That is, an increase of understanding each other by one point is associated with an increase of perception of relationship success by 0.998 point in husband and by 1.022 point in wife. Using bootstrapping, both total effects were statistically significant (the 95% CI ranged from 0.838 to 1.196 for the effect involving husband's outcome and from 0.863 to 1.219 for the effect involving wife's outcome).

Contrasting the dyad-level effect and the individual-level direct effects using Equations 1 and 2 (or a computer program that enables the specification of contrasts) reveals that they do not differ in magnitude ($i_h - i_w = -0.024$, $SE = 0.058$; $p = .687$;

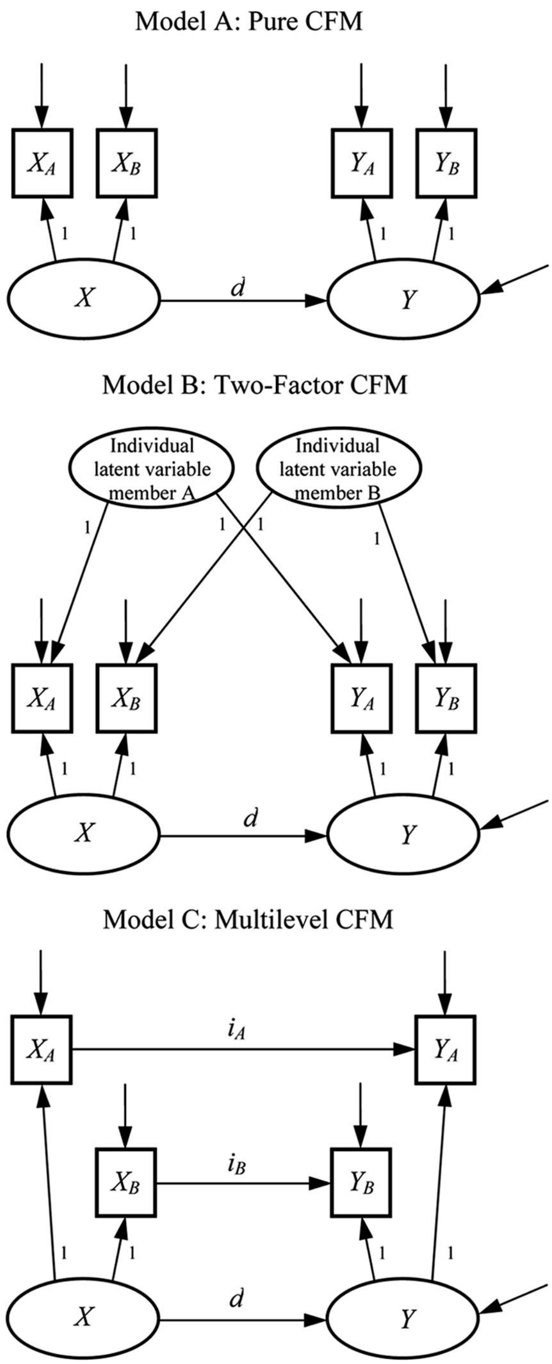

Figure 2. Three different common fate models.

$d - i_h = 0.122$, $SE = 0.158$; $p = .437$; $d - i_w = 0.099$, $SE = 0.155$; $p = .523$; $d - 0.5(i_h - i_w) = 0.154$, $SE = 0.154$; $p = .471$). Consequently, the simple indirect effects did not differ statistically either. Setting all three effects equal, the chi-square difference test strongly supported this more parsimonious model, $X^2_{Diff}(2) = 0.665$, $p = .717$, which showed a good fit, $X^2(3) = 0.892$, $p = .827$. In sum, understanding each other at the dyad-level was associated to the same degree with husband's and wife's perception of relationship success indirectly through relationship success at the dyad-level, and through husband's and wife's perception of understanding each other at the individual-level.

Multilevel CFM for indistinguishable members. For the indistinguishable multilevel CFM (Model 2Ci), the reliabilities were again about the average of those obtained in the distinguishable case. The dyad-level effect was similar to that of the CFM for distinguishable members. The individual-level direct effect was again about the average of those in Model 2. These two direct effects are a direct measure of the two simple indirect effects that link understanding each other with dyad members' relationship success. These two effects did not differ in their magnitude ($d - i = 0.109$, $SE = 0.154$; $p = .478$). The total effect from understanding each other to dyad member's perception of relationship success was 1.012 and statistically significant (the 95% CI ranged from 0.860 to 1.200).

Hybrid Dyadic Models

The simple structural part makes the CFM particularly suitable for the analysis of associations between multiple variables. Especially interesting are hybrid models involving both the common-fate and APIM approach or individual-level variables. Four out of the five previously mentioned CFM studies estimated some form of a hybrid model. Teachman et al.'s model can be described as an I-CF model, because the initial variables were conceptualized as individual-level variables and the outcome was modeled as common fate variable. The model by Matthews et al. might be described as I-I-CF-CF model. Burk and Laursen (2010) linked child's behavior with a common-fate variable. Finally, Conger et al. (1999) fitted a model with both individual-level variables, common-fate variables, and between-dyads variables.

Illustrative Example

We illustrate the estimation of a hybrid model by extending the standard CFM with understanding each other and relationship success to an I-CF-CF model. We used the data and variables from above and, additionally, work-family conflict as initial variable, which was measured by the item "How often do you feel that work roles and family roles conflict" on a five-point scale ranging from 0 (*never*) to 4 (*almost always*). The model is presented in Figure 3. F3 With the addition of a third variable pair we can relax the factor loadings of one member and so test whether the factor loadings differ significantly across members. The fit of the model with free factor loadings for wife was good, $\chi^2(3) = 3.308$, $p = .347$. Wife's factor loadings were 0.703 ($SE = 0.197$) for understanding each other and 0.710 (0.199) for relationship success. We found that these loadings did not differ statistically from one, and so they did not differ from those of the husband. ($X^2_{Diff}(1) = 1.744$, $p = .187$ for the comparison of the model with 3 *df* and the model with the factor loading for wife's perception of understanding each other fixed to one, $X^2_{Diff}(1) = 1.625$, $p = .202$ for the comparison of the model with 3 *df* and the model with the factor loading for wife's perception of relationship success fixed to one, and $X^2_{Diff}(2) = 1.805$, $p = .406$ for the comparison of the model with 3 *df* and the model with all factor loading fixed to one). Consequently, we used the more parsimonious model with all factor loadings fixed to one that showed a good fit $\chi^2(5) = 5.113$, $p = .402$. In this model, all direct effects from husband's and wife's work-family conflict to

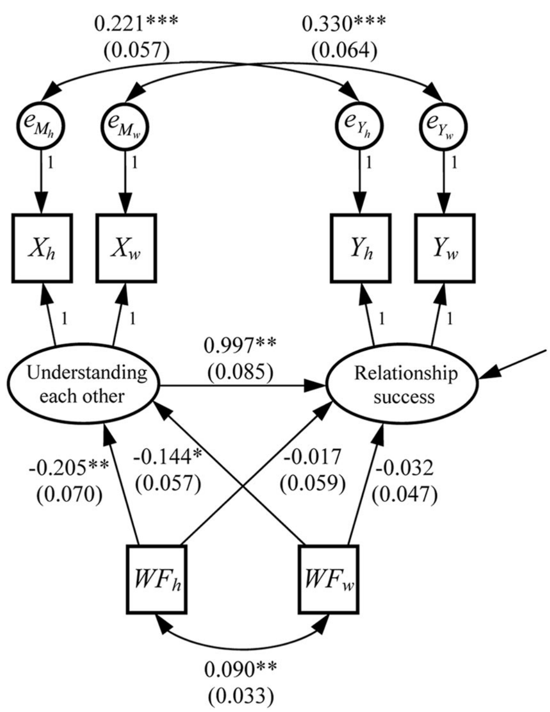

Figure 3. An I-CF-CF model with unstandardized estimates. *Note.* Standard errors are presented in brackets. h = husband, w = wife; WF = work-family conflict. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

common relationship success were significant, except the direct effects between work-family conflict and common relationship success (see Figure 3). These statistically significant direct effects constitute two indirect effects differing in the initial variable but not the mediator and the outcome. Both indirect effects were negative and statistically significant. The indirect effect from work-family conflict to relationship success was −0.204 (95% CI: −0.369, −0.051) for husband and −0.143 (95% CI: −0.264, −0.032) for wife. The corresponding total effects were significant, too, with −0.221 (95% CI: −0.382, −0.056) for husband and −0.175 (95% CI: −0.307, −0.043) for wife. Contrasting the effects, we found no evidence for gender differences for the indirect effects (difference = 0.103; 95% CI: −0.269, 0.137) and the corresponding total effects (difference = 0.115; −0.275, 0.172). In sum, husband's and wife's work-family conflict affected both his and her perception of relationship success through understanding each other and relationship success at the dyadic level.

Discussion

The CFM is an important data-analytic tool in dyadic research that allows researchers to model shared influences that have an effect on both members of a dyad. In this paper, we have shown how to estimate the CFM for distinguishable and indistinguishable members. Moreover, we have outlined three alternative models to test specific assumptions. For the analysis of the standard CFM in the indistinguishable case, we have presented a multilevel SEM approach. By implementing common-fate variables, complex dyadic models benefit, as their structural parts become simpler. For instance, if we use the APIM to assess mediation in dyadic data with distinguishable members, there are eight possible indirect effects and four total effects (Ledermann, Macho, & Kenny, 2011). For each variable pair that is conceptualized as a common-fate variable, the number of effects is halved. The same would also be true for an APIM expanded to test moderation effects (Ledermann & Bodenmann, 2006). Also promising is the combination of the CFM with the APIM into a hybrid model. This allows researchers to study relations between a set of personal and shared variables without making the structural part of the model overly complex.

The common-fate approach is not limited to dyads; it has also been extended to the study of small groups (Gonzalez & Griffin, 2001, 2002; Kenny & La Voie, 1985). For example, in studying families, the family climate rated by spouses and their target child can be modeled as common-fate variable with husband's, wife's, and child's ratings as indicators. The common-fate concept can also be applied using an observer rating in addition to the rating of the dyad members (e.g., Matthews et al., 1996). With three or more persons, we can relax the assumption of equal loadings, and we could fix one member's loading to one while the other persons' loadings are set free. In doing so, we could establish which person was the more reliable informant.

For the implementation of common-fate variables, there are two prerequisites. First, it requires that the theoretical variable, measured for both dyad members, must be conceived as influencing the reports of both members. Second, the observed variables need to be reliable indicators of the latent common-fate variables. The reliability of an indicator in this case equals the standardized loading squared. Studies have shown that the impact of the size of the loadings on the appropriateness of the measurement model depends on the sample size (Ximénez, 2006). Because factor loadings are commonly fixed to be equal and are not estimated in common-fate models, latent common variables can be estimated with smaller intradyadic correlations, perhaps as low as .20. More research is needed in this area. Finally, if the intradyadic correlation is low and even negative, it might suggest that the indicators are formative and not reflective (Bollen & Lennox, 1991), and that a between-within or APIM analysis might be more informative.

In the common-fate models presented here, the factor loadings were set to one, implying that they are equal to each other. We note that this assumption is tested in the standard, two-factor, and multilevel CFM in that every model has one *df*. If this assumption does not hold, one could free one factor loading and fix the other three loadings to one. In doing so, the free-estimated loading represents the influence of the underlying latent variable on, say, men's Y variable relative to that on women's Y variable with fixed factor loading. The problem is that only one of the two latent variables can have a free loading, and there is no way of knowing if the second factor still has equal loadings. We think that it is unlikely that the researcher would know that one latent variable would have equal loadings and the other had unequal loadings. However, with the addition of individual-level or common-fate variables either as predictors or outcomes, one could fix the factor loadings to one for one member, and free the two factor loadings for the other member. We suggest that when this is done, the researcher tests the constraint that those free loadings equal the same value. We note that the pure CFM can always,have free loadings and still be estimated. Also, as we previously discussed, if there are three or more informants of the CF, the equal-loading assumption can be relaxed. If it is possible to allow for unequal loadings, it can be assessed which dyad member is more reliable. Finally, we note that when dyad members are indistinguishable, it makes no sense to allow the loadings to vary.

Conclusion

In this paper, we discussed an important alternative to the APIM, the CFM, which can be a useful vehicle for modeling common-fate variables in dyadic data. However, this important alternative model has only been infrequently applied in the substantive literature. The CFM deserves much more attention especially from a conceptual standpoint. For studies with variables that exert an effect on both dyad members, the CFM is seriously to be considered. The papers mentioned above that make use of it and the illustrative example presented here demonstrate how useful the implementation of the common-fate concept can be.

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