Mediation in Dyadic Data at the Level of the Dyads: A Structural Equation Modeling Approach

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An extended version of the Common Fate Model (CFM) is presented to estimate and test mediation in dyadic data. The model can be used for distinguishable dyad members (e.g., heterosexual couples) or indistinguishable dyad members (e.g., homosexual couples) if (a) the variables measure characteristics of the dyadic relationship or shared external influences that affect both partners; if (b) the causal associations between the variables should be analyzed at the dyadic level; and if (c) the measured variables are reliable indicators of the latent variables. To assess mediation using Structural Equation Modeling, a general three-step procedure is suggested. The first is a selection of a good fitting model, the second a test of the direct effects, and the third a test of the mediating effect by means of bootstrapping. The application of the model along with the procedure for assessing mediation is illustrated using data from 184 couples on marital problems, communication, and marital quality. Differences with the Actor-Partner Interdependence Model and the analysis of longitudinal mediation by using the CFM are discussed.

Keywords: mediation, dyadic data, Common Fate Model, Structural Equation Modeling, bootstrapping

Mediation occurs when an independent variable affects an outcome variable through a third variable, called mediator (Baron & Kenny, 1986; James & Brett, 1984). In the last decade, researchers have begun to analyze such associations in dyadic data. For example, Campbell, Simpson, Kashy, and Fletcher (2001) found that in couples the association between warmth/trustworthiness and relationship quality is mediated by ideal-partner matching. Among the models developed to analyze such data (see, e.g., Gonzalez & Griffin, 1997, 1999; Kashy & Kenny, 2000; Kenny, 1996), two are particularly suitable for the estimation and testing of mediation effects in dyads: The Actor-Partner Interdependence Model (APIM), designed to assess causal associations between personal variables at the level of the dyad members (individuals), and the Common Fate Model (CFM), developed to analyze causal associations between common dyadic variables at the level of the dyads.

The APIM (e.g., Kenny & Cook, 1999; Kenny, 1996) has been designed to estimate the impact of a person’s independent variable on his or her own dependent variable (actor effect) and on the dependent variable of the partner (partner effect). It implies that two dyad members influence each other in the form of partner effects, which create non-independence between members. Details of how to assess mediation using this type of model can be found elsewhere (Ledermann & Bodenmann, 2006). Several researchers, including Campbell et al. (2001; see above), have used this model to analyze mediation in marital research (e.g., Bodenmann, Ledermann, & Bradbury, 2007; Srivastava, McGonigal, Richards, Butler, & Gross, 2006).

The CFM (e.g., Griffin & Gonzalez, 1995; Kenny, 1996) has been developed to estimate and test associations at the dyadic level between variables that have an effect on both partners of a dyad (see Figure 1). In this type of model, the variables measured in both partners are presumed to be indicators of dyadic variables (constructs) that affect both members and thus make them non-independent. Although this type of model is ideal for analyzing effects between dyadic constructs, such as marital harmony or relationship cohesion, it is not yet widely used in research. One of the few published mediation models that uses such dyadic variables is the model by Matthews, Conger, and Wickrama (1996). By implementing two mediators in a CFM combined with an APIM, the results indicate that husbands’ and...
wives’ work-family conflict affect both one’s own and the partner’s psychological stress (first mediator), which have an effect on the quality of interaction (second mediator), which, in turn, influences marital quality at the dyadic level. The constructs marital quality and quality of interaction were modeled as latent dyadic variables with husbands’ and wives’ self-report (and an additional observer’s report for quality of interaction) as observed indicators in a CFM, whereas psychological distress and work family conflict were interpreted as personal variables modeled in an APIM. The objective of this article is to describe a framework to estimate and test mediation in dyadic data at the level of the dyads using Structural Equation Modeling (SEM), which allows the estimation of causal associations between latent variables and to model measurement errors.

The statistical analysis of causal associations in dyads depends on whether the dyadic partners are distinguishable or indistinguishable (see Gonzales & Griffin, 1997; Kenny & Cook, 1999). Distinguishable members belong to different classes of categories (e.g., heterosexual couples), whereas indistinguishable, also called interchangeable or exchangeable members, belong to the same class or category (e.g., monozygotic twins). The model presented here can be applied for both distinguishable and indistinguishable dyad members. Variables measured in both partners that can vary within and between dyads, such as relationship satisfaction, are called mixed variables (Kashy & Kenny, 2000; Kenny, 1996; Kenny, Kashy, & Cook, 2006).

The structure of this article is as follows. First, we describe the mediation model and its basic assumptions and explain when it can be used and how it is to set up for distinguishable as well as indistinguishable dyad members. Second, we elucidate the procedure for testing mediation effects when using SEM. Third, we illustrate the application of the model using coupled data on marital problems, communication, and marital quality. Finally, we discuss the strengths of the model along with possible extensions and combinations with other data-analytic approaches and point out its limitations.

The Common Fate Mediation Model

The CF mediation model shown in Figure 1 is an extension of the classical CFM (e.g., Cook, 1998; Griffin & Gonzalez, 1995; Kenny, 1996; Kenny & La Voie, 1985) and is made up of one exogenous (independent) and two endogenous (dependent) measurement models and a structural model. A measurement model is that part of a general model that describes how the manifest (observed) variables, commonly referred to as effect indicators, are related to the unobserved latent variables. In Figure 1, the three measurement models consist of three latent variables, X, M, and Y; three pairwise manifest variables measured in Person A and Person B (e.g., husband and wife), XA, XB, MA, MB, YA, and YB; and six error terms, e1 to e6. In measurement models of this type, each manifest indicator is determined by two components: the theoretical construct represented by the latent variable and an individual-specific component represented by the error term. This implies that variation in the latent variable (construct) leads to variation in its indicators (Bollen, 1989). In each CF measurement model, the covariance (correlation) between two manifest indicators is assumed to be due to the influence of a common dyadic variable (fate).

The structural model is that part of the general model that prescribes the assumed associations between the latent variables. In Figure 1, the structural model consists of the three latent variables, X, M, and Y, and two residual terms, resM and resY. It represents the most basic form of a mediational model, which consists of one independent variable, one mediator, and one outcome variable. The relations between the three latent variables are conceptualized as causal associations at the dyadic level.

The CFM has two advantages over methods that model dyadic constructs by calculating weighted or unweighted dyad means (i.e., the means of two members’ scores) and that assume the measures are perfectly reliable (e.g., Gonzales & Griffin, 1997). First, the CFM takes into account measurement errors (e1 to e6) whose non-consideration may lead to an attenuation of the effects between the variables of interest. Second, it allows the estimation of covariances between the error terms (cov1 to cov6) whose omission can substantially bias the estimates of the parameters and affect the overall fit of a model, especially when the covariances reveal significant.

Basic Assumptions and Utilization of the Common Fate Model

The CF mediation model is based on the three assumptions that (a) dyad members are affected by a common influence, (b) mediation takes place and should be modeled at the dyadic level, and (c) the variables measured in both dyad members are reliable indicators of the latent variables. As to the first assumption, dyad members can be affected by two kinds of common influences: characteristics of their
own relationship and influences external to the relationship (Gonzalez & Griffin, 2002; Kenny, 1996; Woody & Sadler, 2005). A typical example of a relationship characteristic that influences both partners is relationship cohesion (Cook, 1998; Cook & Kenny, 2006). Relationship adaptation, consensus (agreement), relationship closeness, relationship climate, and relationship harmony are other constructs that are theoretically expected to function as common dyadic variables that exert an effect on both partners. In addition, common external forces, such as shared contextual and environmental influences, the quality of the home environment, housing, or neighborhood, are likely to affect dyad members.

The answer to the question whether a particular construct represents a common dyadic variable that exerts influence on both partners is not always obvious. In relationship research, marital quality, for example, has been treated as a common dyadic variable modeled in CFM (Matthews et al., 1996) as well as a personal variable modeled in an APIM (Campbell et al., 2001). Dyadic coping, quality of relationship communication, relationship problems, or dyadic conflicts are further examples of constructs that can be conceived of as common dyadic constructs as well as personal variables. A dyadic construct expected to function as a common dyadic variable that affects both partners underlies the assumption that the focus is on the dyad rather than the individual. For measures assessing a common dyadic construct, it is important that the object of measurement (target) is the same for both members of dyad. Using questionnaires or interviews, this applies when the items (along with the instruction for the respondents) are constructed in such a way that each item refers to the dyadic construct to be measured and when both partners are addressed. In self-report measures, the items would typically use the word “we” or “our” (e.g., “We support each other when things get tough” or “We have a good relationship with our neighbors”) while the introducing instruction would ask to rate one or more aspects of the relationship or the external fate, respectively (see, e.g., Huston & Vangelisti, 1991; Norton, 1983). A dyadic construct assessed in both dyad members by a measure constructed in this fashion is conceptually best interpreted as a latent common variable that can be adequately modeled in a CF measurement model.

By contrast, measures assessing personal variables, such as individual attitudes, beliefs, dispositions, skills, or behaviors, are conceptually unsuitable for the use as indicators in a CF measurement model. In self-report measures, this is indicated when the items contain the word “my,” “I,” or “me” (e.g., “My partner supports me when things get tough” or “I have a good relationship with our neighbors”). Measures that reflect personal variables, including a person’s individual attitude toward a shared external influence, are particularly suitable for being implemented in an APIM (e.g., Kenny & Cook, 1999; Kenny, 1996).

The second model assumption concerns the level on which mediation occurs. The CF mediation model presumes that the independent variable causes the outcome variable indirectly through the mediator at the dyadic level. Consequently, the theoretical conceptions and rational thoughts underlying the model being tested must be reconcilable with the assumption of the CFM that mediation takes place at the dyadic level. The level on which the causal associations should be analyzed depends in particular on the constructs to be measured (see Woody & Sadler, 2005). When the constructs represent common dyadic variables that exert influence on both partners, causal associations between the variables may be best modeled at the dyadic level in a CFM. When the constructs reflect personal variables, the associations between the variables may be best assessed at the level of the dyad members, for example, in an APIM.

The third assumption concerns the indicator reliability. The factor loadings (l1 to l6 in Figure 1) measure the extent to which a given set of indicators is influenced by the respective latent variable. 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 (i.e., the variance that is not explained by the latent variable), the higher the influence of the latent variable on the indicator and, hence, the better the indicator represents the latent construct. Schumacker and Lomax (2004, p. 212) consider standardized factor loadings of .70 (i.e., 49% explained variance) or higher as adequate. If one of the measurement models is inadequate due to low factor loadings, the general model is likely to be wrong. Thus, measurement models with low reliabilities (explained variances clearly below 50%) should not be used in a CFM.\(^1\)

In summary, the CFM is based on the assumptions that dyad members are affected by common influences, mediation occurs at the dyadic level, and the measures are reliable indicators of the latent variables. Thus, the model can be used if the measured variables represent common dyadic variables that affect both partners (see Gonzalez & Griffin, 2002; Woody & Sadler, 2005), if the causal associations between the variables take place and should be modeled at the level of the dyads, and if the mixed variables are reliable indicators of the dyadic constructs.

The Common Fate Model for Distinguishable Dyad Members

In SEM, latent variables have no natural metric, as they are not observed directly, and thus a metric has to be defined for each latent variable. This is often done by fixing in each measurement model the loading of one indicator to 1 and the mean of the latent variable to 0. In this case, the loadings of the other indicators represent the influence of the latent variable relative to that of the scaling indicator with fixed factor loading.

In specifying the CFM, it is common to set the factor loadings of all indicators to 1 (Cook, 1998; Gonzalez & Griffin, 1999; Woody & Sadler, 2005). In the distinguish-

\(^1\) In measurement models with two indicators and both factor loadings fixed to 1, the product of the standardized factor loadings equals the correlation between the two indicator variables when in the measurement model the covariance between the two error terms is set to 0.
able case, however, it may be reasonable that factor loadings differ across the two types of dyad members. If so, researchers may relax one of the pairwise factor loadings of each latent variable (e.g., women’s factor loadings, whereas men’s loadings are fixed to 1).

In addition, it is common to include covariances (cov1 to cov6 in Figure 1) between the measurement errors of each type of dyad member (Gonzalez & Griffin, 1999; Woody & Sadler, 2005). A substantial error covariance indicates that two indicators measure something in common not represented by their respective latent constructs. This may be due to a common method variance (e.g., response biases or tendencies). Using SEM, the estimation of such error covariances, sometimes referred to as individual-level effects (e.g., Gonzalez & Griffin, 1997), increases the complexity of a given model and can lead to a poor model fit if these covariances turn out to be small. Therefore, not substantial error covariances (not significant and standardized coefficients < .10) may be removed. If a particular model does not fit the empirical data, the model may be modified using diagnostic statistics, such as modification indices or expected parameter changes, along with theoretical considerations (e.g., McDonald & Ho, 2002).

The Common Fate Model for Indistinguishable Dyad Members

The application of the CFM for indistinguishable dyad members requires a series of specific equality constraints across members and an adjustment of the model fit statistics (Olsen & Kenny, 2006; see also Kashy, Donnellan, Burt, & McGue, 2008). Data for indistinguishable dyad members can be arranged in the same manner as data for distinguishable members by listing both members of a dyad on one row (i.e., each row in the data set contains the data of both dyad members and, thus, the number of rows equals the number of dyads). Using this form of data arrangement, know as dyadic arrangement, the two members of each dyad are randomly assigned to the designations of Person A and Person B in the Figure 1.

In specifying the CFM for indistinguishable dyad members with all factor loadings fixed to 1, the intercepts of the indicator variables, the variances of the error terms, and the error covariances must be constrained to equality across members (i.e., intercept $x_A = x_B$, intercept $M_A = M_B$, and intercept $Y_A = Y_B$; var($e1$) = var($e2$), var($e3$) = var($e4$), and var($e5$) = var($e6$); cov1 = cov2, cov3 = cov4, and cov5 = cov6). Olsen and Kenny (2006) pointed out that the overall chi-square statistic and other model fit indices, such as the root-mean-square error of approximation (RMSEA) computed by standard SEM programs, are incorrect for the model restricted for indistinguishable dyad members. (However, the chi-square difference statistic is not affected when comparing a restricted model with a more general model.) The dyadic data arrangement requires a correction of the chi-square statistic by adjusting the chi-square value, the degrees of freedom ($df$), and, hence, the corresponding $p$-value (Olsen & Kenny, 2006). The adjusted (correct) chi-square value is the difference between the chi-square of the specified model for indistinguishable members and the chi-square of the saturated model for indistinguishable members, which is defined by pairwise equality constrains on the means, variances, and covariances across dyad members (Olsen & Kenny, 2006; see also Kashy et al., 2008). That is, $\chi^2_a = \chi^{Specified}_a - \chi^{Saturated}_a$, where $\chi^a$ is the adjusted chi-square, $\chi^{Specified}_a$ is the chi-square of the specified model, and $\chi^{Saturated}_a$ is the chi-square of the saturated model for indistinguishable members. The adjusted degrees of freedom ($df_a$) can be obtained by calculating the difference between the degrees of freedom for the specified model and the degrees of freedom for the saturated model for indistinguishable members (i.e., $df_a = df_{Specified} - df_{Saturated}$). The degrees of freedom for the saturated model for indistinguishable members can also be calculated by the equation: $df_{Saturated} = p_r(p_r + 1)$, where $p_r$ is the number of pairwise indicators in the CFM (Olsen & Kenny, 2006). For a model with three measured indicator pairs, the $df_{Saturated}$ equals 12. The adjusted $p$-value is determined by the adjusted chi-square value and the adjusted degrees of freedom (i.e., $\chi^2_a$ and $df_a$). The RMSEA, which is an estimate of the lack of fit of a given model, can be computed by

$$RMSEA = \sqrt{\frac{\chi^2_a - 1}{df_a - \frac{df}{N} - 1}},$$

where $N$ is the sample size (number of dyads). When $\chi^2/df < 1$, the RMSEA is defined to be zero. When testing the restricted model for indistinguishable dyad members, $\chi^a$ and $df_a$ has to be substituted by $\chi^a$ and $df$, respectively, in order to obtain the correct RMSEA (Olsen & Kenny, 2006).

In sum, the CFM allows the analysis of mediation in dyadic data at the level of the dyads for both distinguishable and indistinguishable dyad members. Following this presentation of the CFM, we now turn to the description of the procedure for estimating and testing mediation when using SEM.

Testing Mediation

In mediation models consisting of one independent variable, one mediator, and one final outcome variable (as the structural model of the CFM shown in Figure 1), the effect of the independent variable $X$ on the final outcome variable $Y$ can be decomposed into two component effects: the indirect (mediating) effect $ab$, which is the product of the direct effects $a$ and $b$, and the direct effect $c$ (controlled

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2 Olsen and Kenny (2006) explain also how incremental fit indices can be calculated for indistinguishable dyad members and illustrate the necessary adjustments for the Tucker-Lewis Index (TLI).
In terms of mediation, there are two types: partial and complete mediation. Partial mediation occurs when the direct effect $c$ is different from zero and of the same sign as the mediating effect $ab$. The magnitude of $c$ reflects the degree to which $M$ fails to explain completely the association between $X$ and $Y$. When the indirect effect $ab$ and the direct effect $c$ have opposite signs, suppression takes place (see Maassen & Bakker, 2001; MacKinnon, Krull, & Lockwood, 2000; Shrout & Bolger, 2002). If the mediation is partial, a quantity of interest is the relative proportion of the mediating effect on the total effect, which is given by the ratio $ab/(ab + c)$. The accuracy of this ratio, however, has been found to be poor when sample sizes are small (MacKinnon, Warsi, & Dwyer, 1995; Shrout & Bolger, 2002).

Complete mediation (also called full or perfect mediation) occurs when the direct effect $c$ is not substantial in size. In the (unlikely) case that this effect is zero, the indirect effect of $X$ on $Y$ through $M$ equals the total effect of $X$ on $Y$. In three-variable mediation models, complete mediation occurs if the model suggesting complete mediation (having no direct effect between $X$ and $Y$) is consistent with the data when using SEM. The CF mediation model displayed in Figure 1 implies that the mediation is partial, because it includes a direct path between $X$ and $Y$.

Using SEM, we propose three steps to estimate and test mediation. The first step is a selection of a reasonable model that is consistent with the data. After setting up the model as described above (including within-person error covariances and all factor loadings fixed to 1), we suggest, in line with Baron and Kenny (1986; see also Kenny, 2008), to start with a model that implies partial mediation (i.e., the model with direct effect $c$). If it turns out that $c$ is not substantial (not significant and standardized coefficient $< .10$), this effect may be fixed to zero (removed) unless there are theoretical reasons to keep it. Mediational models without a direct effect between the initial and the final outcome variable (suggesting complete mediation) are generally superior to models indicating partial mediation in terms of statistical power to detect a substantial mediation effect, as there is no direct effect between the independent and the final outcome variable in the complete mediation model. (When suppression takes place the indirect effect is generally stronger than the total effect).

The second step consists of testing the structural coefficients $a$ and $b$ that constitute the mediating effect using the model selected (cf. Baron & Kenny, 1986). For mediation to occur, both coefficients have to be significant because it makes little sense to speak of mediation if not both $a$ and $b$ are substantial (although the product $ab$ may yield significant). If the model selected implies partial mediation, coefficient $c$ is tested for significance too. If this direct effect is not substantial in size (either insignificant or $< .10$), the hypothesis of partial mediation is rejected and the model indicating complete mediation may be estimated.

In the final step, the mediating effect $ab$ is tested for significance. There is a growing consensus that the significance of indirect effects is best tested by Efron and Tibshirani’s (1993) bootstrap method (see Bollen & Stine, 1990; Cheung, 2007; MacKinnon, Lockwood, & Williams, 2004; Preacher & Hayes, 2008; Shrout & Bolger, 2002), which is a resampling technique for estimating statistical parameters, such as standard errors and confidence intervals. On the basis of multiple samples, each containing $N$ cases that are randomly drawn with replacement from the original sample with $N$ cases, effects are estimated for each bootstrap sample, and these estimates are rank ordered to determine the cutoffs for the desired percentile confidence intervals (e.g., 2.5 and 97.5% percentiles for the 95% interval). To test indirect effects, the bias-corrected bootstrapped confidence limits have been proposed as more reliable than the percentile confidence intervals (Efron & Tibshirani, 1993; see also Cheung, 2007; MacKinnon et al., 2004). A given effect is significant if the respective confidence interval does not contain zero.

In order to obtain reliable estimates of the percentile and bias-corrected confidence limits, thousands of bootstrap samples should be used (Efron & Tibshirani, 1993). In this work, we will use 5000 such samples. Bootstrapping is implemented in several SEM programs, including EQS, AMOS, Mplus, LISREL, and Mx. Details on how to run bootstrap analyses using AMOS and EQS are given by Fan (2003) and Shrout and Bolger (2002).

**Illustration**

**Method**

To illustrate the model, we use data from heterosexual couples (distinguishable dyad members) that participated in a larger study on the recruitment and selection of couples for intervention research (Rogge et al., 2006). A total of 184 engaged and newlywed people provided self-report information on marital problems, communication, and marital quality. The mean age was 29.1 years ($SD = 5.2$) for men and 27.9 years ($SD = 5.1$) for women. Twenty percent of the couples were married, and 21.5% had children.

Marital problems, which can be considered as a dyadic construct, were measured using the *Marital Problem Inventory* (MPI; Geiss & O’Leary, 1981). Individuals’ ratings of 17 sources of relationship problems, such as religion, household management, and friends, were summed up to a total score ranging from 17 to 187 with higher scores indicating more problems (11-point rating scale. $1 = not a problem, 11 = major problem; M = 49.2, SD = 21.2$ for men, $M = 50.1, SD = 21.1$ for women; Cronbach’s $\alpha = .86$ for men and .84 for women). Here, the items referring to children (lack of variation) and communication (redundant with...
communication questionnaire) were excluded. Estimating the measurement model for marital problems with both factor loadings set to 1 and zero degrees of freedom (i.e., the model is saturated), the proportion of variances explained by the latent variable were 47% for men and 49% for women. These reliabilities, which are slightly below 50%, can be improved by increasing the within-dyad correlation (i.e., the correlation between men’s and women’s variable), which was .48. This correlation, in turn, can be enhanced by excluding the two items money management and showing affection/intimacy with a within-dyad correlation of .40 for each, which was considerably lower than the within-dyad correlation of the total scores. The resulting reliabilities were 51% and 50% (see Figure 2), the within-dyad correlation .50. The Cronbach’s α for the scale with 15 items was .83 for men and .82 for women. For the estimation of the CFM, we used this shorter scale due to the higher proportion of variances explained by the latent variable.

Communication was assessed by the Communication Patterns Questionnaire (CPQ; Christensen & Sullaway, 1984) that aims to measure dyadic communication at the relationship level. Here, the subscale constructive communication (with the items mutual discussion, expression, and negotiation) was used to assess how often constructive communication (with the items mutual discussion, expression, and negotiation) was used to assess how often constructive communication behaviors occur in relationships. The three items with a 9-point rating scale (1 = very unlikely, 9 = very likely) were summed up, yielding scores from 3 to 27 with higher scores indicating more constructive communication (M = 21.3, SD = 5.1 for men, M = 21.9, SD = 5.0 for women; Cronbach’s α = .77 for men and .81 for women; within-dyad correlation = .57).

Marital quality was measured by the Quality of Marriage Index (QMI; Norton, 1983), a six-item scale assessing the extent to which individuals agree or disagree with general statements about the quality of their relationship (e.g., “We have a good marriage”; “My relationship with my partner is very stable”). The five items used here have a 7-point rating scale (1 = very strong disagreement, 7 = very strong agreement), yielding scores from 5 to 35 with higher scores reflecting higher marital quality (M = 31.4, SD = 4.3 for men, M = 31.5, SD = 4.4 for women; Cronbach’s α = .94 for men and .93 for women; within-dyad correlation = .56).

Marital quality assessed by the QMI can be conceptualized as a latent dyadic variable that exerts an effect on both dyad members because the underlying construct can be considered as a characteristic of the dyadic relationship (see Matthews et al., 1996) and because the scale consists of items that refer to the relationship.

In order to conduct bootstrap analyses, one case (0.54%) with missing data was excluded from the analyses. Another eight cases (4.34%) were excluded due to extreme values, resulting in 175 dyads providing complete data. The three within-dyad Pearson correlations for marital problems, communication, and marital quality were as expected positive and large in magnitude, ranging from .50 to .57.

**Specification of the Model**

To illustrate the analysis of mediation, we set up the model as shown in Figure 2 with marital problems as independent variable (X), communication as mediator (M), and marital quality as final outcome variable (Y). This model assumes that the effect of marital problems on marital quality is partially mediated by communication. This assumption is in line with the stress model by Bodenmann (2000; see also Bodenmann et al., 2007), according to which stress influences relationship outcomes directly and indirectly through marital communication. We set up the model

![Figure 2](https://example.com/figure2.png)

*Figure 2. The Common Fate Mediation Model with standardized coefficients testing the association between marital problems, communication, and marital quality. MPI = Marital Problem Inventory; CPQ = Communication Patterns Questionnaire; QMI = Quality of Marriage Index. Percentages indicate explained variances. * p < .05. ** p < .01. *** p < .001.*
for distinguishable dyad members with covariance arcs between the error terms ($cov_1$ to $cov_6$) and with all factor loadings ($l_1$ to $l_6$) set to 1.

**Testing Mediation**

**Step 1: Selection of a good fitting CF mediation model.** To evaluate the goodness of fit of the model, we used the Chi-square statistic and the RMSEA with $RMSEA \leq .05$ indicating close fit (Browne & Cudeck, 1993; Hu & Bentler, 1999). Using the program Amos 6, the CFM indicating partial mediation was consistent with the data: $\chi^2(3) = 2.200, p = .532$; $RMSEA < .001$. All the reliabilities (proportion of explained variances) of the single measures were 50% or higher indicating that most of the variance in the indicators is due to the latent dyadic variables (see Figure 2).

**Step 2: Testing the direct effects.** Both direct effects $a$ and $b$ that constitute the indirect effect were significant (see Figure 2 and Table 1). Also significant was the direct effect $c$, which provides evidence that the mediation between marital problems and marital quality through communication is partial.

**Step 3: Testing the mediation effect.** To test the indirect effect between marital problems and marital quality, bootstrap analyses were conducted to estimate the confidence limits of the direct effects and the indirect effect on the basis of 5000 bootstrap samples. (The fit of the model was also good when using 5000 bootstrap samples, Bollen-Stine bootstrap $p^5 = .572$). The bias-corrected (and the percentile) bootstrapped confidence limits revealed a significant indirect effect $ab$ (Table 1).^6

**Interpretation**

The results support the assumption that the association between marital problems and marital quality is partially mediated by communication at the dyadic level. The mediation was partial because there was a significant direct effect between marital problems and marital quality that was of the same sign as the indirect effect. Using the parameter estimates given in Table 1, the relative proportion of the mediation effect on the total, which is the ratio of the indirect effect $ab$ to the total effect $ab + c$ (i.e., $-0.066/-0.154 \cdot 100\%$, was 30.2%. The finding that all error covariances, whose signs were consistent with the signs of the direct effects between the latent variables, were significant indicates that the manifest indicators measure something in common that is not represented by the respective latent variables. These significant associations may be due to individual response tendencies, such as social desirability, that can be observed when using self-report measures.

**Discussion**

The purpose of this article was to delineate a framework to estimate and test mediation in dyadic data at the level of the dyads for both distinguishable and indistinguishable dyad members. The Common Fate Model (CFM) presented here to assess mediation can be used if the observed variables represent dyadic constructs that exert influence on both partners (see Gonzalez & Griffin, 2002; Woody & Sadler, 2005), if the causal associations between the constructs should be analyzed at the dyadic level, and if the observed variables are reliable indicators of the latent variables (explained variances of 50% or higher).

A variable measured in both members of a dyad can be conceptualized as a latent dyadic variable in a CF measurement model when the underlying construct that is supposed to be measured reflects a characteristic of the dyadic relationship or an external influence that has an effect on both partners (e.g., relationship cohesion and harmony or quality of housing and the neighborhood). In relationship research, constructs, such as relationship quality, marital communication, or problems, can be considered as relationship characteristics that affect both partners when the items along with the instructions refer to the relationship between the partners and/or when both partners are addressed. If the measured variables represent personal variables (e.g., state trait variables, personal attitudes, individual skills, or behavior), which cannot be conceived of as common dyadic constructs, the Actor-Partner Interdependence Model (APIM) may be considered to assess mediation in dyads (see e.g., Kenny, 1996; Ledermann & Bodenmann, 2006). In contrast to this type of model, the CFM has generally more statistical power to detect substantial mediating effects than mediational models based on the APIM, because there is only one mediating effect in the CF mediation model with three latent common fate constructs, whereas there are eight such effects in the API mediation model with three mixed variable pairs.

To estimate and test mediation by means of the SEM framework, we proposed a three-step procedure. The first step is a selection of a reasonable model that is consistent with the empirical data. The second step comprises a test of the structural coefficients using the selected model. The third step is a test of the mediating effect by estimating the bootstrapped confidence limits.

The CFM is not limited to cross-sectional data but can be expanded to longitudinal designs. Using data with two or more repeated response measures, Cole and Maxwell (2003; Maxwell & Cole, 2007) provided details on how mediational effects could be estimated in individual data by means of SEM. The longitudinal model approach of these authors can be combined with the dyadic model presented here.

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5 The Bollen-Stine bootstrap $p$ (Bollen & Stine, 1992) is an adjusted $p$-value of the model chi-square statistic. If Bollen-Stine bootstrap $p < .05$, the model is rejected.

6 An alternative method for testing indirect effects is the $z$-statistic (see Fritz & MacKinnon, 2007; MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002). The $z$-statistic can be obtained by dividing the product $ab$ through its standard error (i.e., $z = ab/SE_{ab}$). An approximate standard error can be computed by Sobel’s (1982) widely used formula, i.e., $SE_{ab} = \sqrt{SE_a^2 + b^2SE_b^2}$. The result of this test, which works well in large samples (larger than the current sample) and which requires normal distributed data, led to the same conclusion as the bootstrapped confidence limits.
When measuring each manifest variable of the model shown in Figure 1 three times with a fixed time interval, we could set up an autoregressive CF mediation model with nine latent dyadic variables (i.e., \( X_1, X_2, X_3, M_1, M_2, M_3, Y_1, Y_2, Y_3 \), with numbers denoting the time measurement). By connecting the latent variables measuring the same construct by six paths representing the autoregressive effects (i.e., \( X_1 \) with \( X_2, X_2 \) with \( X_3 \), and likewise for \( M \) and \( Y \)) and the variable \( X_1 \) with \( M_2, X_2 \) with \( M_3, M_1 \) with \( Y_2, M_2 \) with \( Y_3 \) (all with a lag of 1 time unit), and \( X_1 \) with \( Y_3 \) (2 time units), we could estimate and test the direct effects and the indirect effect between \( X_1 \) (independent variable), \( M_2 \) (mediator), and \( Y_3 \) (outcome variable). These effects are of most interest because they reflect the mediation process. Models like this one that take into account autoregressive processes and time lags lead to more accurate estimates of the effects of interest (Maxwell & Cole, 2007).

The CFM may be modified in at least two ways. First, additional pairs of dyadic variables may be incorporated to set up a model with multiple latent mediators, which allows researchers to test more complicated mediation processes (for a discussion on multiple mediators see MacKinnon, 2008; Preacher & Hayes, 2008; Taylor, MacKinnon, & Tein, 2008). Second, the CFM can be combined with the APIM consisting of both latent dyadic variables and variables that do not represent dyadic influences (see Matthews et al., 1996). In particular, such a combination is especially interesting to study spillover effects of non-shared external influences that affect relationship characteristics, such as marital harmony, or to examine causal associations between personality traits and characteristics of the relationship.

The presented data-analytic model is based on several assumptions. First, the maximum likelihood estimation method requires a set of assumptions that includes multivariate normal distributed indicator variables and linear relations between the variables.

Second, the mediation model assumes that the direction of the causal associations is correct because statistical analysis alone (including SEM) cannot prove causality. This problem is further exacerbated by the fact that there are alternative models that are statistically equivalent with respect to the goodness of overall fit and thus not comparable among each other (Lee & Hershberger, 1990; MacCallum, Wegener, Uchino, & Fabrigar, 1993; Spirtes, Glymour, & Scheines, 1993). For the model estimated here, examples of statistically equivalent models are the model assuming that marital quality influences communication, which, in turn, influences marital problems, or the model including marital quality as mediator (marital quality → marital quality → communication). This concern is alleviated if theoretical considerations make alternative models implausible or if the time ordering of the variables excludes alternative models.

A third concern is the problem of omitted third variables. The structural part of the CF mediation model indicating partial mediation is saturated (just identified). Consequently, it cannot be determined whether unmeasured third variables cause statistical dependencies between the variables and thus preventing the consistent estimation of the structural coefficients. Implementing instrumental variables\(^7\) that affect the mediator but not the outcome variable could solve this problem (e.g., Pearl, 2000).

Despite these limitations, the CFM permits an efficient and focused evaluation of mediation processes in dyads if the variables measured in both partners represent dyadic constructs that can be expected to influence both partners, if the causal associations between the constructs should be analyzed at the level of the dyads, and if the variables measured in both partners are reliable indicators of the latent variables.

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\(^7\) An instrumental variable is a variable that (a) has an effect on the independent variable (e.g., \( X \) or \( M \)), that (b) has no direct effect on the outcome variable, that (c) is not associated with unmeasured causes of the outcome variable, and that (d) is not caused by the any variables in the model (James & Singh, 1978).

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### Table 1

<table>
<thead>
<tr>
<th>Estimator</th>
<th>Estimate</th>
<th>SE</th>
<th>( z )</th>
<th>95% CI</th>
<th>Bootstrapping (5000 samples)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( X \rightarrow M; = a )</td>
<td>(-0.187)</td>
<td>0.028</td>
<td>(-6.59^{**} )</td>
<td>(-0.242, -0.131)</td>
<td>0.041</td>
</tr>
<tr>
<td>( M \rightarrow Y; = b )</td>
<td>0.356</td>
<td>0.088</td>
<td>4.06^{**}</td>
<td>0.184, 0.528</td>
<td>0.111</td>
</tr>
<tr>
<td>( X \rightarrow Y; = c )</td>
<td>(-0.154)</td>
<td>0.028</td>
<td>(-5.54^{**} )</td>
<td>(-0.208, -0.099)</td>
<td>0.036</td>
</tr>
<tr>
<td>( X \rightarrow M \rightarrow Y; = ab )</td>
<td>(-0.066)</td>
<td>0.019</td>
<td>(-3.46^{**} )</td>
<td>(-0.104, -0.029)</td>
<td>0.025</td>
</tr>
</tbody>
</table>

Note. Estimates are unstandardized. \( X = \) Marital Problem Inventory (MPI); \( M = \) Communication Patterns Questionnaire (CPQ); \( Y = \) Quality of Marriage Index (QMI); \( SE = \) standard error; \( M = \) mean; \( CI = \) confidence interval; \( BC = \) bias-corrected. The formula used to compute \( z \) of the mediation effect is \( ab/SE_{ab} \). The formula used to compute normal 95% CI is estimate \( \pm 1.96 \) SE.

\(^{**} p < .001\).
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