

# Assessing Mediation in Dyadic Data Using the Actor-Partner Interdependence Model

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The assessment of mediation in dyadic data is an important issue if researchers are to test process models. Using an extended version of the actor–partner interdependence model the estimation and testing of mediation is complex, especially when dyad members are distinguishable (e.g., heterosexual couples). We show how the complexity of the model can be reduced by assuming specific dyadic patterns. Using structural equation modeling, we demonstrate how specific mediating effects and contrasts among effects can be tested by phantom models that permit point and bootstrap interval estimates. We illustrate the assessment of mediation and the strategies to simplify the model using data from heterosexual couples.

**Keywords:** mediation, dyadic data, APIM, phantom models, bootstrapping

Models of mediation are common and of great importance, as they can provide information about causal relationships between variables that are mediated by one or more sets of intervening variables. Mediation refers to a mechanism through which an initial ( $X$ ) influences an outcome ( $Y$ ) by a third variable ( $M$ ), termed *mediator* or *intervening* variable (Baron & Kenny, 1986; Judd & Kenny, 1981). In this mediation model, the effect from  $X$  to  $M$  is commonly designated as  $a$ , the effect from  $M$  on  $Y$  as  $b$ , and the effect from  $X$  on  $Y$  as  $c'$  (MacKinnon, 2008). The mediating or indirect effect (IE) of  $X$  on  $Y$  equals  $ab$  and the total effect equals  $ab + c'$ .

Over the last decade, researchers have begun to examine mediating mechanisms in dyadic data. The most commonly used model for this purpose is the actor–partner interdependence

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model (APIM; Kenny, 1996; Kenny & Cook, 1999). This model allows a researcher to study the impact of a person's causal variable on his or her own outcome variable (actor effect) and on the outcome variable of the partner (partner effect). Extending this standard APIM by a third variable pair we get the actor-partner interdependence mediation model or APIMeM (Ledermann & Bodenmann, 2006). The APIMeM with three pairs of variables,  $X$ ,  $Y$ , and  $M$  for two members, has been used in several studies. For example, studying heterosexual couples, Riggs, Cusimano, and Benson (2011) found that one's own attachment anxiety mediated the effect of one's own childhood emotional abuse on both one's own and the partner's dyadic adjustment. Campbell, Simpson, Kashy, and Fletcher (2001) reported that in couples the effect of one's own warmth and trustworthiness on his or her relationship quality is mediated by both the own and the partner's ideal-partner matching. Ledermann, Bodenmann, Rudaz, and Bradbury (2010) showed that the effect of one's own external stress on both one's own and the partner's marital quality was mediated by one's own relationship stress.

An important issue in dyadic research in general and in using the APIM in particular is whether dyad members are distinguishable or indistinguishable (Kenny, Kashy, & Cook, 2006). The two dyad members are distinguishable if they can be assigned to two different groups for substantive reasons. Examples of distinguishable dyad members are husband and wife or father and child. Homosexual couples and same-sex twins are instances of indistinguishable dyad members.

In this article, we address conceptual, statistical, and strategic issues in the assessment of mediation in dyadic data using the APIMeM. We shall see that mediation in this model is complex and that special procedures can be beneficial to deal with this complexity. We begin with a description of the APIMeM and the different effects that can potentially be estimated in this model. We then discuss how the APIMeM can be simplified and show how different mediating effects and contrasts among effects can be assessed by calculating bootstrap intervals using structural equation modeling (SEM) techniques. Finally, we illustrate the assessment of mediation using data from heterosexual couples.

## THE APIMeM

The basic version of an APIMeM enabling the assessment of mediation in dyadic data is given in Figure 1. It consists of three pairs of measured variables (represented by rectangles) and two pairs of error terms (represented by circles). The  $X$  variables represent the initial variables, the  $M$  variables represent the mediators, and the  $Y$  variables the outcomes. The two persons are designated 1 and 2 and might be husband and wife or twin 1 and 2. The model consists of six actor (horizontal) and six partner (diagonal) effects indexed by  $A$  and  $P$ , respectively. The double-headed arrows represent covariances. The covariances between the error terms of the mediators and of the outcome variables indicate that the residuals covary between dyad members due to unmeasured common causes.

### Illustrative Example

To illustrate the APIMeM, we use data from the 500 Family Study (1998–2000 in the United States) conducted by Schneider and Waite (2008). The purpose of this study was to investigate

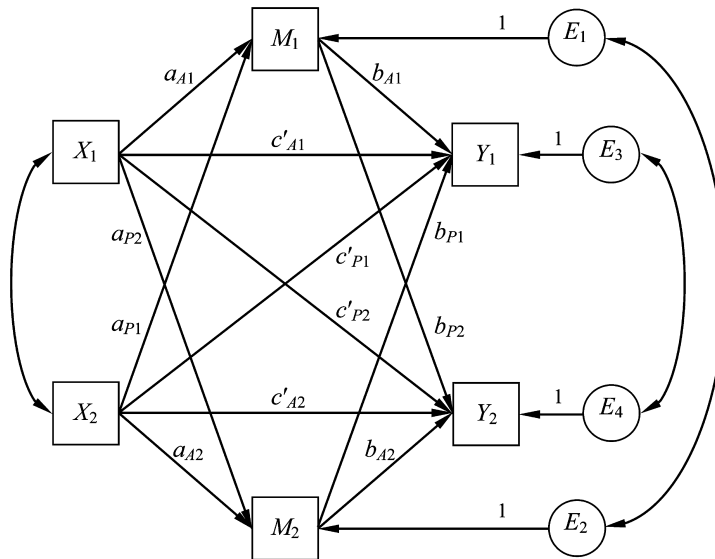


FIGURE 1 The actor-partner interdependence mediation model.

middle-class, dual-career families living in the United States. For our illustration, we used data from 319 heterosexual couples (husbands and wives) who provided complete data on the variables of interest. We used feeling of cannot cope with everything ( $X$ ) to predict marital satisfaction ( $Y$ ) through depressive symptoms ( $M$ ). The cannot-cope measure could range from 0 (*never*) to 4 (*very often*), the measure of depressive symptoms measured by the Center for Epidemiologic Studies Depression (CES-D; Radloff, 1977) could range from 0 to 60 with higher scores indicating more depressive symptoms, and the marital satisfaction scale (15 items of the ENRICH marital inventory; Olson, Fournier, & Druckman, 1983) could range from 15 to 50. Note, the standardized direct effects reported here are obtained by standardizing each variable in our data set prior to the analysis using the mean and standard deviation calculated across both husbands and wives (see Kenny et al., 2006, p. 179).

### Distinguishable Members

The standard APIMeM for distinguishable dyad members is a saturated model that has 27 free parameters: six actor and six partner effects, one mean and one variance for each initial variable, one intercept for each mediator and outcome, one variance for each error term, one covariance between the initial variable, one covariance between the mediators' error terms, and one between the outcomes' error terms. To distinguish the partner effects in the APIMeM, we label those effects by referring to the dyad member of the explained variable. So, the effect from husband  $X$  to wife  $M$  is the wife partner effect and the effect from wife  $X$  to husband  $M$  is the husband partner effect.

The estimates of the unconstrained APIMeM for the example are presented in Table 1 (with index 1 indicating husband and 2 indicating wife). For the *a* effects, both actor effects are positive and statistically significant and both partner effects are not significant. The four *b* effects are all negative and statistically significant. For the four *c'* effects, both actor effects are negative and statistically significant, whereas the partner effects are not statistically significant.

In the APIMeM, there are four effects between *X* and *Y* that potentially can be mediated, which are the *XY* husband actor effect ( $X_1 \rightarrow Y_1$ ), the *XY* wife actor effect ( $X_2 \rightarrow Y_2$ ), the *XY* husband partner effect ( $X_2 \rightarrow Y_1$ ), and the *XY* wife partner effect ( $X_1 \rightarrow Y_2$ ). Each of these *XY* effects has two different simple IEs resulting in a total of eight simple IEs. We refer to each simple IE by whether the *a* and *b* effects are actor or partner effects. For instance, the husband actor–actor effect refers to the effect  $X_1 \rightarrow M_1 \rightarrow Y_1$  or  $a_{A1}b_{A1}$ . As the *Y* variable refers to husbands, we call it a husband effect. Each *XY* actor effect has an actor–actor and a partner–partner simple IE. So, the *XY* actor effect, which some considered as not dyadic, can be mediated through the partner’s mediator or  $X_1 \rightarrow M_2 \rightarrow Y_1$  and  $X_2 \rightarrow M_1 \rightarrow Y_2$ . The *XY* partner effects for both husband and wife are mediated by an actor–partner and a partner–actor effect. In the APIMeM, the sum of two IEs for a given *XY* effect is the total IE. The sum of the total IE and the corresponding direct *c'* gives the total effect. These different theoretical effects are presented in Table 2.

In the APIMeM, each direct effect that is part of a simple IE is involved in two simple IEs. For example,  $a_{A1}$  is involved in  $a_{A1}b_{A1}$  and  $a_{A1}b_{P2}$ . As a consequence, the eight IEs are not independent. For instance, if the husband actor–actor IE,  $a_{A1}b_{A1}$ , is zero, then either  $a_{A1}$  or  $b_{A1}$  must be zero, which then implies that either the wife actor–partner,  $a_{A1}b_{P2}$ , or the husband partner–actor IE,  $a_{P1}b_{A1}$ , is zero or that both are zero. More specifically, there are

TABLE 1  
Effect Estimates for the Example Data Set Treating Dyad Members  
as Distinguishable

<i>Effect</i>	<i>Estimate</i>	<i>SE</i>	<i>p</i>	<i>Standard Estimate</i>
<i>a</i> effects ( $X \rightarrow M$ )				
Husband actor effect ( $a_{A1}$ )	3.651	0.392	<.001	.486
Wife actor effect ( $a_{A2}$ )	3.421	0.378	<.001	.455
Husband partner effect ( $a_{P1}$ )	0.368	0.387	.342	.049
Wife partner effect ( $a_{P2}$ )	0.070	0.383	.854	.009
<i>b</i> effects ( $M \rightarrow Y$ )				
Husband actor effect ( $b_{A1}$ )	−0.360	0.052	<.001	−.355
Wife actor effect ( $b_{A2}$ )	−0.319	0.057	<.001	−.315
Husband partner effect ( $b_{P1}$ )	−0.171	0.053	.001	−.169
Wife partner effect ( $b_{P2}$ )	−0.284	0.056	<.001	−.280
<i>c'</i> effects ( $X \rightarrow Y$ )				
Husband actor effect ( $c'_{A1}$ )	−0.842	0.412	.041	−.111
Wife actor effect ( $c'_{A2}$ )	−0.913	0.434	.035	−.120
Husband partner effect ( $c'_{P1}$ )	−0.437	0.404	.280	−.057
Wife partner effect ( $c'_{P2}$ )	−0.221	0.442	.616	−.029

*Note.* *X* = cannot cope with everything; *M* = depressive symptoms; *Y* = marital satisfaction; 1 = husband, 2 = wife; *SE* = standard error.

TABLE 2  
The Total Effects, Total Indirect Effects, Simple Indirect Effects, and Direct Effects  $c'$   
in the APIMeM for Distinguishable Dyad Members

<i>Effect</i>	<i>Coefficient</i>	<i>Label</i>
Husband actor effect		
Total effect	$a_{A1}b_{A1} + a_{P2}b_{P1} + c'_{A1}$	Husband actor total effect
Total IE	$a_{A1}b_{A1} + a_{P2}b_{P1}$	Husband actor total IE
Actor–actor simple IE	$a_{A1}b_{A1}$	Husband actor–actor IE
Partner–partner simple IE	$a_{P2}b_{P1}$	Husband partner–partner IE
Direct effect $c'$	$c'_{A1}$	Husband actor direct effect
Wife actor effect		
Total effect	$a_{A2}b_{A2} + a_{P1}b_{P2} + c'_{A2}$	Wife actor total effect
Total indirect effect	$a_{A2}b_{A2} + a_{P1}b_{P2}$	Wife actor total IE
Actor–actor simple IE	$a_{A2}b_{A2}$	Wife actor–actor IE
Partner–partner simple IE	$a_{P1}b_{P2}$	Wife partner–partner IE
Direct effect $c'$	$c'_{A2}$	Wife actor direct effect
Husband partner effect		
Total effect	$a_{A2}b_{P1} + a_{P1}b_{A1} + c'_{P1}$	Husband partner total effect
Total IE	$a_{A2}b_{P1} + a_{P1}b_{A1}$	Husband partner total IE
Actor–partner simple IE	$a_{A2}b_{P1}$	Husband actor–partner IE
Partner–actor simple IE	$a_{P1}b_{A1}$	Husband partner–actor IE
Direct effect $c'$	$c'_{P1}$	Husband partner direct effect
Wife partner effect		
Total effect	$a_{A1}b_{P2} + a_{P2}b_{A2} + c'_{P2}$	Wife partner total effect
Total IE	$a_{A1}b_{P2} + a_{P2}b_{A2}$	Wife partner total IE
Actor–partner simple IE	$a_{A1}b_{P2}$	Wife actor–partner IE
Partner–actor simple IE	$a_{P2}b_{A2}$	Wife partner–actor IE
Direct effect $c'$	$c'_{P2}$	Wife partner direct effect

*Note.* IE = indirect effect; 1 = husband, 2 = wife.

two constraints on the eight IEs, which are:

$$(a_{A1}b_{A1})(a_{P1}b_{P2}) - (a_{P1}b_{A1})(a_{A1}b_{P2}) = 0 \quad (1)$$

and

$$(a_{A2}b_{A2})(a_{P2}b_{P1}) - (a_{P2}b_{A2})(a_{A2}b_{P1}) = 0. \quad (2)$$

These equations state that if we know three particular IEs, we know a fourth IE. These constraints need to be taken into consideration, as we discuss later, when simplifying the model.

### Indistinguishable Members

As we have previously discussed, sometimes there is not a variable like gender to distinguish dyad members and the dyad members are said to be *indistinguishable*. The APIMeM for indistinguishable dyad members within SEM requires 12 equality constraints: six for the effects, one for mean, two for intercepts, and three for variances. Additionally, there are adjustments that need to be made on fit statistics (Olsen & Kenny, 2006).

Alternatively, one might have theoretically distinguishable dyad members, but the actor and partner effects do not vary by the distinguishing variable. Thus, if effects are theoretically indistinguishable, one can create the following set of constraints:  $a_{A1} = a_{A2}$ ,  $b_{A1} = b_{A2}$ ,  $c'_{A1} = c'_{A2}$ ,  $a_{P1} = a_{P2}$ ,  $b_{P1} = b_{P2}$ , and  $c'_{P1} = c'_{P2}$ . One could test these six constraints individually or by an omnibus test. If the constraints hold, we would say the direct effects are empirically indistinguishable. Testing the six constraints individually, partial indistinguishability can occur (i.e., the equality constraints hold for some out of the six effects).

Using the APIM, we can define three types of empirical indistinguishability. The first is the earlier discussed model with equality constraints on the direct effects. The second type is a model with equality constraints on the direct effects and on the variances. The third type is a model with equality constraints on the means and intercepts in addition to the previous constraints. This third model allows one to test whether dyad members are empirically distinguishable, as opposed to theoretically indistinguishable.

Testing for indistinguishability of the direct effects for the sample data, none of the six husband and wife effects were significantly different when tested individually:  $a_{A1}$  and  $a_{A2}$ ,  $\chi^2(1) = 0.070$ ,  $p = .792$ ;  $a_{P1}$  and  $a_{P2}$ ,  $\chi^2(1) = 0.003$ ,  $p = .959$ ;  $b_{A1}$  and  $b_{A2}$ ,  $\chi^2(1) = 0.130$ ,  $p = .719$ ;  $b_{P1}$  and  $b_{P2}$ ,  $\chi^2(1) = 1.149$ ,  $p = .284$ ;  $c'_{A1}$  and  $c'_{A2}$ ,  $\chi^2(1) = 1.244$ ,  $p = .265$ ;  $c'_{P1}$  and  $c'_{P2}$ ,  $\chi^2(1) = 2.146$ ,  $p = .143$ . Not surprisingly, the model incorporating these six equality constraints provides an excellent fit,  $\chi^2(6) = 4.284$ ,  $p = .638$ . Thus, we can use this more parsimonious model with empirically indistinguishable  $a$ ,  $b$ , and  $c'$  effects. Note here that we do not test the second and third type of indistinguishability with equality constraints on the variances and means and intercepts because those constraints do not have an effect on the number of unstandardized effects in an APIM.

The effect estimates of the simplified model are presented in Table 3. We see that for  $a$ , only the actor effect is statistically significant. However, for  $b$  both the actor and partner effects were statistically significant, and for  $c'$ , again, only the actor effect is statistically significant.

Setting up the APIMeM for indistinguishable members, there are three actor and three partner effects to be estimated that imply just two direct effects from  $X$  to  $Y$ : one actor and

TABLE 3  
Effect Estimates for the Example Data Set Setting the Direct Effects  
Equal across Dyad Members

Effect	Estimate	SE	p	Standard Estimate
<i>a</i> effects ( $X \rightarrow M$ )				
Actor effect	3.532	0.272	<.001	.470
Partner effect	0.218	0.272	.424	.029
<i>b</i> effects ( $M \rightarrow Y$ )				
Actor effect	-0.339	0.039	<.001	-.335
Partner effect	-0.225	0.039	<.001	-.222
<i>c'</i> effects ( $X \rightarrow Y$ )				
Actor effect	-0.888	0.295	.003	-.117
Partner effect	-0.340	0.295	.248	-.045

Note.  $X$  = cannot cope with everything;  $M$  = depressive symptoms;  $Y$  = marital satisfaction;  $SE$  = standard error.

TABLE 4  
The Total Effects, Indirect Effects, Total Indirect Effects, and Direct Effects  
in the APIMeM for Indistinguishable Dyad Members

<i>Effect</i>	<i>Coefficient</i>	<i>Label</i>
Actor effect		
Total effect	$a_A b_A + a_P b_P + c'_A$	Actor total effect
Total IE	$a_A b_A + a_P b_P$	Actor total IE
Actor–actor simple IE	$a_A b_A$	Actor–actor IE
Partner–partner simple IE	$a_P b_P$	Partner–partner IE
Direct effect	$c'_A$	Actor direct effect
Partner effect		
Total effect	$a_A b_P + a_P b_A + c'_P$	Partner total effect
Total IE	$a_A b_P + a_P b_A$	Partner total IE
Actor–partner simple IE	$a_A b_P$	Actor–partner IE
Partner–actor simple IE	$a_P b_A$	Partner–actor IE
Direct effect	$c'_P$	Partner direct effect

*Note.*  $A$  = actor effect;  $P$  = partner effect; IE = indirect effect;  $SE$  = standard error.

one partner effect. These two effects can be mediated by four simple IEs and two total IEs (see Table 4). Two IEs mediate the  $XY$  actor effect (i.e., the actor–actor and partner–partner IE), and two others mediate the partner  $XY$  effect (i.e., actor–partner and partner–actor IE).

As with the model for distinguishable members, the four IEs are not independent of each other. The constraint on the four IEs in the indistinguishable case is

$$(a_A b_A)(a_P b_P) - (a_P b_A)(a_A b_P) = 0. \quad (3)$$

Again, this fact needs to be considered when simplifying the model.

## ASSESSING MEDIATION

In a mediation model, the effect of an initial variable on an outcome variable can be partially, completely, or inconsistently mediated. Partial mediation occurs when the IE and the corresponding direct effect  $c'$  are of the same sign. Complete mediation occurs when the IE is nonzero and the direct effect  $c'$  is zero. Inconsistent mediation (sometimes called suppression) occurs when the IE and the direct effect  $c'$  are nonzero but have opposite signs (Maassen & Bakker, 2001; MacKinnon, Krull, & Lockwood, 2000).

To assess mediation and to test whether partial, complete, or inconsistent mediation occurs, the estimation and testing of all direct effects and all IEs has been recommended (Ledermann & Macho, 2009). In addition, one might wish to compare the magnitude of specific effects. For instance, a researcher might want to know if a given simple IE is greater than the corresponding direct effect. Moreover, because each effect is mediated by two IEs, it might be of interest to know if these two are different from each other. Also in models with two or more mediators, a researcher might wish to know whether one IE is larger than another. In the APIMeM, each IE can be compared with the corresponding direct effect  $c'$  and contrasts can potentially be tested among the IEs and the total effects.

Because IEs have nonnormal distributions even if the direct effects are normally distributed, the bootstrap method has been advocated for assessing both IEs (e.g., MacKinnon, Lockwood, & Williams, 2004; Preacher & Hayes, 2008) and contrasts among effects (Williams & MacKinnon, 2008). Some popular SEM programs, including Amos (Arbuckle, 1995–2009) and EQS (Bentler, 2006), are limited in testing IEs as the built-in procedure permits point and interval estimates of the direct effects, the total IEs, and the total effects in a given model, but not of specific IEs that are part of a total IE (e.g.,  $a_{A1}b_{A1}$  in model of Figure 1). Specific IEs that are part of a total IE as well as contrasts among effects can be tested by means of phantom models (Macho & Ledermann, 2011) that permit both point and interval estimates. The programs *Mplus* (Muthén & Muthén, 1998–2010), *OpenMx* (Boker et al., 2011), and *LISREL* (Jöreskog & Sörbom, 2006) have built-in routines enabling the estimation of specific effects and contrasts (see Cheung, 2007).

In complex models like the APIMeM, a phantom model can be built for each specific hypothesis whose testing is otherwise prevented by the capability of certain software packages such as Amos (see Macho & Ledermann, 2011, for guidance on how to build phantom models). Figure 2 presents six different examples of phantom models to test various hypotheses about IEs: Model 2A enables the assessing of the actor–actor IE  $a_{A1}b_{A1}$ ; Model 2B provides estimates for the difference between the actor–actor IE  $a_{A1}b_{A1}$  and the direct effect of  $c'_{A1}$ ; Model 2C tests whether the actor IE  $a_{A1}b_{A1} + a_{P2}b_{P1}$  differs from the direct effect of  $c'_{A1}$ ; Model 2D compares the husband actor–actor IE  $a_{A1}b_{A1}$  with the wife actor–actor IE  $a_{A2}b_{A2}$ ; Model 2E compares the husband actor IE  $a_{A1}b_{A1} + a_{P2}b_{P1}$  with the wife actor IE or  $a_{A2}b_{A2} + a_{P1}b_{P2}$ ; and finally, Model 2F compares the husband actor total effect  $a_{A1}b_{A1} + a_{P2}b_{P1} + c'_{A1}$  with the wife actor total effect of  $a_{A2}b_{A2} + a_{P1}b_{P2} + c'_{A2}$ .

To identify a phantom model, each path coefficient in the phantom model is set equal to the coefficient of the corresponding path in the main model (e.g.,  $a_{A1}$  in Model 2A is equated to  $a_{A1}$  in Model 1A) or to  $-1$ . In addition, the variance of the initial phantom variable  $P_{in}$  is set to 1. To obtain the point estimate of a specific effect or a contrast represented by a phantom model, the total effect is estimated between  $P_{in}$  and  $P_{out}$ . To test a specific effect, the bootstrap confidence interval (CI) of the phantom model's total effect is calculated. If the interval does not include zero, the effect is considered to be statistically significant.

### Measuring and Testing Mediation in the Example Data

To determine whether an IE or a total effect is statistically significant, we use the bias-corrected bootstrap 95% CI for the unstandardized effects. The bootstrap estimates presented here are based on 5,000 bootstrap samples.

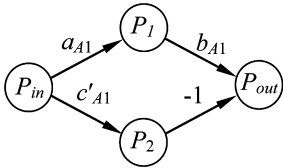
Table 5 presents the total effects, total IEs, simple IEs, and direct effects for the APIMeM specified for distinguishable dyad members. For both husband and wife, we find that all IEs involving one of the  $a$  partner effects are weak and not statistically significant, whereas all IEs involving one of the  $a$  actor effects were statistically significant. That is, four of the eight simple IEs are statistically significant. In addition, all four total effects and total IEs are significant. We see that for husband and wife the actor–actor IEs are about 60% and 50%, respectively, of the actor total effects, and the actor–partner IEs are about 50% and 81% of the partner total effects. We note that none of the  $c'$  effects is significant when using bootstrapping.



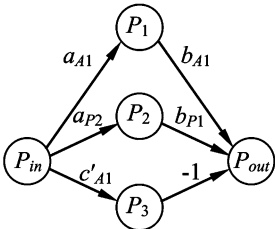
Model A



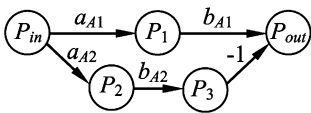
Model B



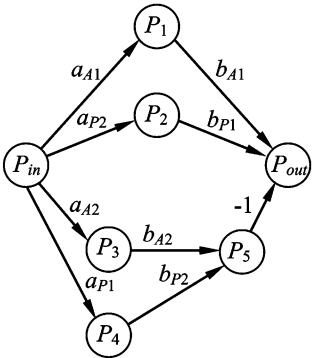
Model C



Model D



Model E



Model F

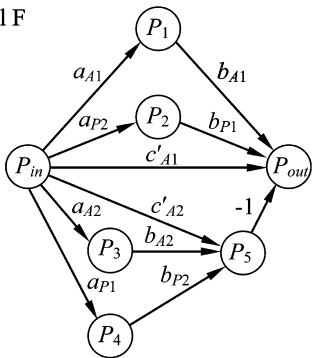


FIGURE 2 Phantom models for assessing indirect effects. Model A: Simple indirect effect  $a_{A1}b_{A1}$ . Model B: Contrast  $a_{A1}b_{A1} - c'_{A1}$ . Model C: Contrast  $a_{A2}b_{A2} + a_{P2}b_{P1} - c'_{A1}$ . Model D: Contrast  $a_{A1}b_{A1} - a_{A2}b_{A2}$ . Model E: Contrast  $a_{A1}b_{A1} + a_{P2}b_{P1} - (a_{A2}b_{A2} + a_{P1}b_{P2})$ . Model F: Contrast  $a_{A1}b_{A1} + a_{P2}b_{P1} + c'_{A1} - (a_{A2}b_{A2} + a_{P1}b_{P2} + c'_{A2})$ .

Table 6 presents the estimates for the total, total IE, simple IE, and direct effects  $c'$  for the simplified model with indistinguishable direct effects. As in the model for distinguishable members, the actor-actor IE and actor-partner IE are statistically significant, whereas the two IEs involving the  $a$  partner effect are not. The significant IEs are 55% and 65%, respectively, of the total effect. In the remainder of the article, we discuss ways in which we can simplify the testing of the APIMeM.

### SIMPLIFYING THE APIMeM

The complexity of the unrestricted APIMeM, especially in the distinguishable case, could act as a deterrent to the use of the APIM for assessing mediation in dyadic data. To overcome

TABLE 5  
The Total Effects, Total Indirect Effects, Simple Indirect Effects, and  
Direct Effects  $c'$  for the Example Data Set Treating Dyad Members  
as Distinguishable

<i>Effect</i>	<i>Estimate</i>	<i>95% CI</i>	<i>Proportion of the Total Effect (multiplied by 100)</i>
Husband actor effect			
Total effect	−2.169	−2.873, −1.394	
Total IE	−1.327	−1.902, −0.857	61.2
Actor–actor IE	−1.315	−1.858, −0.867	60.6
Partner–partner IE	−0.012	−0.142, 0.122	0.9
Direct effect $c'$	−0.842	−1.681, 0.066	38.8
Wife actor effect			
Total effect	−2.108	−3.004, −1.173	
Total IE	−1.196	−1.771, −0.734	56.7
Actor–actor IE	−1.091	−1.629, −0.677	51.8
Partner–partner IE	−0.104	−0.404, 0.114	8.7
Direct effect $c'$	−0.913	−1.861, 0.036	43.3
Husband partner effect			
Total effect	−1.154	−1.912, −0.375	
Total IE	−0.717	−1.244, −0.245	62.1
Actor–partner IE	−0.585	−1.007, −0.221	50.7
Partner–actor IE	−0.132	−0.456, 0.165	18.5
Direct effect $c'$	−0.437	−1.261, 0.388	37.9
Wife partner effect			
Total effect	−1.280	−2.113, −0.444	
Total IE	−1.059	−1.636, −0.540	82.7
Actor–partner IE	−1.037	−1.557, −0.607	81.0
Partner–actor IE	−0.022		2.1
Direct effect $c'$	−0.221	−1.034, 0.660	17.3

*Note.* IE = indirect effect; CI = confidence interval.

this obstacle, the APIMeM can be simplified. For distinguishable members there are two ways, where the second one also applies for indistinguishable members.

Indistinguishability

A first simplification for models with theoretically distinguishable dyads is a model that suggests partial or complete indistinguishable pairwise effects. For complete indistinguishability, we impose constraints on all direct effects; that is,  $a_{A1} = a_{A2}$ ,  $b_{A1} = b_{A2}$ ,  $c'_{A1} = c'_{A2}$ ,  $a_{P1} = a_{P2}$ ,  $b_{P1} = b_{P2}$ , and  $c'_{P1} = c'_{P2}$ . Alternatively, equality constraints could be imposed on the (simple) IEs. For instance, we might assume that the pairwise IEs do not vary by the distinguishing variable; that is,  $a_{A1}b_{A1} = a_{A2}b_{A2}$ ,  $a_{P2}b_{P1} = a_{P1}b_{P2}$ ,  $a_{A1}b_{P2} = a_{A2}b_{P1}$ , and  $a_{P2}b_{A2} = a_{P1}b_{A1}$ . However, we have seen that the IEs are not independent of each other. Given Equation 1 and 2, these four constraints are really just three independent constraints. Also, if we constrain all eight IEs to be the same in a model for distinguishable dyad members, the  $df$  would increase by five. (This type of constraint can be directly imposed in programs like

TABLE 6  
The Total Effects, Indirect Effects, Total Indirect Effects, and Direct Effects  
in the APIMeM for the Example Data Set Setting the Direct Effects Equal  
across Dyad Members

<i>Effect</i>	<i>Estimate</i>	<i>95% CI</i>	<i>Proportion of the Total Effect (multiplied by 100)</i>
<b>Actor effect</b>			
Total effect	−2.135	−2.678, −1.556	
Total IE	−1.247	−1.628, −0.944	58.4
Actor–actor IE	−1.198	−1.560, −0.893	56.1
Partner–partner IE	−0.049	−0.192, 0.067	3.9
Direct effect	−0.888	−1.522, −0.244	41.6
<b>Partner effect</b>			
Total effect	−1.208	−1.766, −0.683	
Total IE	−0.868	−1.250, −0.545	71.8
Actor–partner IE	−0.794	−1.117, −0.507	65.7
Partner–actor IE	−0.074	−0.264, 0.108	8.5
Direct effect	−0.340	−0.936, 0.261	28.2

*Note.* IE = indirect effect; CI = confidence interval.

*Mplus*, OpenMx, or LISREL.) Thus, any equality constraints on these effects need to satisfy conditions in Equations 1, 2, and 3.

### Dyadic Patterns

A second and more conceptually motivated simplification is a model implying one or more dyadic patterns. Kenny and Ledermann (2010; see also Kenny & Cook, 1999) provide details for testing four specific patterns in the APIM: the actor-only, the couple, the contrast, and the partner-only pattern. The actor-only pattern is indicated if the actor affect is nonzero and the partner effect is zero. The couple pattern occurs if both the actor and the partner effects are nonzero and equal in magnitude. The contrast pattern takes place if the actor and partner effects are nonzero and equal in magnitude but of different signs. The partner-only pattern occurs if the partner effect is nonzero and the actor effect is zero.

These different patterns can be estimated and tested using the parameter  $k$ . For the first three patterns,  $k$  is defined as the partner effect divided by the corresponding actor effect. Thus, the actor-only pattern is indicated if  $k$  is 0, the couple pattern is supported if  $k$  is 1, and the contrast pattern occurs if  $k$  is  $-1$ . For the partner-only pattern,  $k$  is defined as the actor effect divided by the partner effect with  $k$  equal to 0.

To test statistically the occurrence of these patterns, Kenny and Ledermann (2010) recommend the computation of a bootstrap CI for  $k$ . These CIs provide direct information on whether a specific pattern takes place: Defining  $k$  as the partner–actor ratio, the actor-only pattern is verified when 0 but not 1 and  $-1$  is in the CI, the couple pattern is supported when 1 but not 0 is in the interval, and the contrast pattern is verified when  $-1$  but not 0 is in the interval. Having tested for dyadic patterns, all  $k$ s that support a specific pattern are fixed to 0 (actor-only or partner-only pattern), to 1 (couple pattern), or to  $-1$  (contrast pattern). Then we reestimate this

simpler model and compare it to the more general model implying no specific pattern. If this comparison favors the more parsimonious model (e.g., the difference of the two chi-squares is not significant), we proceed with this simpler model. As the partner-only pattern is expected to be relatively rare, the focus here is on the  $k$  defined as the partner-actor ratio.

For the indistinguishable APIMeM, there are three  $k$ s: one for the  $a$  effects or  $k_a = a_P/a_A$ , one for the  $b$  effects or  $k_b = b_P/b_A$ , and one for the  $c'$  effects or  $k_{c'} = c'_P/c'_A$ . We can express the three IEs involving one or two partner effects in terms of these  $k$ s and the actor-actor IE of  $a_A b_A$ :

Partner-partner IE:  $a_A b_A k_a k_b$

Actor-partner IE:  $a_A b_A k_b$

Partner-actor IE:  $a_A b_A k_a$

Note that the constraint on the IEs given by Equation 3 is clear when we express the IEs in terms of  $k$ s. We can then describe the mediational structure using the pair of  $k$ s. For instance,  $\{1, 1\}$  mediation implies that both  $k$ s are 1 and that actor and partner effects for both  $a$  and  $b$  are equal. A  $\{0, -1\}$  pattern would imply zero partner effect for the  $a$  path and a contrast pattern for the  $b$  path, the actor and partner effects being equal but of opposite sign. Thus, the use of  $k$  provides a concise way of describing mediational effects. As an example, both Riggs et al. (2011) and Ledermann et al. (2010) appear to have a  $\{0, 1\}$  pattern, whereas Schröder-Abé and Schütz (2011) have  $\{1, 1\}$  mediation. Going beyond the four standard patterns, a researcher might find a  $\{0.5, 0.25\}$  mediation pattern (Campbell et al., 2001).

With distinguishable members, there are six  $k$ s (two for the  $a$  effects, two for the  $b$  effects, and two for  $c'$  effects) and each  $k$  can either be defined in terms of the exogenous (independent) or the endogenous (dependent) variable (Kenny & Ledermann, 2010). Parameter  $k$  defined with respect to the endogenous variable involves two exogenous variables affecting one endogenous variable. For example, for  $X_1$  and  $X_2$  affecting  $M_1$ ,  $k$  is  $a_{P1}/a_{A1}$ . This conception enables a researcher to test whether an endogenous variable is more affected by the actor's or the partner's exogenous variable. In contrast,  $k$  defined with respect to the exogenous variable involves one exogenous variable that affects two endogenous variables. For  $X_1$  affecting both  $M_1$  and  $M_2$ ,  $k$  is  $a_{P2}/a_{A1}$ . This conception is used to test whether a predictor has a stronger effect on the actor's or on the partner's endogenous variable. In both cases,  $k$  can be directly estimated by using phantom variables for programs that do not allow nonlinear constraints (e.g., Amos).

Figure 3 shows the APIMeM with six phantom variables enabling point and interval estimates of the  $k$ s (dashed arrows). To identify the model, constraints need to be placed on the parameters. With indistinguishable dyad members, the partner effects are set equal to the corresponding actor effects (i.e.,  $a_P = a_A$ ,  $b_P = b_A$ ,  $c'_P = c'_A$ ). In the distinguishable case, the constraints depend on whether  $k$  is defined with respect to the exogenous or endogenous variables. For  $k$  defined with respect to the endogenous variables, the constraints are  $a_{P1} = a_{A1}$ ,  $a_{P2} = a_{A2}$ ,  $b_{P1} = b_{A1}$ ,  $b_{P2} = b_{A2}$ ,  $c'_{P1} = c'_{A1}$ ,  $c'_{P2} = c'_{A2}$ . Defining  $k$  with respect to the exogenous variables, the constraints are  $a_{P1} = a_{A2}$ ,  $a_{P2} = a_{A1}$ ,  $b_{P1} = b_{A2}$ ,  $b_{P2} = b_{A1}$ ,  $c'_{P1} = c'_{A2}$ ,  $c'_{P2} = c'_{A1}$ . In simplifying the APIMeM and reducing the number of IEs and total effects of key importance is  $k_a$  and  $k_b$ .

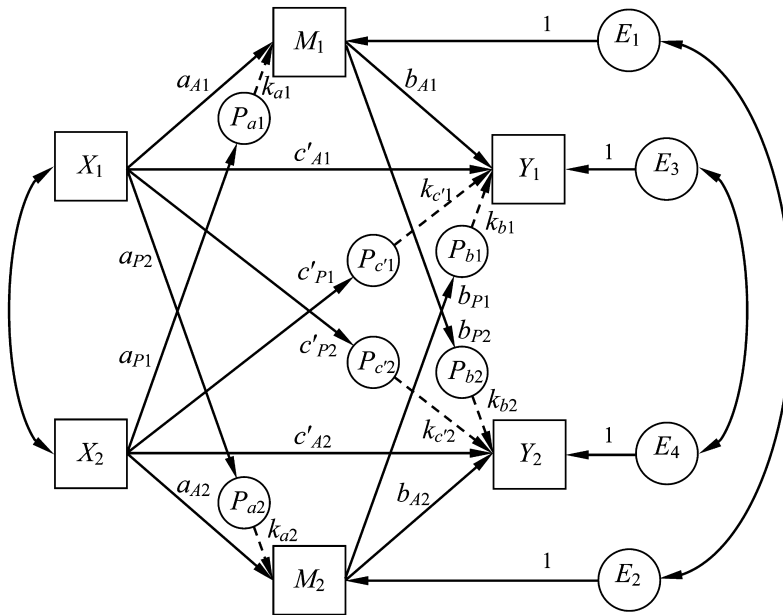


FIGURE 3 The actor-partner interdependence mediation model permitting estimates of  $k$ .

### Recommended Strategy

Kenny and Ledermann (2010) outlined a procedure to simplify the standard APIM that can be adapted for the APIMeM. With distinguishable dyad members, the procedure for the APIMeM consists of six steps. First, we estimate the saturated distinguishable model and test all the effects. Second, we test for indistinguishability of the direct effects and specify a simpler model with those effects constrained to equality for which the indistinguishability assumption is justified. Third, we estimate the  $k$ s and their CIs. Fourth, if for the  $a$  and  $b$  effects either or both the actor and partner effects vary by the distinguishable variable, we compare the  $k$ s for  $a$  and the  $k$ s for  $b$ . If they are statistically equal, we set the corresponding  $k$ s equal. Fifth, we fix the  $k$ s to 1, 0, or  $-1$  in those cases in which the corresponding CIs suggest a specific pattern and determine the relative fit of the model. Sixth, if it is plausible, we respecify the simpler model by constraining effects and removing the  $k$  paths. For instance, if we have a  $\{0, 1\}$  model, we drop the  $a$  partner effects, and we set the  $b$  actor and partner effects equal.

In the case of indistinguishable dyad members, the procedure consists of four steps. First, we estimate the indistinguishable saturated APIMeM and test all effects. Second, we estimate the two  $k$ s of  $k_a$  and  $k_b$  and determine their CIs. Third, we place constraints on  $k_a$  and  $k_b$  to test for specific patterns in those cases where the CIs support specific patterns. Fourth, we remove the paths for the  $k$ s and, if specific patterns occur, we respecify the model and determine whether it is good fitting.

Example Data Set

Earlier we reported the test of indistinguishability, and we found that the direct effects were empirically indistinguishable. In this model implying indistinguishability, we can estimate one  $k$  for the  $a$  effects and one for the  $b$  effects. The  $k$  for the  $a$  effects is 0.062. The 95% CI ranges from  $-0.092$  to  $0.226$ , which supports the actor-only pattern as zero is included in the CI. The  $k$  for the  $b$  effects is 0.662. The 95% CI ranges from  $0.436$  to  $0.896$ , which includes neither 1 nor 0, and so a pattern in between the actor-only and the couple model was indicated for the  $b$  effects. We might describe this model in terms of the  $k$ s as a  $\{0, \frac{2}{3}\}$ , an actor-only with something in between actor-only and couple model.

Consequently, we estimated a model suggesting the actor-only pattern for the  $a$  effects in addition to the indistinguishability constraints. The model comparison test supports this more parsimonious model,  $\chi^2_{\text{Diff}}(1) = 0.639$ ,  $p = .424$ , and so we used this to test the hypothesis that depressive symptoms mediate the association between the feeling of cannot cope with everything and marital satisfaction.

In this final model, there are five effects—one  $a$  effect, two  $b$  effects, and two  $c'$  effects—that generate two IEs— $a_A b_A$  and  $a_A b_P$ —and two total effects— $a_A b_A + c'_A$  and  $a_A b_P + c'_P$ . We find that the  $a$  actor effect is positive (3.556) and statistically significant ( $p < .001$ ), which indicates that the feeling of cannot cope with everything is positively related to depressive symptoms within husbands and within wives. For the  $b$  effects, both the actor and partner effects are negative ( $-0.339$  and  $-0.225$ , respectively) and significant (both  $p < .001$ ). That is, one's marital satisfaction is associated with both one's own and the partner's depressive symptoms. The effect estimates for the IEs, total effects, and specific contrasts are presented in Table 7. Both IEs are statistically significant. Comparing the IEs and the total effects, we found that the actor IEs are statistically stronger than the partner IEs. In sum, one's own depressive symptoms mediated completely the effect of one's own feeling of not coping with everything on both one's own and the partner's marital satisfaction.

TABLE 7  
Indirect Effect, Total Effect, and Contrasts for the Final Model in the Example Data Set

<i>Effect</i>	<i>Estimate</i>	<i>95% CI</i>	<i>Proportion of the Total Effect (multiplied by 100)</i>
Actor effect			
Total effects	−2.095	−2.603, −1.524	
Actor–actor IE	−1.207	−1.566, −0.903	57.6
Direct effect $c'_A$	−0.888	−1.522, −0.244	42.4
Partner effect			
Total effect	−1.140	−1.666, −0.642	
Actor–partner IE	−0.799	−1.122, −0.511	70.1
Direct effect $c'_P$	−0.340	−0.936, 0.261	29.9
Contrasts			
Actor–actor IE − $c'_A$	−0.319	−1.196, 0.555	
Actor–partner IE − $c'_P$	−0.459	−1.274, 0.344	
Actor–actor IE–actor–partner IE	−0.407	−0.746, −0.116	
Actor total effects–partner total effects	−0.955	−1.522, −0.378	

*Note.* IE = indirect effect; CI = confidence interval.

## DISCUSSION

The purpose of this article was to address conceptual, statistical, and strategic issues in the evaluation of mediation in data from dyads when using the APIMeM. We provided guidance on how the APIM for mediation can be simplified by assuming indistinguishability in the case of theoretically distinguishable members and by testing for specific patterns. With distinguishable members, we tested for indistinguishability prior to the analysis of dyadic patterns in this article. However, a researcher could also test for dyadic patterns prior to indistinguishability. Using this strategy, the resulting final model might not be the same, however. To improve the confidence in the results, a researcher might want to use both strategies or conduct cross-validation.

Simplifying the APIMeM by testing for indistinguishability and specific patterns are strategies to reduce the number of IEs and total effects within the model. Another one is the implementation of the common fate model (e.g., Griffin & Gonzalez, 1995; Kenny & La Voie, 1985; Ledermann & Macho, 2009; Woody & Sadler, 2005). The common fate model assumes that two dyad members are affected by a dyadic factor that exerts influence on both members of a dyad. A variable can be conceptualized as a common factor when the measured construct represents a characteristic of the dyadic relationship or an external source that has an effect on both members of dyad (e.g., in couples, relationship cohesion or quality of housing). For each variable pair in the APIMeM that is modeled as a common factor the number of IEs, total IEs, and total effects is divided in half.

When testing mediation, the detection of substantial IEs can fail due to lack of power. There are two strategies that can be employed to increase the statistical power in an APIMeM. First, simplifying the model by treating distinguishable members as indistinguishable or by assuming specific patterns can lead to an increase in power. Second, modeling dyad common variables as common fate factors can also increase the power to detect substantial effects due to the reduction of effects and the separation of systematic variance from error variances. Of course, any model should be in agreement with theoretical and empirical considerations.

The APIMeM depicted in Figure 1 includes only a single mediator. APIMeMs with two mediators have been tested by Cobb, Davila, and Bradbury (2001) and Srivastava, McGonigal, Richards, Butler, and Gross (2006). Fitting an APIMeM with multiple mediators, the strategies outlined in this article to test for indistinguishability and dyadic patterns can be employed, too.

In this article, we used SEM because of its capability to calculate point and interval estimates of specific effects and contrasts and to set specific constraints. In addition, it can easily estimate the entire model and can estimate directly indirect and total effects and point and interval estimates of the  $k$  parameter. As an alternative, we can use multilevel modeling, but currently the capability of standard multilevel modeling packages is limited in both the setting of specific constraints and the calculation of indirect, total, and bootstrap estimates.

In assessing mediation, there are two points we think deserve special attention. First, the estimates from and the goodness-of-fit of a particular APIMeM do not necessarily provide information about the correctness of the causal ordering of the variables in a fitted model. This is due to the existence of alternative models that are statistically equivalent to the APIMeM presented here (Lee & Hershberger, 1990; MacCallum, Wegener, Uchiono, & Fabrigar, 1993; Stelzl, 1986). The saturated APIMeM with inverted causal effects (i.e.,  $Y \rightarrow M \rightarrow X$ ) is an instance of such an equivalent model that is statistically not distinguishable from the  $X$  to  $M$  to  $Y$  APIMeM. For the unconstrained APIMeM, there are several equivalent models that might

suggest very different conclusions (Bentler & Satorra, 2010; Raykov & Marcoulides, 2001, 2007). The number of equivalent models is reduced in overidentified structural models relative to saturated structural models; yet, the causal interpretation of the relations in a fitted model is prevented by the existence of even a single alternative equivalent model, especially if the alternative model is similarly plausible to the original model. Consequently, the problem of equivalent models is alleviated, if theoretical or substantive arguments make alternative models less plausible. Therefore, it follows that the ordering of relations among variables must be based on theoretical grounds, substantive evidence, or both. In the absence of a compelling theoretical foundation and substantive arguments, the experimental manipulation of one or more variables or prior research can make alternative models less meaningful (e.g., MacCallum et al., 1993). In addition, the number of equivalent models can be reduced by introducing an instrumental variable that is related to the mediator but not to the other variables (e.g., MacKinnon, 2008).

Second, all effects in the APIMeM were considered to be the same for all dyads. If dyad members are observed over time or if the dyads are hierarchically clustered in larger groups, techniques proposed by Kenny, Korchmaros, and Bolger (2003), Bauer, Preacher, and Gil (2006), MacKinnon (2008), and Preacher, Zyphur, and Zhang (2010) that allow for random mediation effects can be used to analyze the APIMeM.

## CONCLUSION

A growing number of researchers desire to test for mediation with the APIMeM. The complexity of the model, however, can have a detrimental effect on researchers interested in its use. This can be remedied by treating theoretically distinguishable dyad members as indistinguishable and by testing specific patterns that both allow a researcher to simplify the model. The evaluation of contrasts among IEs allows one to draw conclusions about the relative importance of the intervening variables in a model and to refine the understanding of the mediational process.

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