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Giving dyadic data analysis away: A user-friendly app for actor–partner interdependence models

LARA STAS,[a] DAVID A. KENNY,[b] AXEL MAYER,[c] AND TOM LOEYS[a]
[a]*Ghent University, Belgium;* [b]*University of Connecticut; and* [c]*RWTH Aachen University, Germany*

Abstract

The actor–partner interdependence model (APIM) is widely used for analyzing dyadic data. Although dyadic research has become immensely popular, its statistical complexity can be a barrier. To remedy this, a free user-friendly web application, called *APIM_SEM*, has been developed. This app automatically performs the statistical analyses (i.e., structural equation modeling) of both simple and complex APIMs. It allows the researcher to analyze distinguishable or indistinguishable dyads, to examine dyadic patterns, to estimate actor and partner effects of one or two predictors, and to control for covariates. Results are provided in software and text format, complemented by summary tables and figures. As an illustration, the effect of perception of the partner on satisfaction is assessed by fitting APIMs with varying complexity.

The actor–partner interdependence model (APIM; Kashy & Kenny, 2000) is a widely used framework for analyzing dyadic data. It integrates a conceptual view of interdependence together with the relevant statistical techniques for measuring and testing it (Cook & Kenny, 2005). In essence, the APIM allows researchers to simultaneously examine the effect of one's own predictor score on one's own outcome (i.e., *the actor effect*) and on the outcome of his or her partner (i.e., *the partner effect*). The latter reflects the interdependent nature of relationships.

Since its first appearance in scientific literature, over 600 articles have used the APIM to analyze dyadic data (Ledermann & Kenny, 2015), and further conceptual and statistical additions were made (Garcia, Kenny, & Ledermann, 2015; Kenny & Ledermann, 2010; Ledermann, Macho, & Kenny, 2011). One of the most cited APIM articles is a step-by-step guide for its analysis using SAS or HLM (Raudenbush, Bryk, Cheong, & Congdon, 2001) by Campbell and Kashy (2002), which illustrates the necessity of supporting practitioners with their APIM analysis. A license and/or prior knowledge of SAS or HLM are required, however, to execute the code described in this article. Here, we present a user-friendly online app that automatically performs the statistical analyses associated with both simple and more complex APIMs. Behind the scenes, analyses are automatically performed mainly using lavaan (Rosseel, 2012), an R-package for structural equation modeling (SEM). Because SEM techniques are used to fit the APIM, the app is called *APIM_SEM*. The program that we present is freely accessible and requires neither statistical software nor a detailed background knowledge of the statistical techniques to use all of its features. The program is written in shiny (Chang, Cheng, Allaire, Xie, & Jonathan,

Lara Stas, Depatment of Data Analysis, Ghent University, Gent, Belgium; David A. Kenny, Depatment of Psychology, University of Connecticut; Axel Mayer, Institute of Psychology, RWTH Aachen University, Aachen, Germany; Tom Loeys, Depatment of Data Analysis, Ghent University, Gent, Belgium.

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Correspondence should be addressed to Lara Stas, Ghent University, Department of Data Analysis, Henri Dunantlaan 2, B-9000 Gent, Belgium, e-mail: lara.stas@ugent.be

2015), a web application framework for R (R Core Team, 2016) by RStudio (RStudio Team, 2015), and has an appealing point-and-click interface. Although R is used in the background, users do not have to install R (or any other software) nor do they need to specify any R-code. The program is freely accessible at http://lavaan.org/APIM_SEM/.

The program can be used to analyze data from dyads that are indistinguishable (e.g., two friends of the same gender) or distinguishable (e.g., husbands and wives). It also allows the user to model actor and partner effects for one or more predictors and to control for additional covariates, measured at either the individual or the couple level. After importing the data and specifying the variables of interest, the app automatically produces several types of output. Besides the usual software output, the results are presented in full-text format, complemented with summary tables and figures. The text describes all estimated parameters, along with their interpretation, in words. In addition, *APIM_SEM* can be used to examine dyadic patterns. Exploration of such patterns in the APIM was first presented by Kenny and Ledermann (2010).

The aim of this article is to illustrate the most important features of *APIM_SEM* by means of an example data set on the association between perception of one's partner and relationship satisfaction. Using data from a longitudinal study (Acitelli, 1997; Acitelli, Veroff, & Douvan, 2013), we explore actor and partner effects of the perception of the significant other on satisfaction in 238 heterosexual couples. The data set is included in the app. It can be used to reproduce the presented results and to become familiar with the *APIM_SEM* program.

This article is organized as follows. We start with a description of the data and formulate the research hypotheses of interest. Next, we describe how, with minimum effort, the basic APIM (with a single predictor) can easily be fitted with the app and discuss the automatically generated output. Still focusing on the substantive application, we further illustrate how APIMs with additional actor and partner effects and covariates can be fitted as well. We end with a discussion.

Data and Hypothesis

As an illustrating example, the couple data gathered by Acitelli (1997) are used. In this longitudinal study, data were collected in two waves (Wave 1: March 1993 through January 1994; Wave 2: 1.5–2 years later). Only data from the first wave are included in the analysis, resulting in 238 American couples. Participants rated themselves and their partners on five different topics: being cooperative, mature, friendly, hardworking, and caring about others. The average scores of these five items are calculated and are the self-perception and perception of the significant other, respectively. For the remainder of the text, we refer to these two variables as "Self-Perception" and "Other Perception." We aim to analyze the effect of Other Perception on relationship satisfaction. We are not the first to study this topic. It is a well-documented finding that holding favorable perceptions of the partner is strongly associated with relationship satisfaction (e.g., Luo, Zhang, Watson, & Snider, 2010; Murray, Holmes, & Griffin, 1996; Neff & Karney, 2005). In the first APIM, we explore the link between Other Perception and Satisfaction. Two hypotheses are tested: (a) Do individuals who see their partner in a more positive light experience greater satisfaction? (b) Do intimates who are viewed more positively by their partners experience greater satisfaction? Given that we are interested in the effect of the own and the partner's perception of the significant other on satisfaction (Figure 1), accounting for the correlation of outcomes within couples, the APIM is perfectly suitable to explore these hypotheses. Indeed, the first question can be tested by means of the actor effects, the second by the partner effects. Relying on the APIM in Figure 1, we explore actor and partner effects of Other Perception on the Satisfaction score in the next section and refer to this model as the "basic APIM."

In the second model, a second independent variable is added to the basic APIM. When a variable is correlated with both the independent and dependent variables, it is important to control for this confounder. Even if predictors are strongly associated with the outcome but not with the other predictors, such an adjustment

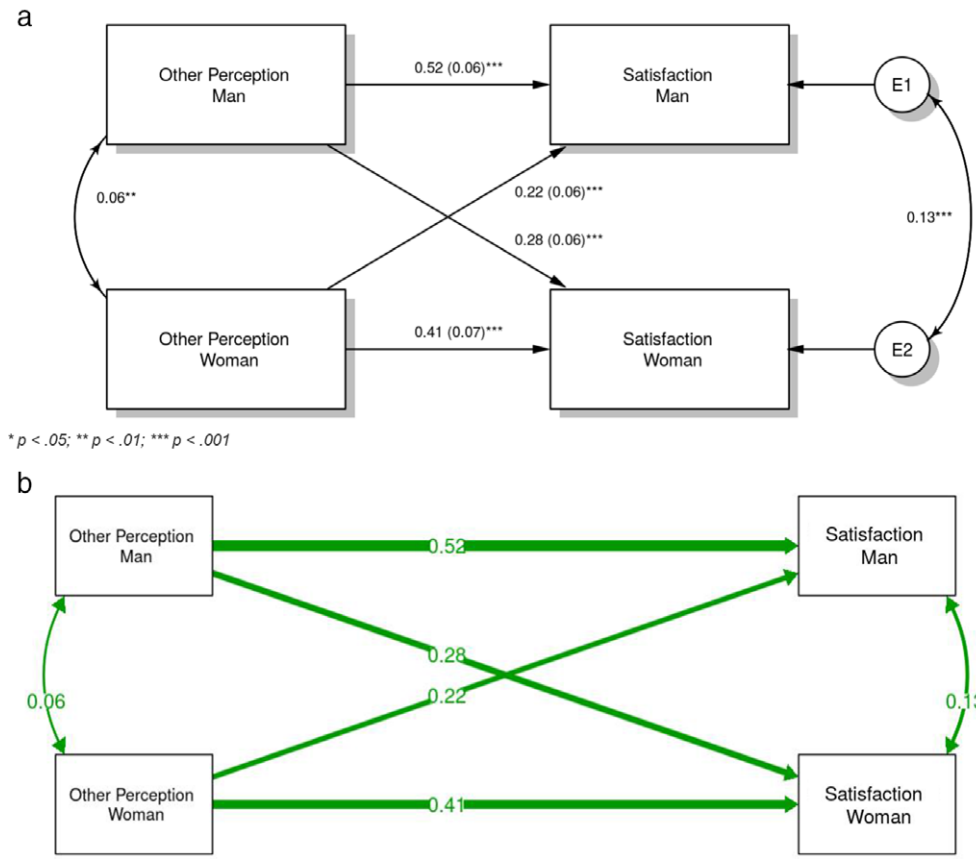

Figure 1. The horizontal output tab "Figures" includes two kinds of path diagrams of the fitted actor–partner interdependence model (APIM). (a) The basic APIM figure is a static black-and-white figure, displaying estimated actor and partner effects with corresponding standard errors and the significance level of a single independent variable. (b) The full APIM figure displays all variables in the fitted model, including possible additional independent variables or covariates. This figure uses color coding with positive estimates indicated by green arrows and negative estimates by red arrows. The stronger the effect, the thicker the line of the arrow. Both: Single-headed arrows represent causal or predictive paths, with horizontal lines in the middle as actor effects and diagonal lines partner effects. The double-headed arrow between "Other Perception Man" and "Other PerceptionWoman" represents its covariance. The double-headed arrow between "Satisfaction Woman" and "Satisfaction Man" is the residual nonindependence in these outcome scores, which is represented by the covariance between their corresponding two error terms. These figures are copied from the *APIM_SEM* app.

still leads to more precise estimators of actor and partner effects. In line with a study of Murray et al. (1996), we control for the variable Self-Perception as a potential confounder. These authors studied the effect of idealization on relationship satisfaction. Idealizing a person is seeing this individual better than he or she really is. So, in order to measure the effect of idealization, we need to control for the true characteristics of these persons. Following Murray et al., a person's self-perception can be used to measure that person's actual characteristics. They called this the *subjective reality baseline* (p. 80) because the partner's own self-perception is not an exact representation of his or her characteristics but a good

approximation to that reality. So, in this second model, we aim to measure an idealization effect by controlling for the self-perception of both dyad members. By doing so, we can then investigate whether the link between Other Perception and Satisfaction still holds when controlling for dyad members' actual characteristics. When controlling for the partner's self-perception, Murray et al. found that people who view their partner in a more positive way are more satisfied. They concluded that an idealized construction is a critical feature for satisfaction in both dating and married couples.

In our search for other potential confounders of the relationship between Other Perception and Satisfaction, we also selected marital status (Murray et al., 1996) and anxious attachment style (see the review of Li & Chan, 2012). In the third model, we adjust for those covariates as well.

In the next sections, we show how these three APIMs can easily be fitted with *APIM_SEM*.

Fitting the APIM with *APIM_SEM*

APIM_SEM is a free online program with a point-and-click interface that can be used for fitting standard or more complex APIMs. Our app provides a graphical user interface that requires only a minimum of input information. No prior knowledge of any (statistical) software is needed to use all features of the app. The program can be freely accessed through the following link: http://lavaan.org/APIM_SEM/.

For a wide variety of researchers, *APIM_SEM* can be a valuable tool: For researchers who are used to working with R or know SEM, the lavaan (i.e., an R-package for SEM) syntax is provided for each fitted model, together with the lavaan output. All users are encouraged to use this syntax in their own follow-up analyses. For researchers who are unfamiliar with R or SEM, all results are presented in full-text format, complemented by illustrating figures and summary tables to aid self-learning.

The *APIM_SEM* app uses color coding to easily explain all its features (see Figure 2). At the top, the program is divided into three main pages, indicated in yellow:

(1) The *Fitting the Actor Partner Interdependence Model* page is used to fit a model and view its output;
(2) The *Extra Info* page contains documentation on how to use the program, as well as background resources for self-study of the APIM, lavaan, and SEM (i.e., webinars and references to papers and books);
(3) The *About & Contact* page provides contact information of the developers.

For this article, the focus is on the first page. On that page, relevant information for the model can be specified in the vertical input tabs: Blue tabs are mandatory (Select Data and Variables), and black tabs are optional (Additional and Download Output). The model is fitted by hitting the "Run Analysis!" button once. After that, the program is reactive, and so, the output will automatically change if the input is modified. The output is displayed in the green horizontal tabs.

For every analysis, the results are presented in the "Lavaan Output" tab, and their interpretation is provided in the "Data 2 Text" tab. Because these results with extensive interpretation speak for themselves, we do not discuss that output tab in much detail here but rather focus on the other output tabs. All information, figures, and tables that are presented in this article are directly obtained from the *APIM_SEM* app. Note that a full report, including all results as produced by the app, can be downloaded in the program in PDF, HTML, or Word format (see Figure 3c).

Fitting a basic APIM

In this section, we illustrate basic features of the app for fitting a basic APIM. Two hypotheses are tested: Intimates who view their partner more positively (a) are more satisfied (i.e., positive actor effect) and (b) have partners that are more satisfied (i.e., positive partner effects). Dyadic patterns are explored as well. The complete output can be consulted in Online Appendix 1.

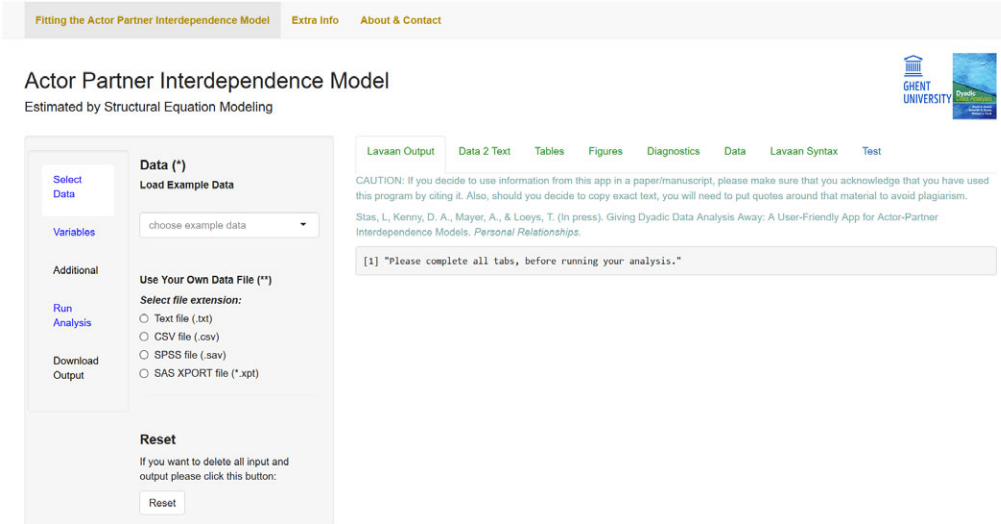

Figure 2. The opening screen of the *APIM_SEM* app. The program uses color coding to easily explain all its features. At the top, the program is divided in three main pages, indicated in yellow: (1) The *Fitting the Actor Partner Interdependence Model* page is used to fit a model and view its output. (2) The *Extra Info* page contains background information and information on how to use the program. Additional resources to self-study the APIM, lavaan, and structural equation modeling are included as well. (3) The *About & Contact* page provides contact information of the developers. The first page is of interest for this article. Here, a distinction can be made between vertical input tabs (in blue and black) and horizontal output tabs (in green). For a default model to be fitted, the blue tabs need to be specified ("Select Data" and "Variables"), and black tabs are optional ("Additional" and "Download Output").

Input

Only three steps are needed to fit a basic APIM: (a) A data set can be uploaded in the app via the blue input tab "Select Data" (see Figure 4) and should have a dyadic structure (i.e., one row for every dyad, sometimes called a *wide format*). If the data set is not yet in that format, the *ItoD* app of Ledermann and Kenny (2015) provides an easy tool to transform a data set from long format (i.e., with one row for each dyad member) to a dyadic data set. The program accepts Text files (.txt), CSV files (.csv), SPSS files (.sav), and SAS XPORT files (.xpt). (b) The independent and dependent variables needs to be specified in the blue input tab "Variables" (see Figure 3a) together with their labels for the text output. Specify Other Perception for women and men (*Other_F* and *Other_M*, respectively) as independent variables and both Satisfaction scores (*Sat_F* and *Sat_M*, respectively) as dependent variables. Because women and men are considered distinguishable dyad members, a distinguishable analysis is requested (see Figure 3a). (c) Hit the button in the blue input tab that says "Run Analysis" (see Figure 3b) to perform the analysis.

Output

A complete description of the summary statistics, the assumed model, and all associated results can be found in the horizontal output tab "Data 2 Text." In that text (see Online Appendix 1), interpretations of the estimated parameters are described in full sentences. In the horizontal output tab "Tables," the means, standard deviations, and minimum and maximum values of both independent and dependent variables can be found by role

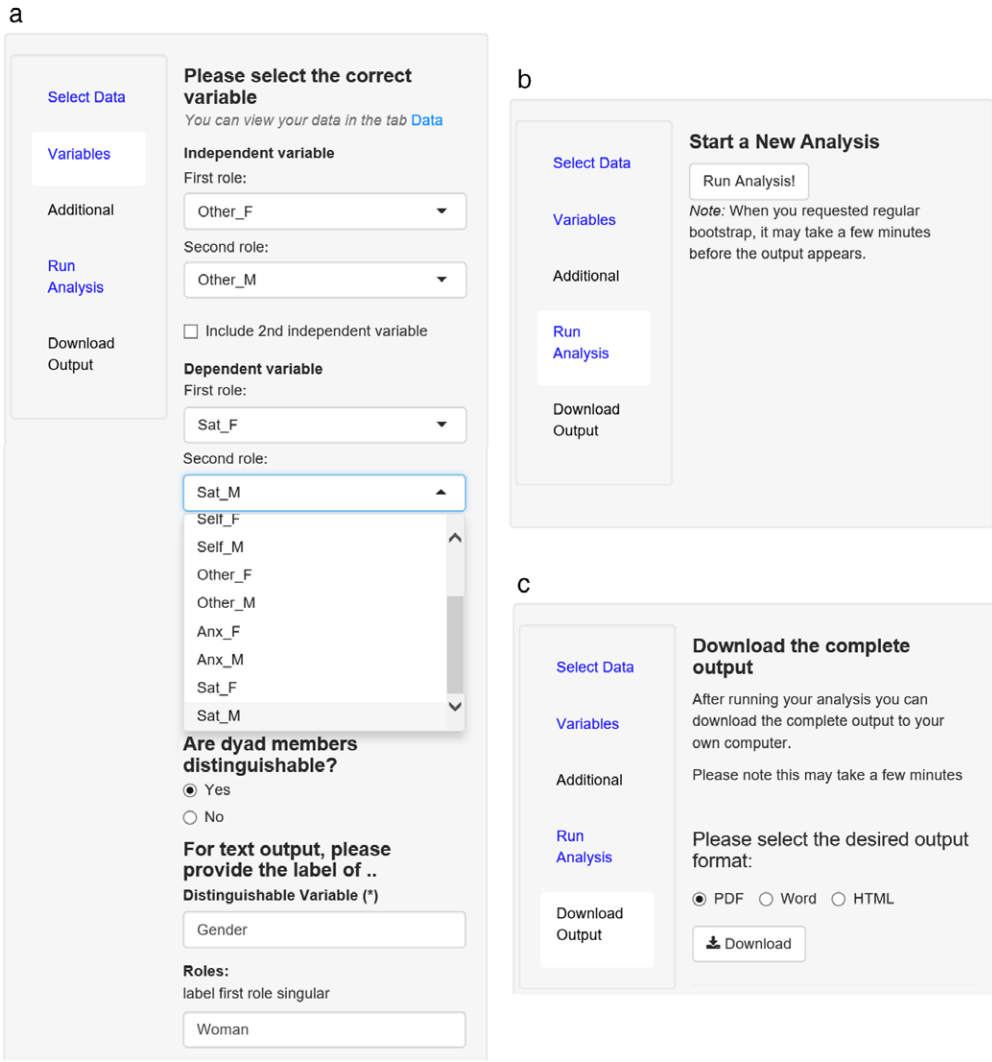

Figure 3. Input tabs of *APIM_SEM*. (a) In the vertical input tab "Variables," the variables of interest can be selected and labels can be specified. The labels will be used for the text output. Users can specify if a distinguishable or indistinguishable analysis needs to be performed. (b) After loading the data and specifying the desired variables with corresponding labels, one can run the analysis by clicking on "Run Analysis!" in the vertical input tab "Run Analysis." (c) The content from all output tabs can be downloaded to your local computer in either PDF, Word, or HTML format from the tab "Download Output."

(see Table 1). There appear to be no meaningful differences between men and women in the means or standard deviations. In the last column, the number of nonmissing observations on both the independent and dependent variables are given for both roles.

A bivariate exploration of the data can be found at the bottom of the output tab "Diagnostics" (see Figure 5). For each role, the outcome of the rater and person being rated are plotted against the independent variable. The left plot shows that—both for men and women—the higher the Other Perception, the more satisfied they tend to be. On the right plot, we see that intimates who are rated more positively by their partner are generally more

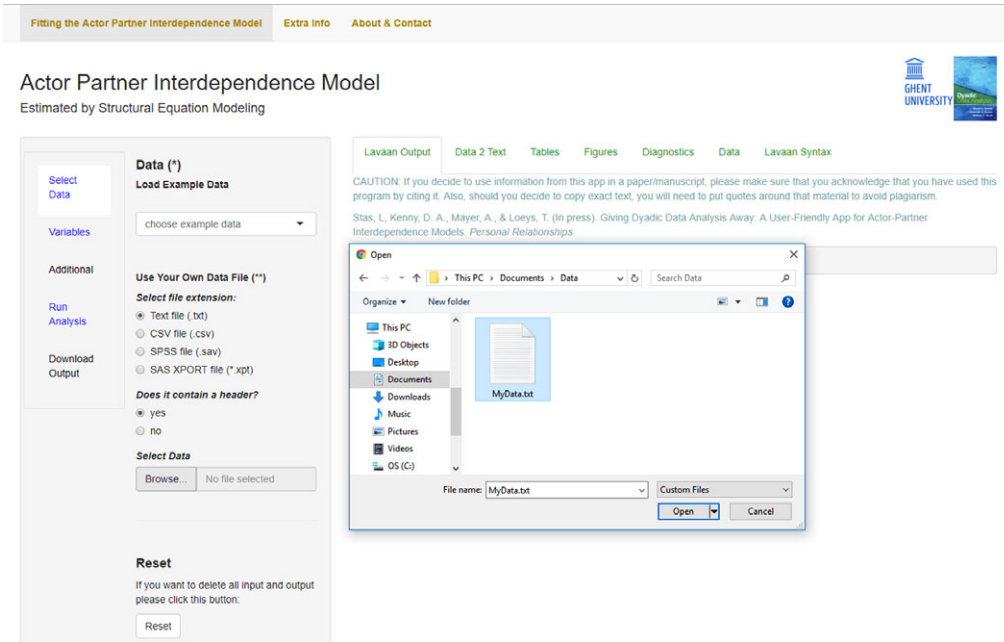

Figure 4. Select data for the analyses. The vertical input tab "Select Data" allows the user to either select an example data set or insert his or her own data set. When choosing a local file, the data will not be stored and can only be used by the user itself. After specifying the extension of the file, the data can be selected and viewed in the output tab "Data."

satisfied. These preliminary findings are in line with our hypotheses. However, it is important to note that these bivariate plots are strictly meant for data exploration because they do not represent pure actor (partner) effects from the APIM. Indeed, in the first plot, the effect of one's own predictor on one's own outcome is not adjusted for the effect of the predictor of the partner and hence does not strictly reflect the actor effect of the APIM. We, therefore, refer to these effects as "semi-actor effects." Similarly, the second plot shows the "semi-partner effects." To assess whether it is reasonable to assume linear effects of the independent variable on the outcome, a smoother (i.e., a non-parametric best fitting curve) is added to the plots as a dotted line.

For an easy graphical representation of the fitted APIM, two types of path diagrams are created in the output tab "Figures": the basic APIM figure and the full APIM figure. The former is a static black-and-white figure, displaying estimated actor and partner effects with corresponding standard errors and the significance level of one independent variable (cf. Figure 1). The second figure displays effects for all variables in the model simultaneously using the R-package semPlot (Epskamp, 2015), including possible additional independent variables or covariates (see extended models discussed later). Here, positive estimates are indicated with green arrows and negative estimates with red arrows. The stronger the effect, the thicker the line of the arrow will be. The actor effects are the strongest effects in the fitted model, as can be seen from Figure 1. These bold green arrows imply that intimates who see their partner more positively experience greater satisfaction (actor effect men = .52, $p < .001$; actor effect women = .41, $p < .001$). In addition, both partner effects are found to be significant (partner effect women to men = .22, $p < .001$; partner effect men to women = .29, $p < .001$), indicating that intimates who are viewed more positively by their partners tend to be more satisfied. These results provide support for our hypotheses. Note that both types of path diagrams can

Table 1. *Basic actor–partner interdependence model (APIM): Descriptive statistics of the raw data (observation 22 removed)*

Variable	Role	*M*	*SD*	Minimum	Maximum	*n*
Other Perception	Women	4.220	0.525	2.600	5.000	237
	Men	4.210	0.553	1.800	5.000	237
Relationship Satisfaction	Women	3.569	0.603	1.500	4.000	236
	Men	3.541	0.609	1.000	4.000	238

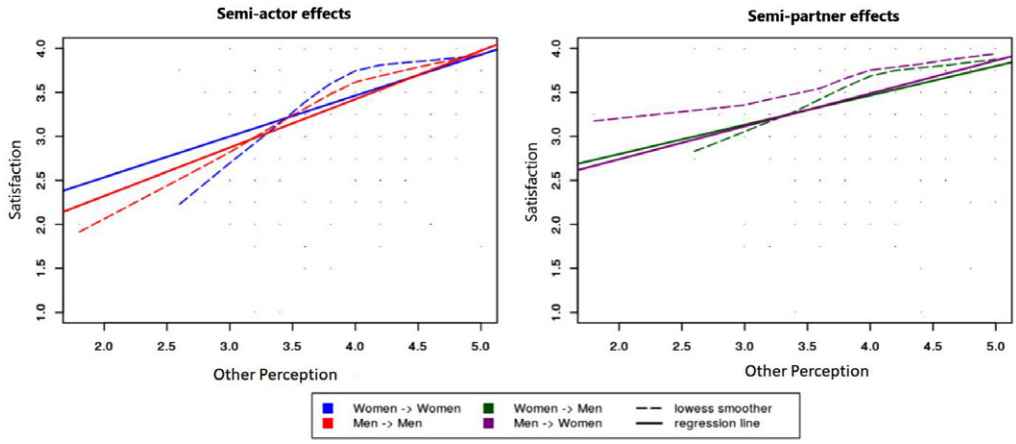

Figure 5. Bivariate exploration of the data. In the horizontal output tab "Diagnostics," the score of Other Perception is plotted against one's own Satisfaction score (i.e., semi-actor effects) and the Satisfaction score of his or her partner (i.e., semi-partner effects) for each role. For detecting nonlinear trends, a LOWESS smoother is added to the plots. Note that these plots are strictly meant for data exploration as they do not take into account any other variables and, therefore, are no real actor (partner) effects. These plots are copied from the *APIM_SEM* program.

be obtained with either raw or standardized estimates.

The "Data 2 Text" tab contains all information of the other tabs in full sentences, as well as information on additional tests. For example, in case of distinguishable dyads, one may want to explore whether the actor and partner effects differ between roles. In the Satisfaction data set, neither the difference in actor effects, −.11, 95% CI [−.30, .08], $p = .250$, nor the difference in partner effects, .06, 95% CI [−.12, .25], $p = .512$, is significant. Because no difference was found, one may wonder whether a model with indistinguishable members would also fit the data. For each analysis with distinguishable dyad members, an additional model that treats the dyad members as indistinguishable is fitted behind the scenes (see Table 2). This model assumes not only equal actor and partner effects for both roles but also equal intercepts, as well as equal error variances for the outcomes in men and women. In addition, the mean and the variance of the predictor variables are assumed to be the same for men and women. This model is sometimes referred to as complete indistinguishability (Kenny, Kashy, & Cook, 2006). In the basic APIM, six parameters are thus constrained to be equal when testing for complete indistinguishability. The app provides a test of complete indistinguishability by performing a model comparison between an APIM with and without these restrictions, as described in the "Data 2 Text" tab:

> In order to test if Gender makes a statistically meaningful difference, a model com-

Table 2. *Basic actor–partner interdependence model (APIM): Results assuming same actor and partner effects for both roles*

Effect	Estimate	95% CI [lower, upper]	*p* value
Intercept	0.500	[−0.081, 1.081]	.092
Actor	0.469	[0.385, 0.554]	<.001
Partner	0.255	[0.170, 0.339]	<.001

parison is performed between a model with distinguishable members and a model with indistinguishable members. This overall test of distinguishability yields a chi square statistic with 6 degrees of freedom which equals 2.922 ($p = .819$). Because this test of distinguishability is not statistically significant, we cannot conclude that members can be statistically distinguished based on the variable Gender. In Table 4 of the tab "Tables," you can find the results of a model that treats the dyad members as indistinguishable. If it is theoretically justifiable, you can perform all analyses with indistinguishable dyad members by selecting indistinguishable dyad members in the input tab "Variables."

Dyadic patterns in the APIM. Kenny and Ledermann (2010) proposed a method to detect and measure different theoretically important dyadic patterns in the APIM based on the interdependence theory (Kelley et al., 2003). To measure these patterns, they suggested the estimation of the parameter k, which is the ratio of the partner effect to the actor effect. Although k can take any value in practice, relationship researchers are particularly interested in three values. If k equals 1, a "couple pattern" is detected, indicating equal partner and actor effects. The outcome of a dyad member is equally influenced by his or her own predictor variable as by the predictor variable of the partner. When k equals −1, a "contrast pattern" is observed, with actor and partner effects equal in size but different in sign. An "actor-only pattern" occurs when k equals 0, indicating a partner effect of zero. In general, for k to be defined, the actor effect must be nonzero to avoid division by zero. For every analysis performed with *APIM_SEM,* such patterns are tested and also described in the "Data 2 Text" tab.

For this basic APIM, the value of k for women equals .69, whereas for men, k equals .43 (see Table 3). Thus, for men, for example, the effect on satisfaction of how they perceive their significant other (i.e., men's actor effect) is almost twice as large as the effect of how their partners perceive them (i.e., men's partner effect). It is useful to supplement the estimator of k with a confidence interval, such that a range of plausible values can be determined, and more firm conclusions can be made about the pattern. Because k is a ratio of estimated parameters, its standard error is not straightforward to calculate, and its distribution is presumably skewed. One may, therefore, alternatively rely on quasi Monte Carlo techniques or bootstrap instead of relying on the normality of the estimator. Both approaches are implemented in *APIM_SEM*: Once the variables and labels are specified in the input tab "Variables," one can select the box *Do you want to bootstrap the CI('s) of the k('s)?* in the input tab "Additional" (see Figure 6). Note that the bootstrapping method is rather computationally intensive and likely takes some time to calculate, whereas the Monte Carlo approximation is much faster. For women, the couple model ($k = 1$) seems plausible because the 95% confidence intervals for k range from .28 to 1.10 (Table 3). This suggests that women's satisfaction is equally influenced by their own perception of their partner as with how these partners perceive them. For men, the model is in between the actor-only ($k = 0$) and the couple ($k = 1$) model, with confidence intervals ranging from .15 to .71. The

Table 3. *Basic actor–partner interdependence model (APIM): Results assuming different actor and partner effects for both roles*

Effect	Role	Estimate	95% CI [lower, upper]	*p* value	$\hat{\beta}_{(o)}$	$\hat{\beta}_{(s)}$	*r*
Intercept	Women	.627	[−0.064, 1.318]	.071			
Actor		.411	[0.280, 0.543]	<.001	.318	.356	.359
Partner		.285	[0.160, 0.410]	<.001	.253	.260	.287
k		.693	[0.282, 1.103]				
Intercept	Men	.407	[−0.253, 1.068]	.140			
Actor		.521	[0.401, 0.641]	<.001	.462	.473	.471
Partner		.223	[0.096, 0.349]	<.001	.197	.192	.216
k		.427	[0.148, 0.707]				

actor-only model implies that their satisfaction score is influenced by their own perception of the partner but not by how these partners perceive them.

An APIM with two independent variables

In line with the study of Murray et al. (1996), we control for the variable Self-Perception as a potential confounder. By doing so, we can investigate if the previous effects still hold after controlling for this variable. Just as Murray et al. did, we aim to investigate the link between idealization and satisfaction. Idealizing a partner is seeing this person as better than he or she really is. Thus, to investigate the degree of idealization, we must control for the actual characteristics of these partners. One's self-perception can be used as a measure of that person's actual characteristics (Murray et al., 1996). In this model, actor and partner effects are therefore estimated for both Other Perception and Self-Perception.

We illustrate how this more complex APIM can easily be fitted with *APIM_SEM*. The complete output is given in Online Appendix 2.

Input

To include a second independent variable, check the box *Include second independent variable* in the input tab "Variables" (see Figure 3a) and select the appropriate variables for both roles (*Self_F* and *Self_M*).

Output

In this model, four actor and four partner effects are simultaneously estimated. In the horizontal output tab "Tables," the results of the fitted APIM are provided in table format (see Table 4). It shows the estimated intercepts and actor and partner effects for each role and independent variable, with associated confidence intervals and *p* values. After controlling for the potential confounding effects of Self-Perception, evidence is still found for our two hypotheses: (a) Intimates who see their partner in a more positive light experience greater satisfaction (actor effect women = .46, $p < .001$; actor effect men = .55, $p < .001$), and (b) intimates who are viewed more positively by their partners are more satisfied (partner effect men to women = .32, $p < .001$; partner effect women to men = .26, $p < .001$). Interestingly, neither actor nor partner effects differ significantly between men and women (difference actor effects = −.09, 95% CI [−.28, .09], $p = .325$; difference partner effects = .06, 95% CI [−.13, .25], $p = .531$), indicating the same pattern for both. In line with Murray et al. (1996), we controlled for the self-perception of the partner as a measure of this partner's actual characteristics. By doing so, the effect of idealization on relationship satisfaction can be examined. We can conclude that, both for men and women, intimates who have more idealized impressions of their partner are more satisfied (i.e., actor effects). In addition, intimates who are idealized more by their partner are more

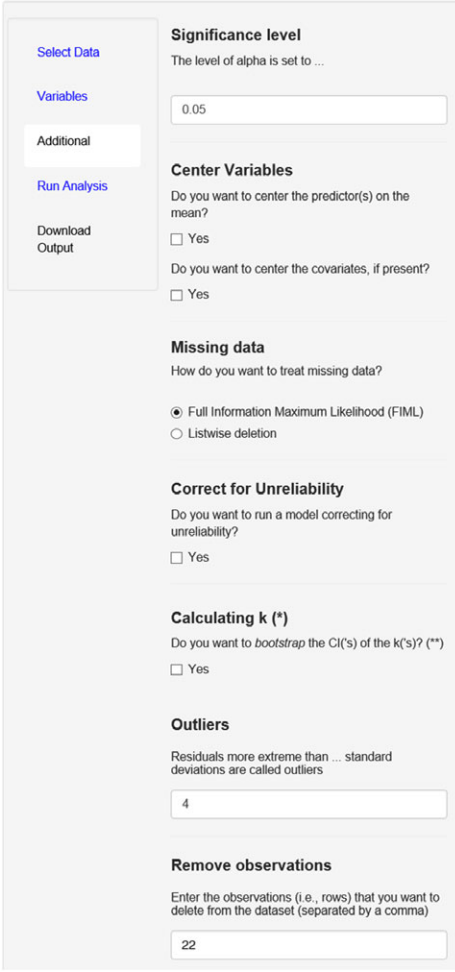

Figure 6. The additional input tab. Additional features that can be applied to all models are found in the "Additional" tab of the *APIM_SEM* program: (a) specifying the significance level; (b) centering predictor variables; (c) centering covariates; (d) how to deal with missing data; and (e) run a model correcting for unreliability.

satisfied (i.e., partner effects). These effects are found for both men and women.

Note that in Table 4, two versions of standardized regression coefficients are presented. The first uses the overall standard deviation across all persons (o) for standardization, and the other uses the standard deviation for women and men separately (s). If betas are to be compared across members, the $\widehat{\beta}_{(o)}$ value should be preferred. Here, the effect of Other Perception on Satisfaction seems to be greater for men than for women ($\widehat{\beta}_{(o)}$ of men = .49; $\widehat{\beta}_{(o)}$ of women = .32). The pairwise partial correlations (i.e., correlation between specific predictor and outcome, after controlling for the other predictor in the model) are given in the last column. For men, a positive correlation is found between Other Perception and Satisfaction after controlling for women's Other Perception ($r = .47$). So, when controlling for how women view their partner, we found that the better these men perceive their partner, the more satisfied they tend to be.

When examining the estimates of Self-Perception, it is perhaps surprising that all estimates are negative. Yet, only the partner effect of women is significant, indicating that the higher men rate themselves, the less satisfied their female partners are (partner effect men to women = −.219, $p = .012$).

Add covariates to the model

In the third model, covariates are added to the previous APIM. A distinction can be made between between-dyad, within-dyad, and mixed covariates. A between-dyad covariate contains a single score for both members of the same dyad, scores only varying between dyads. Marital status (1 = married, −1 = dating) is included as a between-dyad covariate. A within-dyad covariate has a different score for the two members of the same dyad, scores only varying within dyads (e.g., gender). The sum of the two persons' scores is the same for every dyad. A mixed covariate varies both between and within dyads. Previous research pointed out the association between an anxious attachment style and satisfaction (e.g., the review of Li & Chan, 2012). Hence, this variable is included in the final model as a within-dyad covariate. The program currently allows for up to two mixed or within-dyad covariates and three between-dyad covariates, either continuous or binary. The complete output can be consulted in Online Appendix 3.

Input

Check the box under *Do you want to include covariates?* and select the variables of interest

Table 4. *Second actor–partner interdependence model (APIM): Results assuming different actor and partner effects for both roles*

Effect	Role	Estimate	95% CI [lower, upper]	p value	$\hat{\beta}_{(o)}$	$\hat{\beta}_{(S)}$	r
Intercept	Women	1.485	[0.521, 2.448]	.003			
	Men	1.132	[0.206, 2.058]	.017			
Other Perception							
Actor	Women	0.457	[0.321, 0.592]	<.001	.318	.395	.359
Partner		0.323	[0.196, 0.449]	<.001	.286	.294	.287
Actor	Men	0.551	[0.429, 0.673]	<.001	.488	.500	.471
Partner		0.263	[0.133, 0.393]	<.001	.233	.226	.216
Self-Perception							
Actor	Women	−0.073	[−0.238, 0.092]	.388	−.050	−.051	.071
Partner		−0.219	[−0.389, −0.048]	.012	−.150	−.148	.003
Actor	Men	−0.119	[−0.283, 0.044]	.153	−.082	−.080	.063
Partner		−0.124	[−0.282, 0.034]	.125	−.110	−.087	.015

(*Married* as a between-dyad covariate, *Anx_F* and *Anx_M* for the mixed covariate; see Figure 7). Note that *Married* is a dummy variable where 1 indicates married and 0 indicates dating. For every binary variable, its preferred reference category can be specified in the app.

Output

This final model includes three possible confounders: intimates' self-perception, marital status, and anxious attachment style. Figure 8 (from the output tab "Figures") shows the actor and partner effects, taking into account all variables in the model. Figure 8a shows the actor and partner effects from the basic APIM. Figure 8b shows the same actor and partner effects but controls for the effects of the three potential confounders. After controlling for these three variables, there is an increase in intercepts for Other Perception. Concerning the slopes, the trend in both actor and partner effects hardly change (actor effect men = .48, actor effect women = .42; partner effect women to men = .23, partner effect men to women = .25). We conclude that the associations between Other Perception and Satisfaction are robust for potential confounding due to these three variables.

The estimates of the covariates itself are described in the text output. Results show that married men have, on average, a Satisfaction score that is .33 points higher than dating men ($p < .001$). Although married women seem to be more satisfied than dating women as well, this effect is only marginally significant ($b = .13$, $p = .075$). The estimates of the within-dyad covariate show that more anxiously attached women are less satisfied ($b = -.10$, $p = .019$). No significant association held for men ($b = -.06$, $p = .114$).

Additional Features of *APIM_SEM*

So far, the default output for different APIM models has been discussed. The input tab "Additional" contains extra features that can be requested for every model (see Figure 6). First, one can modify the significance level used for calculating the confidence intervals and for assessing the significance of the results in the "Data 2 Text" tab. For instance, one could change alpha from .05 to .01. Second, one can request to center predictor variables and covariates around their mean. Centering predictor variables may facilitate the interpretation of the intercepts. Note that independent variables, as well as within-dyad covariates, are centered around a common mean for both roles (i.e., grand mean centering). Third, one can choose which method should be used to deal with missing data. By default, full information maximum likelihood (FIML) is used, guaranteeing that all available data are used.

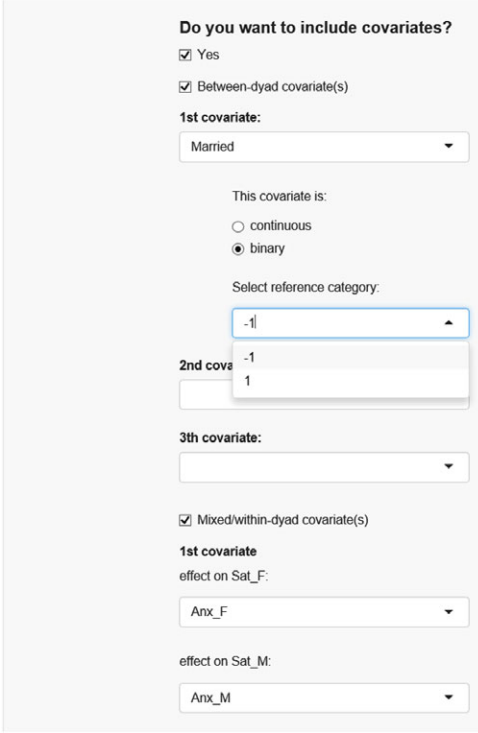

Figure 7. Selecting covariates. In the vertical input tab "Variables," different type of covariates can be added, either continuous or binary. Up to three between-dyad covariates (containing a single score for both members of the same dyad) and two within-dyad covariates (containing different scores for both members of the same dyad) can be added. When binary, the desired reference category can be specified.

This approach will yield valid inference as long as the missingness is missing at random. Alternatively, one can opt for listwise deletion whereby only couples with complete outcomes and predictors are included in the analysis. The latter approach is only valid when data are missing completely at random. Fourth, as predictors in the model may be measured with error, one can request a new fit of the model, correcting for such unreliability. To this end, the user needs to check the box under *Correct for unreliability* and specify the presumed reliability of the different independent variables. Fifth, outliers of the fitted model are listed in the "Data 2 Text" tab with their row numbers. If one desires to remove these outliers (or other rows of the data set), observations can manually be excluded from the analyses in the vertical input tab "Additional" (see Figure 6). This tab also allows users to specify the number of standard deviations used to label an observation as an outlier (see Figure 6). It is important to note that model diagnostics, such as normality of the residuals, can also be obtained in the "Diagnostic" tab (see Figure 9). As with all statistical analyses, users are advised to check their diagnostics and potential outliers before interpreting the APIM estimates. Although not within the scope of this article, guidelines for interpreting these diagnostics are given in the app itself.

Important Notes on Using *APIM_SEM*

In the background, lavaan (i.e., an R-package for analyzing latent variables; Rosseel, 2012) is used. It is strongly advised to save the lavaan script as a record of the analysis performed by the app. This script allows users to easily replicate the results and alter that script for additional analyses and provides other researchers with insight into the analysis, thereby increasing transparency. The lavaan script can be found in the output tab "Lavaan Syntax" and can be directly copy-pasted in R to specify the lavaan model. A URL to a step-by-step tutorial of lavaan can be found in the main tab "Extra Info." This tutorial is suitable for users who have never used R and/or lavaan.

In the "Data 2 Text" tab, interpretations of the estimated parameters are described in full sentences. This is meant to become familiar with all the information that can be retrieved from an APIM analysis and to become acquainted with the method in order to better understand the numeric output. However, users should be able to fully understand all text provided. Therefore, the app also contains additional resources to self-study the AIPM, SEM, and lavaan (i.e., webinars and references to papers and books; see main tab "Extra Info").

Some might be concerned that automated software makes p-hacking (e.g., deleting observations or exploratory multiple testing for obtaining a significant result) easier. We

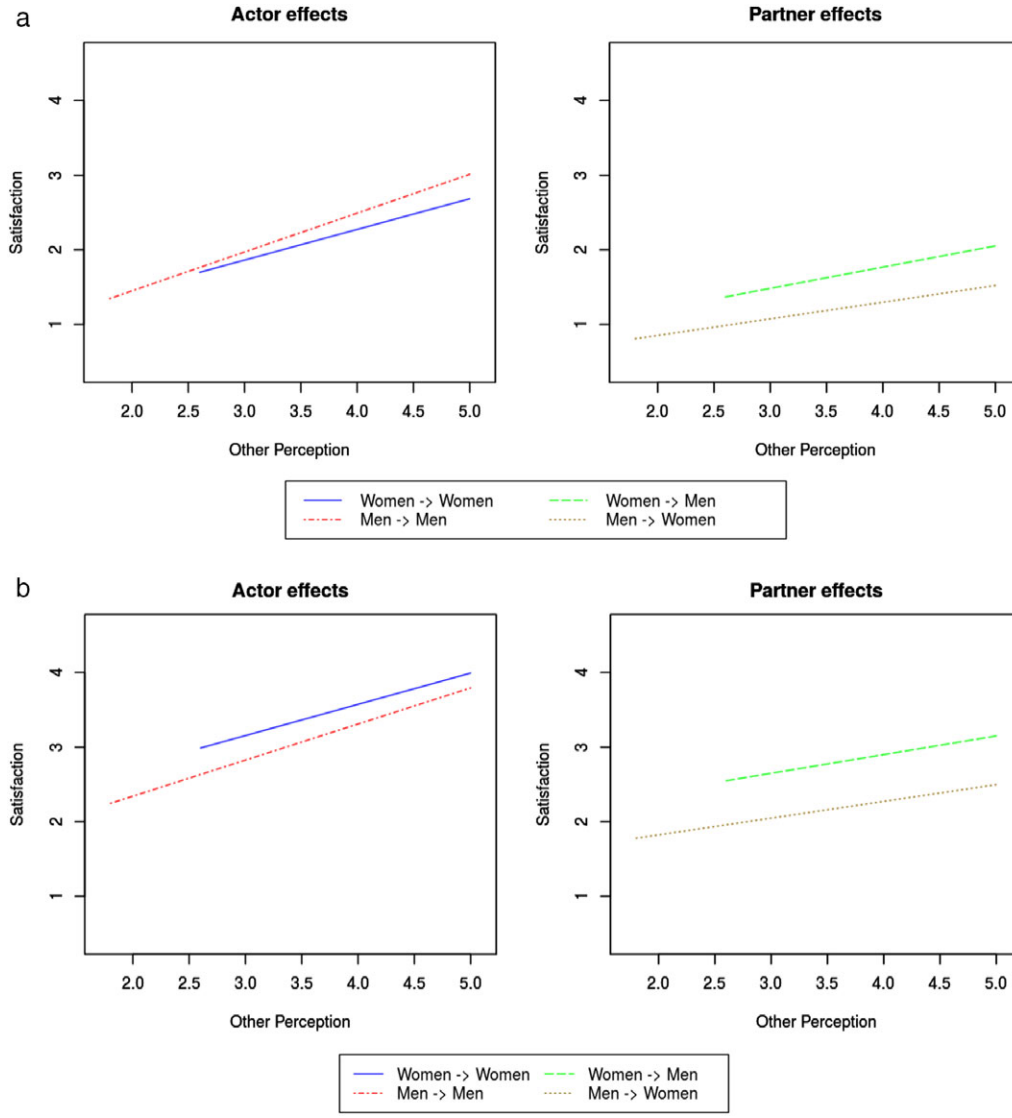

Figure 8. Visualization of actor and partner effects. In the output tab "Figures," the actor and partner effects for both roles are drawn, taking into account all variables in the model. Figure (a) shows the actor and partner effects of a basic actor–partner interdependence model (APIM) with Other Perception as the single independent variable. Figure (b) shows the effects of Other Perception in an APIM that also controls for Self-Perception, marital status, and anxious attachment. These plots are copied from the *APIM_SEM* program.

therefore suggest that researchers preregister a plan in which hypotheses will be tested and how outliers would be handled.

Users that include information from the app in an article/manuscript should make sure they acknowledge using *APIM_SEM* by citing this article.

Discussion

The *APIM_SEM* app is part of a bigger project called DyadR (Kenny, 2016). DyadR[1] is a

1. All apps can be found at http://davidakenny.net/DyadR/DyadR.htm.

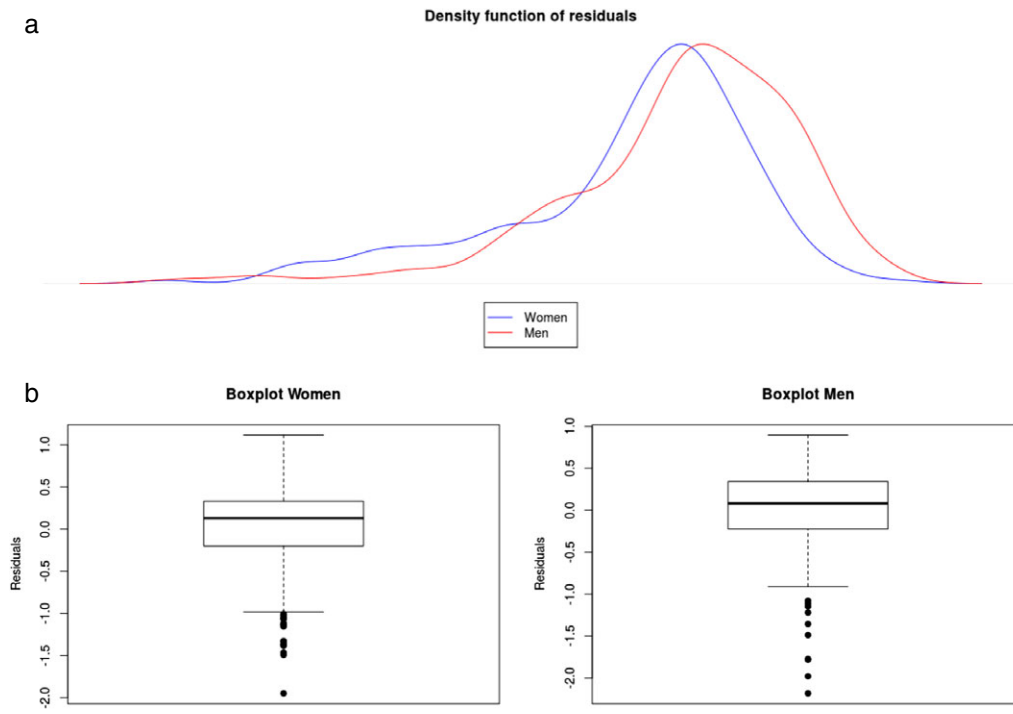

Figure 9. Diagnostics. These two figures are copied from the horizontal output tab "Diagnostics": (a) The distributions of the residuals of the fitted model for both men and women, and (b) boxplots of the residuals of the fitted model for both men and women.

cluster of web applications that have recently been developed to aid researchers in using and understanding both simple and more complex APIM analyses (e.g., APIM with a mediating variable). APIMs can be fitted with either SEM or multilevel models (MLM). There is a similar app based on MLM available (see https://davidakenny.shinyapps.io/APIM_MM/). We believe that the SEM framework offers some key advantages over MLM. First, when dyads are completely indistinguishable, it is easy in both frameworks to set intercepts, actor and partner effect, and variances of the outcomes to be equal between roles. However, there are no reasons why the population mean and the population variances of the predictors in the APIM would be different between roles in case of complete indistinguishability. Any difference observed in the sample should be attributed to chance. In contrast to the MLM framework, the SEM framework allows to constrain the mean and variance of the independent variables and additional within-dyad covariates to be equal across roles. Second, the SEM framework can relatively easily allow for the unreliability of predictors, whereas MLM cannot. Measurement error in the predictors is often ignored in practice. This may lead to attenuation bias (i.e., the estimated actor and partner effects may be wrongly estimated). Although it is not always easy to have a good idea of the reliability factor, we recommend exploring the robustness of findings when accounting for unreliability. Third, in case of missing data, FIML is used by default in *APIM_SEM*, whereas MLM analyses use the likely much inferior method of listwise deletion. Although the app presented in this article already covers a substantial amount of the APIMs described in the literature, further extensions are in progress. Moderation and mediation analysis in the APIM framework, for example, has recently received much attention (Garcia et al., 2015). Currently, two apps have been developed to account for mediation and moderation effects in the APIM as well:

APIMeM and APIMoM, respectively (Kenny, 2015). A power app for the APIM also exists: APIMPowerR (Ackerman & Kenny, 2016). This app determines the power for a given sample size and specified effect sizes. Alternatively, the sample size can be calculated given the power and the effect sizes.

A limitation of the current apps is that they are restricted to outcomes measured at the interval level that follow a normal distribution. Loeys and Molenberghs (2013) explored how generalized linear mixed models can be used to fit the APIM with categorical outcomes and compared their performance with an approach based on generalized estimating equations (GEE). The latter approach may outperform the first, especially when the number of dyads is small. For a nontechnical introduction of the implementation of GEE in SPSS or R, we refer the interested reader to Loeys, Cook, De Smet, Wietzker, and Buysse (2014). The APIM with categorical outcomes can be fitted within the SEM framework (Josephy, Loeys, & Rosseel, 2016).

With longitudinal data, one might also be interested in fitting a cross-lagged model (Kenny et al., 2006). Such model accounts for over-time dyadic data by including the outcome at a previous time point (i.e., its lagged value) as an independent variable, which can be done in *APIM_SEM*. Extending the app for more complex longitudinal dyadic models would be an additional desirable feature (Bolger & Laurenceau, 2013; Kenny et al., 2006).

A general note on the APIM is that when researchers use the same method (e.g., self-report) for the assessment of predictor and outcome, actor or partner effects can be biased (Orth, 2013). Adding latent variables to an APIM analysis with self-report and partner report as indicators could improve the estimates (Ledermann & Kenny, 2017; Orth, 2013). Multimethod data are not always feasible due to their increased complexity and costs (Orth, 2013), so researchers might keep this in mind when interpreting the k parameter.

Conclusion

This article presents a user-friendly online app for fitting the APIM, which is freely accessible from a web browser. The program allows to easily model a regular APIM but also allows to include a second independent variable, to control for different covariates, and to examine dyadic patterns. Output is given in plain computer output, accompanied by full-text output, tables, diagnostics, and summarizing figures.

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Supporting Information

Additional Supporting Information for this article may be found in the online version of this article and on the first author's website at http://bbs.utdallas.edu/pairlab/materials/.

Online Appendix 1

Online Appendix 2

Online Appendix 3