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Extending the Actor-Partner Interdependence Model to Accommodate Multivariate Dyadic Data Using Latent Variables

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Abstract

This study extends the traditional Actor-Partner Interdependence model (APIM; Kenny, 1996) to incorporate dyadic data with multiple indicators reflecting latent constructs. Although the APIM has been widely used to model interdependence in dyads, the method and its applications have largely been limited to single sets of manifest variables. This article presents three extensions of the APIM that can be applied to multivariate dyadic data; a manifest APIM linking multiple indicators as manifest variables, a composite-score APIM relating univariate sums of multiple variables, and a latent APIM connecting underlying constructs of multiple indicators. The properties of the three methods in analyzing data with various dyadic patterns are investigated through a simulation study. It is found that the latent APIM adequately estimates dyadic relationships and holds reasonable power when measurement reliability is not too low, whereas the manifest APIM yields poor power and high type I error rates in general. The composite-score APIM, even though it is found to be a better alternative to the manifest APIM, fails to correctly reflect latent dyadic interdependence, raising inferential concerns. We illustrate the APIM extensions for multivariate dyadic data analysis by an example study on relationship commitment and happiness among married couples in Wisconsin. In cases where the measures are reliable reflections of psychological constructs, we suggest using the latent APIM for examining research hypotheses that discuss implications beyond observed variables. We conclude with stressing the importance of carefully examining measurement models when designing and conducting dyadic data analyses.

Translational Abstract

Dyadic data contain rich information about dynamic relationships that occur within a pair of people. The Actor-Partner Interdependence model (APIM; Kenny, 1996) has been widely used to study the interdependence of dyad members, defining its patterns by the relative strength of influence that members receive from their partners. This study proposes to add measurement models to the APIM to analyze multiple correlated variables as manifestations of underlying theoretical constructs that are interrelated between dyad members. In addition to this *latent* APIM approach, two other extensions of the APIM for multivariate data are presented in comparison: Instead of including measurement models, the *manifest* APIM uses observed variables simultaneously, and the *composite-score* APIM analyzes sums of observed variables. The usage of the three methods and their interpretations are presented with publicly available data from married couples. Using a simulation study, we also examine cautionary circumstances when each of the three methods may not be suitable and provide a list of recommendations for applied researchers on how to choose and apply different APIM approaches in practice. Overall, their performance can differ substantially depending on the context in which the variables in the analysis are related to each other. This article concludes with a discussion of the

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This research uses data from the Wisconsin Longitudinal Study (WLS). A public version of the WLS data can be accessed at https://ssc.wisc.edu/wlsresearch/data/, and a separate preregistration was not made for this study. Codes for both the simulation study and the example analysis are provided as online supplemental materials. Support for this research was provided by the Vilas Faculty Mid-Career Investigator Award from the University of Wisconsin–Madison and the Office of the Vice Chancellor for Research and Graduate Education at the University of Wisconsin–Madison with funding from the Wisconsin Alumni Research Foundation. The content is solely the responsibility of the authors and does not necessarily represent the official views of the funding agencies. The authors thank Dan Bolt, David Kaplan, and Joon Yang for their feedback on an earlier version of this article. The models and analysis results in this article were presented at the International Meeting of Psychometric Society in July 2021 by Hanna Kim. Preliminary work comparing the application of the manifest APIM and the Common Fate Model to the WLS data was published in the IMPS 2020 proceedings and cited as Kim and Kim (2021) in the article. The APIM used in Kim and Kim (2021) does not include a measurement model, which is essential to the latent APIM in this study.

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importance of theory and measurement characteristics in selecting a method to analyze multivariate dyadic data.

Keywords: dyadic data analysis, common factors, composite scores, multivariate analysis, structural equation modeling

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Dyads refer to small groups of two members each, where members share the same environment and actively interact with one another. Whether it is a couple of adults, advisor and student, patient and caregiver, or therapist and participant, their unique interactions involve two parts: interpersonal, mutual influences between the members of a dyad and separate individual, intrapersonal effects. Dyadic data consist of measures on identical contents obtained from both members in a dyad. Within dyadic data, variables that address the same content but measure different members tend to have relatively similar values because they represent members belonging to the same dyad.

As an example, the Wisconsin Longitudinal study (WLS) extended its sampling framework in 2004 to include spouses of their original participants, Wisconsin high school graduates from 1957, constructing a pool of dyadic data on married couples (Herd et al., 2014). Similarly, the National Social Life, Health, and Aging Project (NSHAP) invited coresident spouses and romantic partners of original participants beginning with Wave 2 (O'Muircheartaigh et al., 2014). Such publicly available dyadic data sets are increasing in their number, with many of them being large-scale assessment data encompassing various contents within their survey.

For spouses and couples, it is widely discussed that the emotions of partners in intimate relationships may become connected over time (Finkel et al., 2017; Schoebi & Randall, 2015). Even though the degree and consistency of such connection has been empirically debated (Anderson et al., 2003; Sels et al., 2020), one might pose that the frequency at which one felt negative emotions recently might be closer to that of their spouse than to that of a random person. Such dependency, specifically termed "interdependence" (Galovan et al., 2017) in relationship science, cannot be adequately addressed by conventional models designed for random samples that assume independent units. Models for nested data account for clustering, but only in terms of group-wise means and residual variances, lacking specificity.

One of the most popular ways for modeling interdependence in dyadic data has been the actor-partner interdependence model (APIM; Kenny, 1996). It disentangles dyadic interdependence into a combination of explicit and direct individual influences that members experience owing to either themselves ("actor effects") or their partners ("partner effects"). This allows its users to decompose dyadic relationships into distinct sources of intra- and interpersonal influences and evaluate the strengths and patterns of interdependence between dyad members in contrast to other dyadic data analysis models. For example, the Common Fate model (CFM; Kenny & La Voie, 1985) conceptualizes dyadic interdependence as a uniform process occurring at the dyadic level owing to a shared external factor rather than as a combination of diverse individual influences. Therefore, it is generally advised that the CFM be used when variables are assumed to reflect a dyad-level relationship rather than interpersonal interactions (Ledermann & Macho, 2009). For more types of dyadic data analysis models or works on intensive longitudinal dyadic data, please refer to other textbooks and journal articles (Brinberg et al., 2021; Chow et al., 2018; De Haan-Rietdijk et al., 2016; Gin et al., 2020; Kenny et al., 2006).

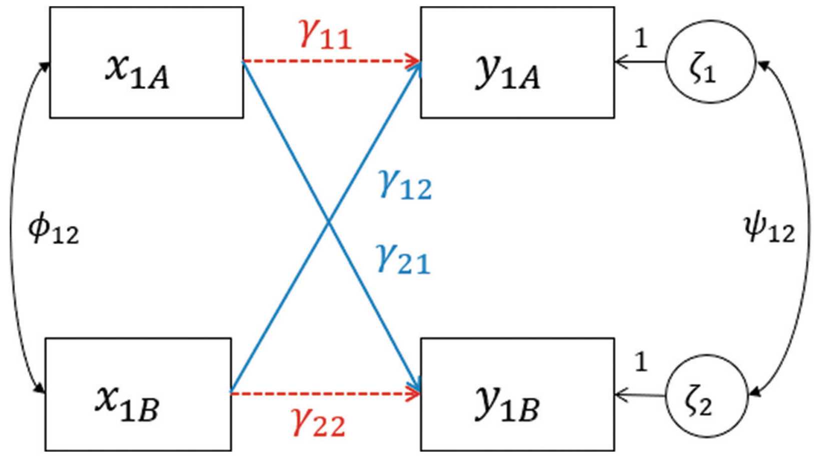
In Figure 1, a predictor x_1 is measured for members A and B in each dyad (x_{1A}, x_{1B}), which is then modeled to predict the outcome y_1 for the members (y_{1A}, y_{1B}) in terms of two actor effects (γ_{11}, γ_{22}; the red dashed horizontal arrows) and partner effects (γ_{12}, γ_{21}; the blue solid diagonal arrows). Actor effects show the impact of one's own predictor on their own outcome as in a typical regression model, whereas partner effects represent the influence on one's outcome received from their partner's predictor value. It is these partner effects by which the APIM captures dyadic interdependence.[1]

Even though most applications of the APIM involve single sets of predictors (x_{1A}, x_{1B}; predictor x_1 measured for members A and B in dyads) and outcomes (y_{1A}, y_{1B}; outcome y_1 measured for members A and B in dyads) as presented in Figure 1, often multiple measures are involved to cover broader constructs in psychological studies. For example, a study may aim to evaluate the relationship between perceived relationship commitment and happiness among married couples, using multiple items to collectively measure those concepts. Then, modeling each of the multiple indicators of relationship commitment or happiness separately with several models might not adequately answer the initial research question; instead, simultaneous evaluation of the variables may cast a clearer picture of the dyadic dynamics (Kim & Kim, 2021).

Previous studies have shown the possibility of incorporating two or more sets of variables within dyadic data analysis models such as using cross-informant data (van Dulmen & Goncy, 2010), correlated explanatory variables (Stas et al., 2018), or moderators (Garcia et al., 2015). Kim and Kim (2021) extended the APIM to cover two sets of manifest predictors and outcomes simultaneously. There have also been studies that partially or fully incorporated latent variables within the APIM to combine multiple indicators as shared predictors or outcomes. Some studies form latent variables to portray longitudinal relationships with APIM (Foran & Kliem, 2015; Gistelinck et al., 2018; Laurenceau & Bolger, 2012), which is beyond the scope of this article.

[1] Note the convention to label the partner effect of member A attributable to member B (the path of x_{1B} to y_{1A}) as γ_{12}, and vice versa (Garcia et al., 2015). To whom the outcome variable belongs, or in other words who receives the partner effect, is what matters in naming the partner effect parameters.

Figure 1
The Traditional Actor-Partner Interdependence Model



Note. Notations were modified from Kenny (1996) to maintain consistency throughout this article. Actor effects (the red dashed horizontal arrows denoted as γ_{11} and γ_{22}) show the impact of one's own predictor (x_{1A}, x_{1B}) on one's own outcome (y_{1A}, y_{1B}) for members A and B as in a typical regression model. Partner effects (the blue solid diagonal arrows denoted as γ_{12} and γ_{21}) assess the influence on one's outcome coming from their partner's predictor. Residual terms of the outcomes (the circles denoted as ζ_1 and ζ_2) represent the parts of the outcome that are not explained by the predictors. Covariance is allowed between predictors (ϕ_{12}) and outcome residuals (ψ_{12}). See the online article for the color version of this figure.

Alexandrowicz (2015) extended the APIM to combine multiple items into latent factors that were linked by covariances, resembling a multidimensional IRT model. However, covariances were used in place of the actor and partner effects, rendering this extension more suitable for specific instances such as modeling the results of a test with multiple discretized binary item scores. Similarly, a model for dyadic item response theory (dIRT) has been proposed, extending the social relations model (SRM) to incorporate individual- and dyad-level latent traits consisting of multiple items (Gin et al., 2020). Including such latent variables within the SRM enables researchers to retain informative measures from the IRT framework as well as to make inferences on the two-directional interaction between the latent variables. However, unlike the APIM, the SRM considers cases where individuals can change partners, not necessarily belonging to a single dyad.

It is notable that latent variable modeling has been used within dyadic data analysis, including models other than the APIM. The common fate model (CFM) actively uses latent variables to represent a shared external cause and a joint outcome at the dyad-level (Kenny & La Voie, 1985). However, if latent variables are to be used in the APIM, they need to be formed separately for each member (Hong & Kim, 2019). Unlike the CFM where indicators of the same content for both members are grouped into constructs representing the entire dyad, the APIM would need to represent latent concepts for each individual. It is this distinction of measures between members that makes it possible for the APIM to track inter- and intrapersonal influences directly. Consequently, the measurement models of the APIM will not be equivalent to that of the CFM, resulting in a conceptually different model.

It is therefore encouraging to see studies that combined multiple items on existing scales into latent variables before applying the APIM. For example, Moorman (2016) postulated husbands' and wives' martial satisfaction or loneliness in relation to actor and partner effects of marital conflict or four different dimensions of marital quality. This implies the necessity of combining measurement models with the APIM to understand dyadic relationships between certain theoretical concepts of dyad members. Despite such empirical motivation, a methodological investigation remains to be made regarding the benefits and caveats of using latent variables to accommodate multivariate dyadic data.

Correspondingly, it should be discussed how to implement the APIM for analyzing dyadic data containing multiple measures of latent variables. It is shown that without applying a latent variable framework, an APIM with multiple predictors and outcomes results in a complex model even with two indicators each for a predictor and an outcome (Kim & Kim, 2021). Thus, multiple manifest variables are often transformed into a composite score by summing or averaging the responses and then analyzed using a univariate model. However, composite scores do not sufficiently cover the distinction in the contents reflected in multiple indicators.

Measuring constructs or concepts that are not directly observable is an important aspect of scientific and practical research, and using manifest indicators that reflect change based on latent constructs has been the dominant measurement approach for decades (Hardin, 2017). Correspondingly, using measurement models to connect latent constructs and manifest indicators has been a core idea in factor analysis (FA), classical test theory (CTT), item response theory (IRT), and structural equation modeling (SEM) (Crocker & Algina, 1986; Embretson & Reise, 2013;

Harman, 1976; Kline, 2015). However, this fundamental measurement theory has not been used broadly in the framework of dyadic data analysis. Therefore, we highlight the value of adding measurement models to the APIM and present the latent APIM as a methodologically attractive alternative to the composite-score APIM or an APIM with multiple manifest variables when analyzing multivariate dyadic data. In addition to exhibiting the interpersonal influences in terms of shared unobservable concepts closer to substantive research questions, extending the APIM within a latent variable framework will also control for measurement errors for multivariate dyadic data analysis.

The remainder of the paper is organized as follows. In section 2, we first describe how the traditional APIM can be extended to multivariate dyadic data by incorporating multiple manifest variables. Then, we discuss in section 3 the benefits of including a measurement model in the APIM to reflect latent constructs underlying multiple manifest indicators. Consequently, the parameter structure of a latent APIM is presented as a way to integrate measurement theory and multivariate dyadic data analysis. In section 4, a simulation study presents how models with and without latent constructs may lead to distinct results for characteristic dyadic relationships. The following section illustrates how to implement the models in the context of investigating the relationship between relationship commitment and happiness among married couples, using example data from the WLS. Finally, section 6 concludes with potential implications and practical recommendations for extending the APIM to multivariate dyadic data analyses.

The Actor-Partner Interdependence Models Using Manifest Variables

Generalizing the Traditional APIM as a Structural Equation Model

In this section, we describe how the traditional APIM can be applied to multivariate dyadic data by introducing a general matrix expression and expanding the dimensions of parameter and variable matrices. For consistency, we will closely follow the LISREL notation (Jöreskog, 2001) widely used to describe structural equation models by grouping parameters into vectors or matrices having distinct roles.

The APIM in general can be described as

$$\boldsymbol{y_i} = \boldsymbol{\alpha} + \boldsymbol{\Gamma}\boldsymbol{x_i} + \boldsymbol{\zeta_i} \tag{1}$$

where $\boldsymbol{y_i}$ is a $2p$-dimensional vector of endogenous outcome variables for dyads $i = 1, 2, \ldots, n$ with p being the number of observed outcome variables for each member of a dyad; $\boldsymbol{\alpha}$ is a $2p$-dimensional vector of intercepts; $\boldsymbol{x_i}$ is a $2q$-dimensional vector of exogenous predictor variables with q being the number of observed predictor variables for each member of a dyad; $\boldsymbol{\Gamma}$ is a $2p \times 2q$ matrix of actor and partner effects linking variables in $\boldsymbol{y_i}$ and $\boldsymbol{x_i}$; and $\boldsymbol{\zeta_i}$ is a $2p$-dimensional vector of residual terms of the outcome variables for dyads $i = 1, 2, \ldots, n$. Hereafter, we omit the intercepts $\boldsymbol{\alpha}$ with no loss of generality, and parameters without subscripts i are assumed to be equal across dyads.

Applying $p = q = 1$ to (1), the traditional APIM (Kenny, 1996) in Figure 1 can be reformatted as

$$\begin{bmatrix} y_{1Ai} \\ y_{1Bi} \end{bmatrix} = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix} \begin{bmatrix} x_{1Ai} \\ x_{1Bi} \end{bmatrix} + \begin{bmatrix} \zeta_{1i} \\ \zeta_{2i} \end{bmatrix}. \tag{2}$$

Expressing the APIM as in (1) and (2) shows that actor and partner effects can be understood as path coefficients of a path analysis model that link variables from dyadic data consisting of n dyads. In addition, residual covariance ($\psi_{12} = \psi_{21}$) is allowed to reflect any remaining covariance between the two members' outcomes not captured by the partner effects (Cook, 1998). Similarly, covariance is also allowed between the predictor variables ($\phi_{12} = \phi_{21}$), reflecting the belief that the predictors of members within a dyad are not independent. This results in variance-covariance matrices of predictors and outcome residual terms as

$$\begin{aligned} \boldsymbol{\Psi} &= var(\boldsymbol{\zeta_i}) = \begin{bmatrix} \psi_{11} & sym. \\ \psi_{21} & \psi_{22} \end{bmatrix}, \\ \boldsymbol{\Phi} &= var(\boldsymbol{x_i}) = \begin{bmatrix} \phi_{11} & sym. \\ \phi_{21} & \phi_{22} \end{bmatrix}, \end{aligned} \tag{3}$$

where sym. denotes symmetric matrices hereafter.

Extending the Traditional APIM to Multivariate Dyadic Data Analysis

The APIM in (1) to (3) can be intuitively extended to the analysis of dyadic interdependence contained in multivariate dyadic data. Figures 2 and 3 illustrate the APIM with two and three predictors ($x_1, x_2, q = 2; x_1, x_2, x_3, q = 3$) and outcomes ($y_1, y_2, p = 2; y_1, y_2, y_3, p = 3$), respectively, for dyad members A and B. The APIM with multiple predictors and outcomes (called *the manifest APIM*) is a direct extension of the traditional APIM in (2) in that the variable vectors $\boldsymbol{x_i}$ and $\boldsymbol{y_i}$ are longer, such that

$$\begin{bmatrix} y_{1Ai} \\ y_{1Bi} \\ y_{2Ai} \\ y_{2Bi} \end{bmatrix} = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \gamma_{24} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} & \gamma_{34} \\ \gamma_{41} & \gamma_{42} & \gamma_{43} & \gamma_{44} \end{bmatrix} \begin{bmatrix} x_{1Ai} \\ x_{1Bi} \\ x_{2Ai} \\ x_{2Bi} \end{bmatrix} + \begin{bmatrix} \zeta_{1i} \\ \zeta_{2i} \\ \zeta_{3i} \\ \zeta_{4i} \end{bmatrix} \tag{4}$$

for a manifest APIM with $p = q = 2$, and

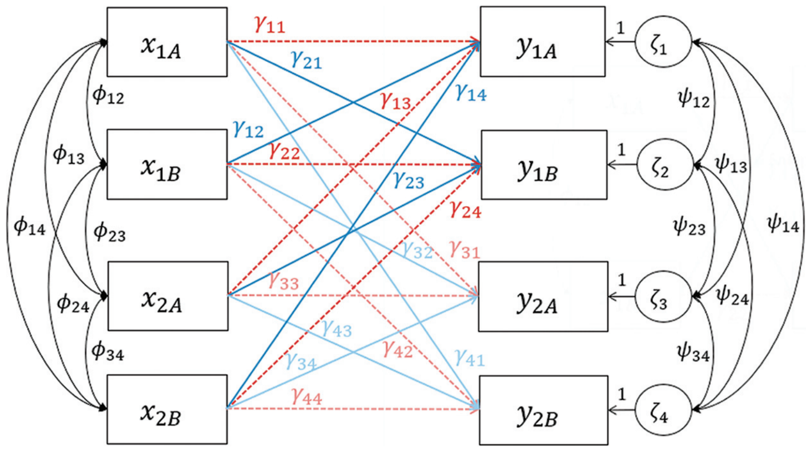
$$\begin{bmatrix} y_{1Ai} \\ y_{1Bi} \\ y_{2Ai} \\ y_{2Bi} \\ y_{3Ai} \\ y_{3Bi} \end{bmatrix} = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} & \gamma_{15} & \gamma_{16} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \gamma_{24} & \gamma_{25} & \gamma_{26} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} & \gamma_{34} & \gamma_{35} & \gamma_{36} \\ \gamma_{41} & \gamma_{42} & \gamma_{43} & \gamma_{44} & \gamma_{45} & \gamma_{46} \\ \gamma_{51} & \gamma_{52} & \gamma_{53} & \gamma_{54} & \gamma_{55} & \gamma_{56} \\ \gamma_{61} & \gamma_{62} & \gamma_{63} & \gamma_{64} & \gamma_{65} & \gamma_{66} \end{bmatrix} \begin{bmatrix} x_{1Ai} \\ x_{1Bi} \\ x_{2Ai} \\ x_{2Bi} \\ x_{3Ai} \\ x_{3Bi} \end{bmatrix} + \begin{bmatrix} \zeta_{1i} \\ \zeta_{2i} \\ \zeta_{3i} \\ \zeta_{4i} \\ \zeta_{5i} \\ \zeta_{6i} \end{bmatrix} \tag{5}$$

for an extension with $p = q = 3$.

Consequently, the variables are now linked by multiple actor and partner effects contained in an also larger parameter matrix $\boldsymbol{\Gamma}$. This implies that the actor and partner effects indicate unique effects of a specific predictor on a particular outcome considering other predictors and outcome variables. Comparing standardized actor or partner effects provides a sense as to which path demonstrates stronger interdependence among members belonging to the same dyad. We can examine whether a member's predictor level is associated with their own outcome by estimating corresponding actor effects or investigate whether one's outcome level is affected by their partner's predictor level by estimating partner effects. It should be

Figure 2

The Actor-Partner Interdependence Model With Two Predictors and Outcomes (Manifest APIM, p = q = 2)



Note. Compared with the traditional APIM in Figure 1, actor effects (the red dashed arrows denoted as $\gamma_{11}, \gamma_{22}, \ldots, \gamma_{44}$) and partner effects (the blue solid arrows denoted as $\gamma_{12}, \gamma_{21}, \ldots, \gamma_{43}$) now connect two sets of predictors $(x_{1A}, x_{1B}, x_{2A}, x_{2B})$ and outcomes $(y_{1A}, y_{1B}, y_{2A}, y_{2B})$. Actor and partner effects related to the second set of outcomes (y_{2A}, y_{2B}) are denoted with lighter colors for distinction. Residual terms of the outcomes $(\zeta_1, \zeta_2, \ldots, \zeta_4)$ are allowed to have covariances $(\psi_{12}, \psi_{13}, \ldots, \psi_{34})$. Covariance is also allowed between predictors $(\phi_{12}, \phi_{13}, \ldots, \phi_{34})$. See the online article for the color version of this figure.

noted that unstandardized actor or partner effects are inappropriate for this purpose because they reflect the amount of variance for related variables.

The difference in the effects can also be tested by comparing models with and without equality constraints (Laurenceau & Bolger, 2012; Maroufizadeh et al., 2018). Additionally, the ratio of a member's partner effect to their actor effect (k) can be used to identify the "dyadic pattern" of the relationship in that it illustrates the relative amount and direction of interpersonal influences compared with intrapersonal effects. Characteristic dyadic patterns include the actor-only pattern ($k = 0$), couple pattern ($k = 1$), and the contrast pattern ($k = -1$; Kenny & Ledermann, 2010).

Now covariance terms can be set between all residual errors of the outcomes $(\psi_{12}, \psi_{13}, \ldots)$ as well as between predictors $(\phi_{12}, \phi_{13}, \ldots)$ as in (6) for a manifest APIM with two sets of variables and (7) for a manifest APIM with three sets of variables. This is to incorporate any remaining covariances among the outcomes not explained enough by the actor and partner effects or natural correlations between predictors of members within the same dyad.

$$\boldsymbol{\Psi} = var(\boldsymbol{\zeta}_{\mathbf{i}}) = var\begin{bmatrix} \zeta_{1i} \\ \zeta_{2i} \\ \zeta_{3i} \\ \zeta_{4i} \end{bmatrix} = \begin{bmatrix} \psi_{11} & & & sym. \\ \psi_{21} & \psi_{22} & & \\ \psi_{31} & \psi_{32} & \psi_{33} & \\ \psi_{41} & \psi_{42} & \psi_{43} & \psi_{44} \end{bmatrix},$$

$$\boldsymbol{\Phi} = var(\boldsymbol{x}_i) = var\begin{bmatrix} x_{1Ai} \\ x_{1Bi} \\ x_{2Ai} \\ x_{2Bi} \end{bmatrix} = \begin{bmatrix} \phi_{11} & & & sym. \\ \phi_{21} & \phi_{22} & & \\ \phi_{31} & \phi_{32} & \phi_{33} & \\ \phi_{41} & \phi_{42} & \phi_{43} & \phi_{44} \end{bmatrix}. \tag{6}$$

$$\boldsymbol{\Psi} = \mathrm{var}(\boldsymbol{\zeta}_{\mathbf{i}}) = var\begin{bmatrix} \zeta_{1i} \\ \zeta_{2i} \\ \zeta_{3i} \\ \zeta_{4i} \\ \zeta_{5i} \\ \zeta_{6i} \end{bmatrix} = \begin{bmatrix} \psi_{11} & & & & & sym. \\ \psi_{21} & \psi_{22} & & & & \\ \psi_{31} & \psi_{32} & \psi_{33} & & & \\ \psi_{41} & \psi_{42} & \psi_{43} & \psi_{44} & & \\ \psi_{51} & \psi_{52} & \psi_{53} & \psi_{54} & \psi_{55} & \\ \psi_{61} & \psi_{62} & \psi_{63} & \psi_{64} & \psi_{65} & \psi_{66} \end{bmatrix},$$

$$\boldsymbol{\Phi} = var(\boldsymbol{x}_i) = \mathrm{var}\begin{bmatrix} x_{1Ai} \\ x_{1Bi} \\ x_{2Ai} \\ x_{2Bi} \\ x_{3Ai} \\ x_{3Bi} \end{bmatrix} = \begin{bmatrix} \phi_{11} & & & & & sym. \\ \phi_{21} & \phi_{22} & & & & \\ \phi_{31} & \phi_{32} & \phi_{33} & & & \\ \phi_{41} & \phi_{42} & \phi_{43} & \phi_{44} & & \\ \phi_{51} & \phi_{52} & \phi_{53} & \phi_{54} & \phi_{55} & \\ \phi_{61} & \phi_{62} & \phi_{63} & \phi_{64} & \phi_{65} & \phi_{66} \end{bmatrix}. \tag{7}$$

For detailed descriptions of notation, please refer to Table 1.

When the APIM in (1) is believed to have generated a set of dyadic data, its model-implied variance and covariance terms can be derived as

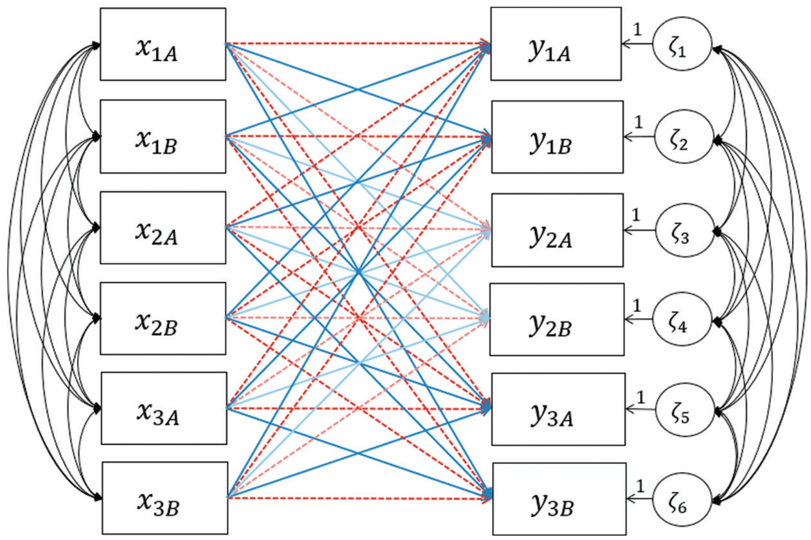
$$\begin{aligned} \Sigma_{yy}(\theta) &= \boldsymbol{\Gamma\Phi\Gamma}' + \boldsymbol{\Psi}, \\ \Sigma_{xy}(\theta) &= \boldsymbol{\Phi\Gamma}' \end{aligned} \tag{8}$$

which indicates how the actor and partner effects constitute the variances and covariances between variables in dyadic data in combination with the variances and covariances of explanatory variables.[2] Because the manifest APIM covers multivariate dyadic data with larger dimensions and more parameters, model-implied (co)variances reflect more explanatory variables and parameters compared with those of the

[2] (8) is derived from the model-implied covariance matrix of a path analysis model introduced in Bollen (1989) (4.7) to (4.9), where there are no paths between endogenous variables.

Figure 3

The Actor-Partner Interdependence Model With Two Predictors and Outcomes (Manifest APIM, $p = q = 3$)



Note. Compared with the models in Figures 1 and 2, actor effects (the red dashed arrows; parameters $\gamma_{11}, \ldots, \gamma_{66}$ omitted in figure for brevity) and partner effects (the blue solid arrows; parameters $\gamma_{12}, \ldots, \gamma_{65}$ omitted in figure for brevity) now connect three sets of predictors ($x_{1A}, x_{1B}, \ldots, x_{3B}$) and outcomes ($y_{1A}, y_{1B}, \ldots, y_{3B}$). Residual terms of the outcomes ($\zeta_1, \zeta_2, \ldots, \zeta_6$) as well as predictors are allowed to have covariances ($\psi_{12}, \psi_{13}, \ldots, \psi_{56}$; $\phi_{12}, \phi_{13}, \ldots, \phi_{56}$; parameters omitted in figure for brevity). Actor and partner effects related to the second set of outcomes (y_{2A}, y_{2B}) are denoted with lighter colors for distinction. See the online article for the color version of this figure.

traditional APIM.[3] As a result, the parameters of the manifest APIM with multiple variables reflect partial effects controlling for other sources of variance, compared with those of a traditional APIM.

It should also be noted that the number of parameters for a manifest APIM equals the number of unique variances and covariances in the data. The number of parameters of a manifest APIM with $2p$ endogenous variables and $2q$ exogenous variables where $p = q$ becomes $8p^2 + 2p$ with $(2p)^2$ parameters for $\mathbf{\Gamma}$ and $\frac{2p(2p+1)}{2}$ parameters each for $\mathbf{\Psi}$ and $\mathbf{\Phi}$. This equals the number of unique variances and covariances in the data, i.e., $\frac{1}{2}(2p + 2q)(2p + 2q + 1) = 2p(4p + 1)$. For instance, the models presented in Figures 2 and 3 have 36 and 78 parameters each, being equal to the number of nonredundant (co)variances when $p = q = 2$ and $p = q = 3$, respectively.

Therefore, under the counting rule (Bollen, 1989; Kaplan, 2009), the manifest APIM is always "just-identified" unless specific constraints are imposed. When a model is just-identified, also referred to as saturated, the model has zero degrees of freedom ($df = 0$) and has only one solution. In structural equation modeling, the solution of a just-identified model consists of a set of parameter estimates that perfectly reproduces the observed covariance matrix. This is a critical limitation because the fit of a just-identified model to observed data cannot be tested, and we have no means to investigate whether the model is reasonable. We might still compare several restricted models to the full model to evaluate various hypotheses such as whether a particular actor or partner effect is present or whether their magnitudes are the same across members. However, reduced models are simpler versions of the corresponding full model, with representations bounded by the full model. Unless we can investigate how well the full model suits observed data, it is difficult to empirically justify one of its reduced models with added constraints.

Analyzing Multivariate Dyadic Data With Composite Scores

When multiple variables are measured either to reflect a shared psychological construct or to represent multiple related concepts, modeling each variable separately with multiple univariate models fails to capture the correlations within such multivariate data. The manifest APIM presented above can be meaningful in that it evaluates the dyadic dynamics simultaneously, instead of conducting separate univariate evaluations. However, it also poses two difficulties in that the manifest APIM applied to multivariate dyadic data produces multiple partial actor or partner effects controlling for every other variable included in the model.

First, the actor and partner effects from the manifest APIM may be of less interest unless we have specific interest in distinguishing the unique effect of a specific predictor to an outcome after removing all other actor or partner effects in the model. If we are more

[3] Visit Table C-1 in the online supplemental materials to see how components involving the same variables x_1 and y_1 (e.g., $var(y_{1A}), cov(x_{1A}, y_{1B})$) represent different combinations of parameters and (co)variances depending on the underlying model, manifest APIMs with $p = q = 1$ vs. $p = q = 2$.

Table 1
Notations for the Multivariate Manifest APIM

Symbol	Description
x_{1Ai} $(x_{2Ai}, x_{3Ai}, \ldots, x_{qAi})$	Observed predictor variable 1 (2, 3, . . . , q) for dyad member A in dyads $i = 1, 2, \ldots, n$
x_{1Bi} $(x_{2Bi}, x_{3Bi}, \ldots, x_{qBi})$	Observed predictor variable 1 (2, 3, . . . , q) for dyad member B in dyads $i = 1, 2, \ldots, n$
y_{1Ai} $(y_{2Ai}, y_{3Ai}, \ldots, y_{pAi})$	Observed outcome variable 1 (2, 3, . . . , p) for dyad member A in dyads $i = 1, 2, \ldots, n$
y_{1Bi} $(y_{2Bi}, y_{3Bi}, \ldots, y_{pBi})$	Observed outcome variable 1 (2, 3, . . . , p) for dyad member B in dyads $i = 1, 2, \ldots, n$
$\gamma_{pq}(\gamma_{11}, \gamma_{12}, \ldots, \gamma_{pq}, \ldots, \gamma_{2p2q})$	The actor or partner effect linking the pth element of $\boldsymbol{y_i}$ to the qth element of $\boldsymbol{x_i}$ in a manifest APIM
$k_{pq,pp'}(k_{12,11}, \ldots, k_{2p.2(q-1),2p.2p'})$	The ratio of partner effect $\gamma_{pq}(\gamma_{12}, \ldots, \gamma_{2p.2(q-1)})$ to actor effect $\gamma_{pp'}(\gamma_{11}, \ldots, \gamma_{2p.2p'})$, indicating the dyadic pattern for the pth (first, . . . , 2pth) element of $\boldsymbol{y_i}$ in relation to the qth (first, . . . , 2(q−1) th) element of $\boldsymbol{x_i}$ and the p'th element of $\boldsymbol{x_i}$ with the same item as the qth element measured for a different dyad member.
$\zeta_{1i}(\zeta_{2i}, \zeta_{3i}, \ldots, \zeta_{2pi})$	Residual error term of the first (second, third, . . . , 2pth) element of $\boldsymbol{y_i}$
$\psi_{11}(\psi_{12}, \ldots, \psi_{2p.2p})$	Variance term of ζ_{1i} (covariance term between ζ_{1i} and ζ_{2i}, . . . , variance term of ζ_{2pi})
$\phi_{11}(\phi_{12}, \ldots, \phi_{2q.2q})$	Variance term of the first element of $\boldsymbol{x_i}$ (covariance term between the first and second element of $\boldsymbol{x_i}$, . . . , variance term of the 2qth element of $\boldsymbol{x_i}$)

interested in the collective dyadic interaction, the multivariate manifest APIM may be less attractive. Second, estimating and interpreting a lot of parameters becomes too complicated as the number of variables per dyad member (p, q) increases (Kim & Kim, 2021). Many of the parameter estimates may be small or statistically insignificant, which may indicate negligible parameter values or a lack of power to detect multiple parameters.

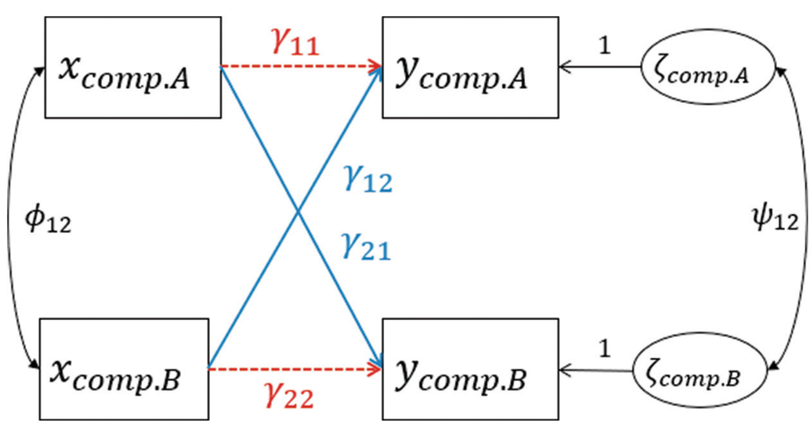
Because of such practical concerns, using composite scores that sum or average multiple variables has been a popular alternative (Ledgerwood & Shrout, 2011; Rhemtulla et al., 2020; Rush et al., 2020). Composite scores have also been widely used in dyadic data analysis literature, including cases where composite scores were used to summarize multiple items (Bardach et al., 2019; Decuyper et al., 2018) or to simplify longitudinal data analysis (Foran & Kliem, 2015). If we create composite scores to analyze an APIM with multivariate dyadic data (called *the composite-score APIM*) as in Figure 4, the model eventually resembles the traditional APIM with single variables $(p = q = 1)$ as in Figure 1, because composite scores are used in place of the individual variables.

When we let

$$\begin{aligned} x_{comp.Ai} &= x_{1Ai} + x_{2Ai} + \ldots + x_{qAi}, \\ x_{comp.Bi} &= x_{1Bi} + x_{2Bi} + \ldots + x_{qBi}, \\ y_{comp.Ai} &= y_{1Ai} + y_{2Ai} + \ldots + y_{pAi}, \\ y_{comp.Bi} &= y_{1Bi} + y_{2Bi} + \ldots + y_{pBi}, \end{aligned}$$

the composite-score APIM can be described as

Figure 4
The Actor-Partner Interdependence Model With Composite-Scores as Predictors and Outcomes (Composite-Score APIM, p = q = 1)



Note. Actor effects (the red dashed horizontal arrows denoted as γ_{11} and γ_{22}) show the impact of one's predictor composite score ($x_{comp.A}$, $x_{comp.B}$) on one's own outcome composite score ($y_{comp.A}$, $y_{comp.B}$) for members A and B. Partner effects (the blue solid diagonal arrows denoted as γ_{12} and γ_{21}) assess the influence on one's outcome composite score coming from their partner's predictor composite score. Residual terms of the outcome composite scores ($\zeta_{comp.A}$, $\zeta_{comp.B}$) represent parts of the outcome composite scores that are not explained by the predictor composite scores. Covariance is allowed between predictor composite scores of dyad members (ϕ_{12}) and outcome composite score residuals (ψ_{12}). See the online article for the color version of this figure.

$$\boldsymbol{y_{comp.i}} = \boldsymbol{\Gamma x_{comp.i}} + \boldsymbol{\zeta_{comp.i}} \tag{9}$$

where $\boldsymbol{y_{comp.i}}$ is a 2-dimensional vector of outcome composite scores and $\boldsymbol{x_{comp.i}}$ is a 2-dimensional vector of predictor composite scores for dyads $i = 1, 2, \ldots, n$. $\boldsymbol{\Gamma}$ is a 2×2 matrix of actor and partner effects linking variables in $\boldsymbol{y_{comp.i}}$ and $\boldsymbol{x_{comp.i}}$, and $\boldsymbol{\zeta_{comp.i}}$ is a 2-dimensional vector of residual terms of the outcome composite scores for dyads $i = 1, 2, \ldots, n$. In expanded form, (9) can be reformatted as

$$\begin{bmatrix} y_{comp.Ai} \\ y_{comp.Bi} \end{bmatrix} = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix} \begin{bmatrix} x_{comp.Ai} \\ x_{comp.Bi} \end{bmatrix} + \begin{bmatrix} \zeta_{comp.Ai} \\ \zeta_{comp.Bi} \end{bmatrix}. \tag{10}$$

Now the actor and partner effects $(\gamma_{11}, \ldots, \gamma_{22})$ represent relationships between composite scores of the predictors or outcome variables, such that they convey comprehensive actor and partner effects compared with those of the multivariate manifest APIM. Even though such a univariate approach reduces the complexity of estimating and interpreting a manifest APIM, it remains a question whether simple sums of variables contain sufficient information about multivariate dyadic relationships.

Residual covariance between the outcome composite scores $(\psi_{12} = \psi_{21})$ as well as covariance between predictor composite scores $(\phi_{12} = \phi_{21})$ are allowed in a similar fashion to the univariate manifest APIM, such that the variance-covariance matrices are defined as

$$\begin{aligned} \boldsymbol{\Psi} &= var(\boldsymbol{\zeta_{comp.i}}) = var\begin{bmatrix} \zeta_{comp.Ai} \\ \zeta_{comp.Bi} \end{bmatrix} = \begin{bmatrix} \psi_{11} & sym. \\ \psi_{21} & \psi_{22} \end{bmatrix}, \\ \boldsymbol{\Phi} &= var(\boldsymbol{x_{comp.i}}) = var\begin{bmatrix} x_{comp.Ai} \\ x_{comp.Bi} \end{bmatrix} = \begin{bmatrix} \phi_{11} & sym. \\ \phi_{21} & \phi_{22} \end{bmatrix}. \end{aligned} \tag{11}$$

For detailed descriptions of notation, please refer to Table 2.

The Latent Actor-Partner Interdependence Model

Benefits of Having Measurement Models Within the APIM

Measures are almost always imperfect and contain measurement errors. This is especially the case when researchers examine individual characteristics such as affect or stress in that they are observed rather than manipulated (Ledgerwood & Shrout, 2011; Rush et al., 2020). Also, the abundant use of self-report scales or subjective assessments makes it critical to understand the effects of measurement error on the accuracy and precision of model parameter estimates. Imperfect measures attenuate the relationship among the concepts of interest and may result in severe bias or misleading conclusions. Variables that are intended to measure unobserved constructs such as relationship commitment and happiness not only reflect underlying constructs but also capture the unique variances/disturbances of the indicators.

However, the composite-score APIM and manifest APIM do not account for measurement error, nor do they isolate the variability of common factors from the unique variances of indicators that are not shared by other variables. Therefore, when constructs of interests are best viewed as reflected by their corresponding indicators as in our analysis of the WLS dyadic data, the latent APIM is a truer representation of the underlying relationships between relationship commitment and happiness among the husbands and wives, rather than the manifest APIM or composite-score APIM.

In the path analysis context, Cole and Preacher (2014) showed that measurement error can make different path coefficients over- or underestimated, cause valid models to appear invalid, and change the substantive conclusions. The study also warned that these problems become increasingly serious and intractable as models become more complex. To prevent these problems, the authors concluded that researchers should use more reliable measures, correct for measurement error, or obtain multiple measures for latent variable modeling.

In measurement theory, manifest and latent variables form distinct layers depending on the contents they convey. Unlike manifest variables, latent variables represent unmeasurable entities that are related to several empirical variables or are theoretical sources of the correlation among them (Cohen et al., 1990). It is argued that latent variables are more appropriate for many psychological research questions unless variables can be measured deterministically without unexplained sources of variation (Borsboom, 2008). As a consequence, manifest or observed variables are rarely sufficient in psychology, making it reasonable to conceive of latent variables until we have ground to believe they can be directly observed. Therefore, if a set of observed variables are measured in the expectation to portray an underlying concept, they should be analyzed with methods that acknowledge the common factor behind the measures.

Using a latent variable approach can be a theoretical breakthrough when conceptualizing a way to apply the APIM to dyadic data with multiple variables. More often, the variables we observe are limited manifestations of theoretical concepts that we cannot directly measure. Even though we may apply models like the

Table 2
Notations for the Composite-Score APIM

Symbol	Description
$x_{comp.Ai}(x_{comp.Bi})$	The composite score of predictor variables of dyad member A (B) in dyads $i = 1, 2, \ldots, n$
$y_{comp.Ai}(y_{comp.Bi})$	The composite score of outcome variables of dyad member A (B) in dyads $i = 1, 2, \ldots, n$
$\gamma_{11}(\gamma_{22})$	The actor effect of dyad member A (B)
$\gamma_{12}(\gamma_{21})$	The partner effect representing the influence that the outcome composite score of dyad member A (B) receives from the predictor composite score of dyad member B (A)
k_A, k_B	The ratio of partner effect $\gamma_{12}(\gamma_{21})$ to actor effect $\gamma_{11}(\gamma_{22})$, indicating the dyadic pattern for dyad member A (B)
$\zeta_{comp.Ai}(\zeta_{comp.Bi})$	Residual error term of $y_{comp.Ai}$ ($y_{comp.Bi}$)
$\psi_{11}(\psi_{12} = \psi_{21}, \psi_{22})$	Variance term of $\zeta_{comp.Ai}$ (covariance term between $\zeta_{comp.Ai}$ and $\zeta_{comp.Bi}$, variance term of $\zeta_{comp.Bi}$)
$\phi_{11}(\phi_{12} = \phi_{21}, \phi_{22})$	Variance term of $x_{comp.Ai}$ (covariance term between $x_{comp.Ai}$ and $x_{comp.Bi}$, variance term of $x_{comp.Bi}$)

composite-score APIM to analyze indicators designed to collectively represent certain underlying constructs, this can be suboptimal in that the results hardly resonate with our intended research hypotheses drawing on theoretical concepts. In contrast, the latent variable approach groups the indicators together that are believed to have been influenced by a common underlying construct. The factor loadings of the indicators represent the strength of association between the indicator and the latent factor behind the indicators. Having a measurement model to represent such relationships enables direct inferences about the constructs of members in a dyad, instead of their indirect reflections. This way, the results of studies based on observed data can still be interpreted with respect to structural relationships closer to our research hypotheses.

There are also practical benefits to using latent variables within the APIM in that the model becomes more parsimonious compared with a manifest APIM that does not synthesize multiple indicators into latent variables, while also accounting for measurement error. When directional effects such as the actor or partner effects link latent variables instead of individual indicators, dyadic interdependence can be expressed in terms of theoretical constructs, leading to fewer model parameters. For instance, a total of 16 actor and partner effects in Figure 2 can be replaced with just four actor and partner effects when two indicators each are grouped across members and endogenous/exogenous variables. In this way, we yield a handful of representative directional effects compared with the multitude of actor and partner effects linking manifest indicators. Also, unlike the manifest or composite-score APIM, fitting the latent APIM spares us degrees of freedom to test the model fit against observed data with various model diagnostics, which can serve as the starting point to compare reduced models representing separate research hypotheses.

Extending the Traditional APIM to a Latent Variable Framework

We can incorporate latent predictors and outcomes into an APIM by specifying a measurement model in addition to a structural model (called *the latent APIM*). The measurement model defines the indicators as weighted combinations of latent variables and measurement errors, such that

$$\begin{aligned} \boldsymbol{x_i} &= \boldsymbol{\Lambda_x \xi_i} + \boldsymbol{\delta_i}, \\ \boldsymbol{y_i} &= \boldsymbol{\Lambda_y \eta_i} + \boldsymbol{\varepsilon_i}, \end{aligned} \tag{12}$$

where $\boldsymbol{x_i}$ is a $2q$-dimensional vector of exogenous indicators for dyads $i = 1, 2, \ldots, n$ with q being the number of observed predictor indicators for each member of a dyad; $\boldsymbol{\xi_i}$ is a 2-dimensional vector of latent predictor variables, one each for dyad members; $\boldsymbol{\Lambda_x}$ is a $2q \times 2$ matrix of factor loadings linking $\boldsymbol{x_i}$ and $\boldsymbol{\xi_i}$; $\boldsymbol{\delta_i}$ is a $2q$-dimensional vector of measurement errors of the predictor indicators; $\boldsymbol{y_i}$ is a $2p$-dimensional vector of endogenous indicators with p being the number of observed outcome indicators for each member of a dyad; $\boldsymbol{\eta_i}$ is a 2-dimensional vector of latent outcome variables, one each for dyad members; $\boldsymbol{\Lambda_y}$ is a $2p \times 2$ matrix of factor loadings linking $\boldsymbol{y_i}$ and $\boldsymbol{\eta_i}$; and $\boldsymbol{\varepsilon_i}$ is a $2p$-dimensional vector of measurement errors of the outcome indicators. We note that p and q may differ depending on the measurement structure and scale used in practice, but we limit our illustration to cases where $p = q$ for the sake of simplicity.

Next, the structural model represents the relationship between the latent predictors and outcomes as

$$\boldsymbol{\eta_i} = \mathbf{B}\boldsymbol{\xi_i} + \boldsymbol{\zeta_i}, \tag{13}$$

where $\boldsymbol{B}$ is a 2×2 matrix of structural actor and partner effects linking $\boldsymbol{\eta_i}$ and $\boldsymbol{\xi_i}$, and $\boldsymbol{\zeta_i}$ is a 2-dimensional vector of residual errors of endogenous latent variables.

The latent APIM with two indicators for each latent variable ($p = q = 2$) is depicted in Figure 5, the measurement model of which can be formatted as

$$\begin{bmatrix} x_{1Ai} \\ x_{2Ai} \\ x_{1Bi} \\ x_{2Bi} \\ - \\ y_{1Ai} \\ y_{2Ai} \\ y_{1Bi} \\ y_{2Bi} \end{bmatrix} = \begin{bmatrix} 1 & 0 & & \\ \lambda_{x1} & 0 & \multicolumn{2}{c}{\mathbf{0}_{4\times2}} \\ 0 & 1 & & \\ 0 & \lambda_{x2} & & \\ & & 1 & 0 \\ & & \lambda_{y1} & 0 \\ \multicolumn{2}{c}{\mathbf{0}_{4\times2}} & 0 & 1 \\ & & 0 & \lambda_{y2} \end{bmatrix} \begin{bmatrix} \xi_{Ai} \\ \xi_{Bi} \\ - \\ \eta_{Ai} \\ \eta_{Bi} \end{bmatrix} + \begin{bmatrix} \delta_{1i} \\ \delta_{2i} \\ \delta_{3i} \\ \delta_{4i} \\ - \\ \varepsilon_{1i} \\ \varepsilon_{2i} \\ \varepsilon_{3i} \\ \varepsilon_{4i} \end{bmatrix}. \tag{14}$$

Likewise, the measurement model of a latent APIM with three indicators for each latent variable ($p = q = 3$) is depicted in Figure 6. Having three or more indicators to identify latent variables as is generally recommended (Tabachnick et al., 2007) can be done straightforwardly by having variable vectors and parameter matrices of larger dimensions in the measurement model, such that

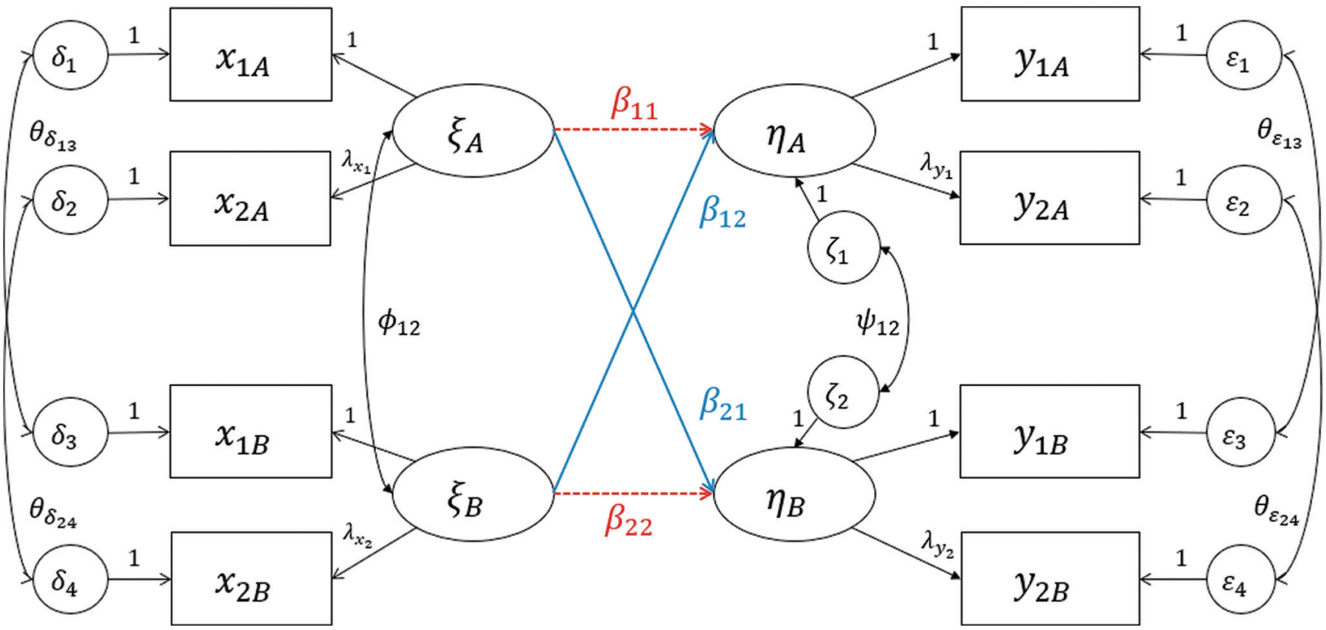
$$\begin{bmatrix} x_{1Ai} \\ x_{2Ai} \\ x_{3Ai} \\ x_{1Bi} \\ x_{2Bi} \\ x_{3Bi} \\ - \\ y_{1Ai} \\ y_{2Ai} \\ y_{3Ai} \\ y_{1Bi} \\ y_{2Bi} \\ y_{3Bi} \end{bmatrix} = \begin{bmatrix} 1 & 0 & & \\ \lambda_{x1} & 0 & \multicolumn{2}{c}{\mathbf{0}_{6\times2}} \\ \lambda_{x2} & 0 & & \\ 0 & 1 & & \\ 0 & \lambda_{x3} & & \\ 0 & \lambda_{x4} & & \\ & & 1 & 0 \\ & & \lambda_{y1} & 0 \\ & & \lambda_{y2} & 0 \\ & & 0 & 1 \\ \multicolumn{2}{c}{\mathbf{0}_{6\times2}} & 0 & \lambda_{y3} \\ & & 0 & \lambda_{y4} \end{bmatrix} \begin{bmatrix} \xi_{Ai} \\ \xi_{Bi} \\ - \\ \eta_{Ai} \\ \eta_{Bi} \end{bmatrix} + \begin{bmatrix} \delta_{1i} \\ \delta_{2i} \\ \delta_{3i} \\ \delta_{4i} \\ \delta_{5i} \\ \delta_{6i} \\ - \\ \varepsilon_{1i} \\ \varepsilon_{2i} \\ \varepsilon_{3i} \\ \varepsilon_{4i} \\ \varepsilon_{5i} \\ \varepsilon_{6i} \end{bmatrix}. \tag{15}$$

For both cases of latent APIMs, the structural model can be described as

$$\begin{bmatrix} \eta_{Ai} \\ \eta_{Bi} \end{bmatrix} = \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \begin{bmatrix} \xi_{Ai} \\ \xi_{Bi} \end{bmatrix} + \begin{bmatrix} \zeta_{1i} \\ \zeta_{2i} \end{bmatrix}. \tag{16}$$

Because the structural coefficients of the latent APIM link latent variables (ξ_A, ξ_B, η_A, and η_B) instead of individual indicators ($x_{1A}, \ldots, y_{pB}$), the actor effects (the red dashed horizontal arrows denoted as β_{11} and β_{22}) reflect intrapersonal effects of the latent predictors on latent outcomes. Similarly, the partner effects (the blue solid diagonal arrows denoted as β_{12} and β_{21}) indicate interpersonal effects on one's latent outcome due to the latent predictor of one's partner. Estimates of these parameters allow us to make inferences on how the

Figure 5
The Actor-Partner Interdependence Model With Latent Predictors and Outcomes (Latent APIM; p = q = 2)



Note. Now the actor effects (β_{11} and β_{22}) and partner effects (β_{12} and β_{21}) connect latent variables ($\xi_A, \xi_B, \eta_A, \eta_B$) instead of individual indicators ($x_{1A}, \ldots, y_{2B}$). They can also be understood as structural coefficients in a full structural equation model. Note that the structural parameters are labeled analogous to the manifest parameters in previous figures so that β_{12} indicates the link between the first latent outcome and the second latent predictor. See the online article for the color version of this figure.

constructs that our indicators are supposed to reflect are influenced both interpersonally and intrapersonally within a dyad, which may be of greater interest than inferences on raw indicators or survey items.

In the latent APIM, covariance terms are estimated between residual errors of the same outcome indicators of different members (e.g., $\theta_{\varepsilon_{13}}$ and $\theta_{\varepsilon_{24}}$) and also between the same predictor indicators of different members (e.g., $\theta_{\delta_{13}}$and $\theta_{\delta_{24}}$) as in (17) for a latent APIM with two sets of indicators ($p = q = 2$), and analogously for latent APIMs with three or more sets of indicators. This is to allow for correlations owing to similar variable contents or any covariances among the indicators that may not be explained by the latent variables for each person. Covariance is also allowed between latent predictors or latent outcomes of members A and B (ϕ_{12} and ψ_{12}) to reflect similarities between the members other than dyadic interdependence captured by partner effects.

$$\boldsymbol{\Theta} = \mathrm{var}\begin{bmatrix} \delta_{1i} \\ \delta_{2i} \\ \delta_{3i} \\ \delta_{4i} \\ - \\ \varepsilon_{1i} \\ \varepsilon_{2i} \\ \varepsilon_{3i} \\ \varepsilon_{4i} \end{bmatrix} = \begin{bmatrix} \theta_{\delta_{11}} & & & & & & & \\ 0 & \theta_{\delta_{22}} & & & & sym. & & \\ \theta_{\delta_{31}} & 0 & \theta_{\delta_{33}} & & & & & \\ 0 & \theta_{\delta_{42}} & 0 & \theta_{\delta_{44}} & & & & \\ & & & & \theta_{\varepsilon_{11}} & & & \\ & & & & & \theta_{\varepsilon_{22}} & & \\ & & \mathbf{0}_{4\times4} & & \theta_{\varepsilon_{31}} & 0 & \theta_{\varepsilon_{33}} & \\ & & & & 0 & \theta_{\varepsilon_{42}} & 0 & \theta_{\varepsilon_{44}} \end{bmatrix},$$

$$\boldsymbol{\Psi} = var\begin{bmatrix} \xi_{A_i} \\ \xi_{B_i} \\ - \\ \zeta_{1i} \\ \zeta_{2i} \end{bmatrix} = \begin{bmatrix} \phi_{11} & & sym. & \\ \phi_{21} & \phi_{22} & & \\ 0 & 0 & \psi_{11} & \\ 0 & 0 & \psi_{21} & \psi_{22} \end{bmatrix}. \tag{17}$$

For detailed descriptions for each notation, please refer to Table 3.

The covariance matrix from data following a latent APIM in (12) and (13) can be expressed as

$$\Sigma_{yy}(\theta) = \boldsymbol{\Lambda}(\mathbf{I} - \mathbf{B})^{-1}\boldsymbol{\Psi}(\mathbf{I} - \mathbf{B})^{-1'}\boldsymbol{\Lambda}' + \boldsymbol{\Theta}, \tag{18}$$

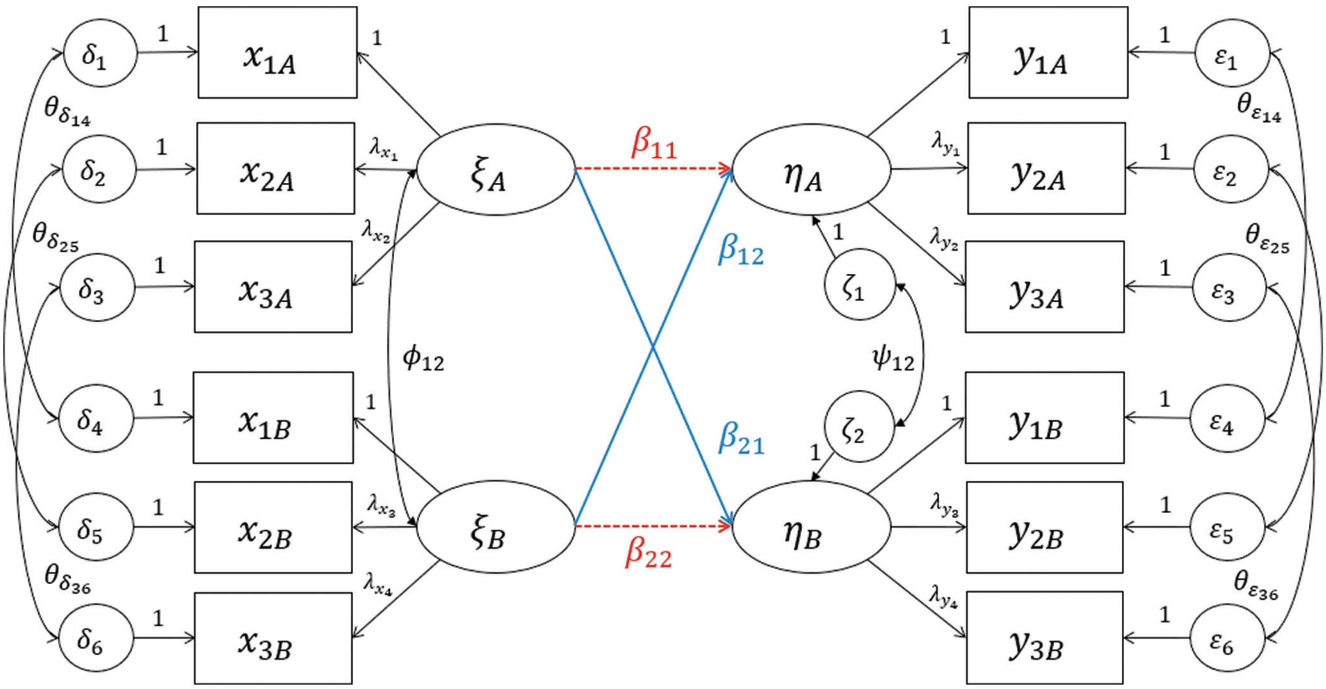
derived from the model-implied covariance matrix of a structural equation model without direct paths between exogenous variables (Bollen, 1989, 8.16–8.17).[4] Consequently, the variances and covariances of latent factors are multiplied by actor or partner effects and factor loadings to form model-implied variance or covariance terms between manifest indicators. As a result, the parameters of the latent APIM act on comprehensive effects among latent variables unlike in the manifest APIM.

It is noteworthy that the number of parameters in the latent APIM in Figure 5 with two sets of indicators for each latent factor ($p = q = 2$) is 26.[5] This is smaller than the maximum number of possible parameters under the counting rule (Bollen, 1989; Kaplan, 2009), $\frac{1}{2}(2p + 2q)(2p + 2q + 1) = \frac{1}{2}(4 + 4)(4 + 4 + 1) = 36$, resulting in the latent APIM being overidentified with additional degrees of freedom ($df = 10$) unlike the manifest APIM. For a latent APIM with three sets of indicators for each latent factor ($p = q = 3$), remaining degrees of freedom increases to 42, as the number of parameters in Figure 6 is 36 and the maximum number

[4] Visit Table C-2 in the online supplemental materials for a comparison of model-implied (co)variances involving y_{1A} in the manifest and latent APIM.

[5] The number of parameters in a latent APIM is $\boldsymbol{\Lambda} = 2(p-1) + 2(q-1)$, $\mathbf{B} = 4$, $\boldsymbol{\Theta} = 3p + 3q$, and $\boldsymbol{\Psi} = 6$, respectively.

Figure 6
The Actor-Partner Interdependence Model With Latent Predictors and Outcomes (Latent APIM; $p = q = 3$)



Note. As $p = q = 3$, there are additional predictor and outcome indicators compared with Figure 5, which leads to increased dimensions for factor loadings and measurement error terms. See the online article for the color version of this figure.

of parameters is 78. Because the degrees of freedom of a latent APIM are a function of the number of indicators p and q, they increase as more sets of indicators are involved in the measurement model. Therefore, model fit statistics of a latent APIM can be calculated even when all parameters are freely estimated.

Further model comparisons can be performed based on such a full model, comparing nested models with different constraints that reflect various research questions. It is notable that factor loadings are also testable within the latent APIM. They reflect the relative strength of relationship between a latent construct and its

Table 3
Notations for the Latent APIM

Symbol	Description
x_{1Ai} $(x_{2Ai}, x_{3Ai}, \ldots, x_{qAi})$	The first (second, third, . . . , qth) indicator of the predictor factor for dyad member A in dyads $i = 1, 2, \ldots, n$
x_{1Bi} $(x_{2Bi}, x_{3Bi}, \ldots, x_{qBi})$	The first (second, third, . . . , qth) indicator of the predictor factor for dyad member B in dyads $i = 1, 2, \ldots, n$
y_{1Ai} $(y_{2Ai}, y_{3Ai}, \ldots, y_{pAi})$	The first (second, third, . . . , pth) indicator of the outcome factor for dyad member A in dyads $i = 1, 2, \ldots, n$
y_{1Bi} $(y_{2Bi}, y_{3Bi}, \ldots, y_{pBi})$	The first (second, third, . . . , pth) indicator of the outcome factor for dyad member B in dyads $i = 1, 2, \ldots, n$
$\lambda_{x_1}\left(\lambda_{x_2}, \ldots, \lambda_{x_{q-1}}\right)$	The second (third, . . . , qth) factor loading representing the strength that $x_{2Ai}(x_{3Ai}, \ldots, x_{qAi})$ reflects ξ_A
$\lambda_{x_q}\left(\lambda_{x_{q+1}} \ldots, \lambda_{x_{2(q-1)}}\right)$	The second (third, . . . , qth) factor loading representing the strength that $x_{2Bi}(x_{3Bi}, \ldots, x_{qBi})$ reflects ξ_B
$\lambda_{y_1}\left(\lambda_{y_2}, \ldots, \lambda_{y_{p-1}}\right)$	The second (third, . . . , pth) factor loading representing the strength that $y_{2Ai}(y_{3Ai}, \ldots, y_{pAi})$ reflects η_A
$\lambda_{y_p}\left(\lambda_{y_{p+1}} \ldots, \lambda_{y_{2(p-1)}}\right)$	The second (third, . . . , pth) factor loading representing the strength that $y_{2Bi}(y_{3Bi}, \ldots, y_{pBi})$ reflects η_B
$\xi_{Ai}(\xi_{Bi})$	The latent predictor for dyad member A (B) in dyads $i = 1, 2, \ldots, n$
$\eta_A(\eta_B)$	The latent outcome for dyad member A (B) in dyads $i = 1, 2, \ldots, n$
$\delta_{1i}\left(\delta_{2i}, \delta_{3i}, \ldots, \delta_{2qi}\right)$	Measurement error unique to the first (second, third, . . . , 2qth) element of $\boldsymbol{x_i}$
$\varepsilon_{1i}(\varepsilon_{2i}, \varepsilon_{3i}, \ldots, \varepsilon_{2pi})$	Measurement error unique to the first (second, third, . . . , 2pth) element of $\boldsymbol{y_i}$
$\beta_{11}(\beta_{22})$	The actor effect of dyad member A (B)
$\beta_{12}(\beta_{21})$	The partner effect representing the influence that the latent outcome of dyad member A (B) receives from the latent predictor of dyad member B (A)
k_A, k_B	The ratio of partner effect $\beta_{12}(\beta_{21})$ to actor effect $\beta_{11}(\beta_{22})$, indicating the dyadic pattern for dyad member A (B)
$\zeta_{1i}(\zeta_{2i})$	The residual error term of $\eta_A(\eta_B)$
$\psi_{11}(\psi_{12} = \psi_{21}, \psi_{22})$	Variance term of ζ_{1i} (covariance term between ζ_{1i} and ζ_{2i}, variance term of ζ_{2i})
$\phi_{11}(\phi_{12} = \phi_{21}, \phi_{22})$	Variance term of ξ_A (covariance term between ξ_A and ξ_B, variance term of ξ_B)
$\theta_{\delta_{11}}\left(\theta_{\delta_{1.(1+q)}}, \ldots, \theta_{\delta_{2q.2q}}\right)$	Variance term of δ_{1i} (covariance term between δ_{1i} and $\delta_{(1+q)i}$, . . . , variance term of δ_{2qi})
$\theta_{\varepsilon_{11}}\left(\theta_{\varepsilon_{1.(1+p)}}, \ldots, \theta_{\varepsilon_{2p.2p}}\right)$	Variance term of ε_{1i} (covariance term between ε_{1i} and $\varepsilon_{(1+p)i}$, . . . , variance term of ε_{2pi})

indicators because at least one factor loading per construct should be fixed to one for model identification. It can also be tested whether they significantly differ for each member or whether they significantly differ from one. This is a procedure of defining a meaningful and reliable measurement model which will be the foundation for further inferences on a dyadic relationship between latent constructs.

After the measurement model is set up, we can also test whether the actor effect linking the predictor and outcome for member A is significantly different from that of member B in the same dyad. This can be done by specifying nested models where one of them imposes equality constraints on the two actor effects. Similar steps apply to testing partner effect equivalence. Even though it may not be of substantive interest, equivalence can also be tested for the two covariance terms between predictor indicators belonging to the same member or the residual covariance between individual outcome indicators. If certain covariance terms do not differ, imposing equality constraints on them can make the model more parsimonious. In the following sections, we inspect how the APIMs with or without measurement models may detect dyadic interdependence differently, varying by the measurement characteristics, dyadic patterns, number of indicators, and sample size.

Simulation

Purpose and Design

In this section, we present a simulation study investigating how various dyadic relationships contained in multivariate dyadic data can be portrayed differently by the models discussed in the previous sections. We examine if estimating the latent, manifest, or composite-score APIM would lead to different inferences in practical dyadic data analysis situations by generating artificial multivariate dyadic data with distinct conditions and fitting the three APIM extensions.

First, data were generated based on either one of the multivariate dyadic data analysis models, the latent APIM or the manifest APIM. By doing so, we expected to evaluate the performance of the APIMs without measurement models in estimating dyadic interdependence among latent variables, as well as the performance of the latent APIM in representing dyadic relationships when unidimensional common factors do not apply to certain multivariate dyadic data. Despite the appeal of composite scores in practice, it is hardly plausible that multiple variables sharing common variance owing to an overarching concept or being representations of correlated notions would stem from an additive process. Also, considering that the composite-score APIM serves as a univariate alternative to the manifest APIM, we focused on examining the potential differences of multivariate data generating models due to different measurement models, especially the use of latent variables.

Second, scale reliability among multiple predictor and outcome indicators was studied as an important factor. Even though scale reliability is reported to be critical when comparing models with or without latent variables (Ledgerwood & Shrout, 2011; Liu & Rhemtulla, 2022; Rush et al., 2020), applied studies frequently overlook to design studies carefully in terms of collecting measures that are more likely to reflect true variability or adopting high-quality scales. In this regard, we created predictors and outcomes that had either mediocre or high reliability to highlight the role of reliability in multivariate dyadic data analysis. We produced cases where all constructs had high reliability (Cronbach's $\alpha = .8$), following guidelines for high α values (Bandalos, 2018) and acknowledging practical difficulties in achieving ideal reliability levels of .90 or .95. In contrast, data with mediocre reliability ($\alpha = .4$) were generated to investigate the performance of APIMs when variables do not serve as reliable indicators of a common factor. This was done by adjusting the amount of covariances among predictors or outcome residuals, while keeping the expected variance of each variable fixed. For exact values of the parameters, refer to Tables C-3 through C-6 in the online supplemental materials.

Additionally, we examined whether additional predictor and outcome indicators improved model estimation and produced more trustworthy results. Even though it is generally expected that adding more items would be beneficial, the strength of such influence needed to be investigated across models and reliability levels. Data with two predictors and outcomes were simulated to illustrate the difference in model parameters among the models, whereas data with three predictors and outcomes were simulated to show the change in performance with an added variable, as well as to represent short-form scales often used in applied studies (Rush et al., 2020).

Similarly, the number of dyads or the sample size was also manipulated. Dyadic data analysis is characteristic in that sample sizes are usually much smaller than what is considered standard in other model analyses, owing to the added difficulty of recruiting both members in a dyad and eliciting reliable responses, as well as the relative scarcity of large-scale data bases containing dyads. Even though sample size reach over 500 dyads in some cases (n = 779, Moorman, 2016; n = 1,648, Hong & Kim, 2019), most of the studies on dyadic data include around 100 to 200 dyads. When studies are conducted longitudinally through multiple assessments or require keeping daily diaries, sample sizes are even around 50 (Chow et al., 2018; Sels et al., 2020). Considering that small sample sizes are common with dyadic data analyses, we compared sample sizes of 200 or 100 dyads to investigate model performances under less favorable situations to make our simulation results more applicable to applied researchers collecting and studying dyadic data.

Finally, different data sets were generated based on characteristic dyadic relationships to see whether certain patterns of underlying dyadic relationships would be less correctly detected under specific conditions. Specifically, −.5, −.25, 0, .25, and .5 were used as the ratio of partner effect to actor effect for both members (e.g., $k_A = \frac{\beta_{12}}{\beta_{11}} = k_B = \frac{\beta_{21}}{\beta_{22}}$ for the latent APIM) to mimic the actor-only ($k = 0$), couple ($k = 1$), and contrast patterns ($k = -1$; Kenny & Ledermann, 2010). Values less extreme than 1 or −1 were used to reflect the likeliness that partner effects usually tend to be smaller in absolute values compared with actor effects in empirical applications. .25 and −.25 were added as levels of k to evaluate the models in terms of detecting small to medium partner effects.

Consequently, our simulation design consists of 80 conditions comparing two data generating models (latent vs. manifest APIM), two scale reliability levels (Cronbach's α of .8 vs. .4), two number of indicators ($p = q = 2$ vs. $p = q = 3$), two sample size conditions ($n = 200$ vs. 100), and five dyadic patterns ($k = \{-.5, -.25, 0, .25, .5\}$) in a completely crossed design.

These five factors and their levels were chosen to represent commonly used design characteristics in actual dyadic data analysis. Because they were the focus of this simulation, all other parameters were held constant across conditions only with slight modifications to maintain specific reliability levels. We simulated 500 replication data sets for each condition using the R software (R Core Team, 2020). Population parameters are presented in Tables C-3 through C-6, along with the R codes used for this simulation in Supplemental Materials A-1 and A-2. No preregistration was made for the simulation study. Evaluation criteria and findings of this simulation study are summarized in the next subsections.

Evaluation of Simulation Results

After generating data sets and fitting the three multivariate APIMs accordingly, we examined how closely and precisely the intended parameters were recovered, as well as how the results of different models compared with each other. Fitting models different than those that generated the data sets would provide us with hypothetical consequences as to what would follow if the measurement structure was erroneously (not) accounted for when analyzing multivariate dyadic data. It should be noted that we focus exclusively on evaluating partner effects hereinafter, since it is the partner effects by which the dynamics within dyads are characterized given equal actor effects.

Parameter recovery was investigated to check whether the data generating process of this simulation was correctly reflecting the intended model, and to explore the performance of the models when models were correctly specified but fitted to data observed under extreme conditions. To assess the accuracy of the latent or manifest APIM in estimating partner effects, percentage bias was calculated as the difference of the mean partner effect estimates across converged replications from the true parameter value, divided by the parameter value and multiplied by 100. Models that failed to converge to a proper solution were excluded from evaluation.[6]

Precision of the partner effect estimates was assessed against the variability in the partner effect estimates by averaging the squared deviation of the estimates from the parameter value and taking its square root (root mean square error [RMSE]). Smaller percentage bias and RMSE indicate better accuracy and precision, respectively. Coverage was assessed as the proportion of replications where partner effect confidence intervals included the true parameter, showing the extent the estimates matched the parameter values from which the data were generated. Last, power was defined as the proportion of replications that produced a statistically significant partner effect estimate under $\alpha = .05$. When the true partner effects were zero ($k = 0$), the same procedure yielded type I error rates indicating the proportion of estimating a statistically significant partner effect our of error.

When we compared estimates of different models, estimated dyadic patterns ($\hat{k}$) were used to represent the amount of partner effects relative to their corresponding actor effects, analogous to assessing accuracy. If the estimated dyadic patterns from the manifest or composite-score APIM did not match that of the latent APIM when data were generated to follow the latent APIM, it would mean that applying the manifest or composite-score APIM to dyadic data that are reflections of common latent variables could produce misleading results. On the other hand, if the latent APIM estimated larger or smaller dyadic patterns out of manifest APIM data, it would show that the latent APIM can only be trusted when there is sufficient justification for using a measurement model grouping multiple variables into indicators of common latent variables.

Next, we calculated detection rates as the proportion of replications with statistically significant partner effect estimates when fitting models other than the one used to generate the data set. To make the manifest APIM with multiple sets of partner effects comparable to the latent or composite-score APIM with only a single set of partner effects, we also considered the rate of detecting at least one partner effect pertaining to a certain dyad member (i.e., the rate of detecting at least one partner effect out of four related to member A in Figure 2). Finally, convergence rates of the models were recorded throughout the simulation to infer minimum bounds required for stable estimation of the manifest, composite-score, or latent APIM.

Behavior of Multivariate APIMs in Discovering Latent Dyadic Relationships

In this section, we consider conditions in which we assume variables are correlated with each other because they are reflections of common unidimensional factors. Data sets with two and three indicators were generated from latent APIMs having different dyadic patterns. Generated data sets based on the latent APIM successfully recovered parameters as intended when the reliability among the indicators measuring the same latent variable was fair (Cronbach's $\alpha = .8$). Figure 7 summarizes parameter recovery for the partner effect β_{12} from Figures 5 and 6, in particular.

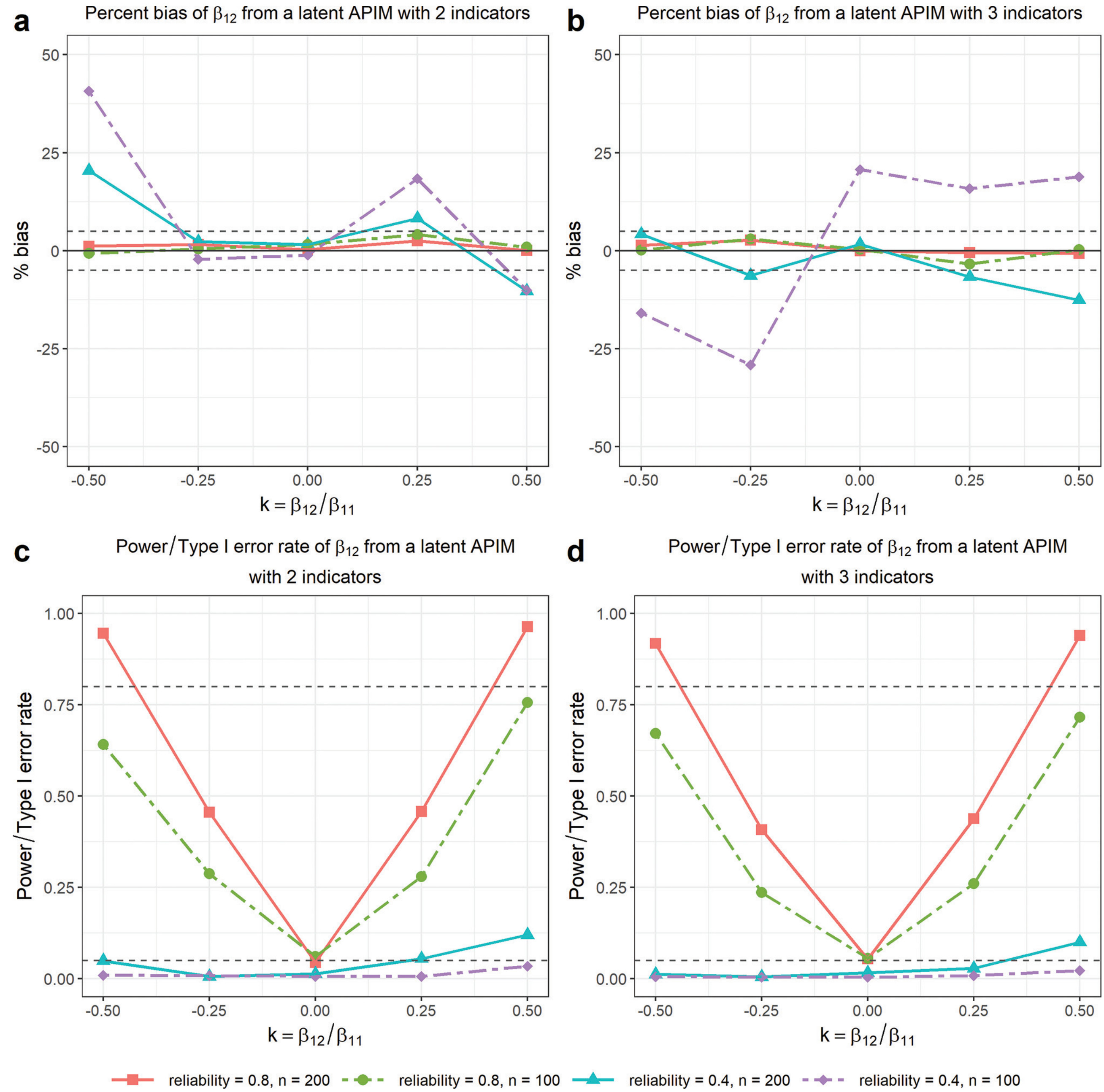
Panels a and b of Figure 7 show that the latent APIM recovered the true partner effect β_{12} with small bias ($<\pm 5\%$) when reliability was relatively high (Cronbach's $\alpha = .8$), even with small sample size ($n = 100$). In contrast, when reliability was relatively low (Cronbach's $\alpha = .4$), latent partner effect estimates were likely to be inaccurate. Estimates were more accurate with larger sample size ($n = 200$), but reliability was more critical in recovering accurate estimates. Consequently, bias was unpredictable and large for conditions with low reliability combined with small sample size. Other than the unpredictable pattern of bias for the least favorable conditions, results were similar for models with 2 and 3 indicators (panel a vs. panel b), as well as for β_{12} and β_{21} estimates (not presented).

Panels c and d of Figure 7 show that power was only acceptable when partner effects were of moderate size ($k = \pm 0.5$) and scale reliability was relatively high (Cronbach's $\alpha = .8$). Power did increase with increased sample size (from $n = 100$ to $n = 200$), but reliability was much more critical in that conditions with low reliability failed to detect existing latent partner effects most of the time for both sample size conditions. As expected, smaller partner

[6] Refer to Tables C-7 and C-8 in the online supplemental materials for convergence rates of models fitted to generated data from all simulation conditions. Convergence of the latent APIM improved with higher scale reliability and larger sample size, as well as with more indicators. The manifest APIM and composite-score APIM did not suffer any convergence problems even in conditions with relatively weak reliability and small sample size.

Figure 7

Parameter Recovery Results for Simulated Latent APIM Data



Note. The x axes present the ratio of partner effects against their corresponding actor effects, or dyadic patterns ($k = \beta_{12}/\beta_{11}$), from the data generating model. The y axes of panels a and b indicate percent bias except when $k = 0$, where they represent bias $\times$ 100 instead of percent bias. The y axes of panels c and d indicate power when $k \neq 0$ and type I error rate when $k = 0$. For all panels, solid lines indicate high reliability conditions (Cronbach's $\alpha = .8$), whereas dashed lines represent low reliability conditions (Cronbach's $\alpha = .4$). Red and blue lines linking squares and triangles, respectively, indicate conditions with relatively larger sample size ($n = 200$), whereas green and purple lines linking circles and diamonds, respectively, represent conditions with relatively smaller sample size ($n = 100$). See the online article for the color version of this figure.

effects were detected with less power, requiring stricter reliability and sample size conditions to guarantee detecting subtle partner effects. It is notable that partner effects of zero ($k = 0$) were only found to be significantly different from zero for 6.1% or less of the total replications, retaining small type I error rates of observing spurious effects by chance. Results were similar for models with 2 and 3 indicators (panel c vs. d), as well as β_{12} and β_{21} estimates (not presented).

When estimating latent partner effects, precision was the best when both sample size and reliability were high (average RMSE

.083 and .090 for 2 and 3 indicators, respectively), followed by the high reliability and small sample size condition (average RMSE .129 and .128 for 2 and 3 indicators, respectively) and low reliability conditions (average RMSE .436 and .680 for 2 and 3 indicators, respectively). The latent APIM performed well in terms of parameter coverage (average coverage = .951) across different dyadic patterns, sample sizes, and reliability levels, implying the generated data sets matched the intended parameter values well.

It should be noted that the simulation conditions covered in this study, even though they intended to resemble typical dyadic data characteristics, are close to the point of threatening stable estimation of latent variable models. Models fitted to data sets with $n \geq 100$ and Cronbach's $\alpha = .8$ almost always converged without producing Heywood cases (convergence rate $>$ .930), whereas they did not converge as well for data sets with $n = 200$ and Cronbach's $\alpha = .4$ (convergence rate = .688 for two indicators, .810 for three indicators) or $n = 100$ and Cronbach's $\alpha = .4$ (convergence rate = .3 for two indicators, .454 for three indicators). This aligns with the latent variable analysis literature arguing that latent variable analyses assume large samples (Bollen, 1989; Kline, 2015), so that at least a sample of size 100 should be obtained when planning to use latent variable models (Hoyle, 1999), which should be increased when the expected effect size is smaller.

Figure 8 depicts the estimated dyadic patterns ($\hat{k}$), or the ratio of partner effect estimates to their corresponding actor effect estimates for the manifest and composite-score APIM fitted to data sets generated by various latent APIMs.[7] Partner effect estimates from both the manifest and composite-score APIM reflected correct dyadic patterns when reliability of the indicators was high, regardless of sample size and number of indicators in the model. However, when reliability was low, both models tended to overreflect the dyadic patterns between latent variables. The degree of overreflection did not seem to be influenced by sample size but was greater when more indicators were involved in the models. The two models behaved similarly in terms of overreflecting latent dyadic patterns.

This is possible because observed indicators or composite scores of them contain both common factor or construct variance, as well as variance unique to themselves such as measurement error (Bollen & Lennox, 1991). When reliability is low, it is plausible that covariances from an underlying common factor is small or indicator variances including measurement error is inflated than when reliability is high. The degree of attenuation or inflation could have acted on the ratio of partner and actor effect estimates of the APIMs assuming manifest variables so that dyadic patterns estimated from those models do not reflect the original dyadic interdependence among latent constructs. Therefore, it is also possible that the accurate dyadic pattern estimates ($\hat{k}$) from our high reliability condition (Cronbach's $\alpha = .8$) may not be retained in other contexts.

The possibility of finding at least one partner effect estimate distinct from zero out of all partner effects related to member A in the manifest APIM was mediocre for most conditions, except when sample size and reliability were both favorable and moderate partner effects existed ($k = \pm 0.5$; See Figure 9a and 9b). Detection rates even worsened as the number of indicators increased from 2 to 3. Although detection rates were influenced by underlying dyadic patterns, sample size, and measurement reliability, latent dyadic patterns were poorly detected within the manifest APIM. Even more concerning is that the manifest APIM tended to find spurious partner effects at a nonnegligible rate when no partner effect existed between each member's latent constructs. The detection rates when $k = 0$ were too high than acceptable type I error rates and were similar to the detection rates for small dyadic patterns ($k = \pm 0.25$) unless reliability and sample size improved. Thus, dyadic patterns presented by the manifest APIM may not agree with those inherent in latent constructs among dyad members.

In contrast, detection rates for one of the partner effects when fitting the composite-score APIM (Figure 9c and 9d) were comparable with the power of latent partner effects (Figure 7c and 7d). When reliability was high, distinct latent dyadic patterns were detected at a rate close to the nominal power of .80, which increased with sample size. It is also notable that positive dyadic patterns were better detected with the composite-score APIM rather than with the latent APIM when reliability was low, which was more pronounced when more indicators were included in the models. However, power was low for both models when reliability was low and dyadic patterns indicated actor and partner effects of opposite signs ($k = -0.25$ or -0.5). Unlike the manifest APIM prone to inflate error rates with multiple tests, the composite-score APIM was free from concerns about falsely detecting nonexistent latent dyadic patterns.

Performance of Multivariate APIMs in Discovering Manifest Dyadic Relationships

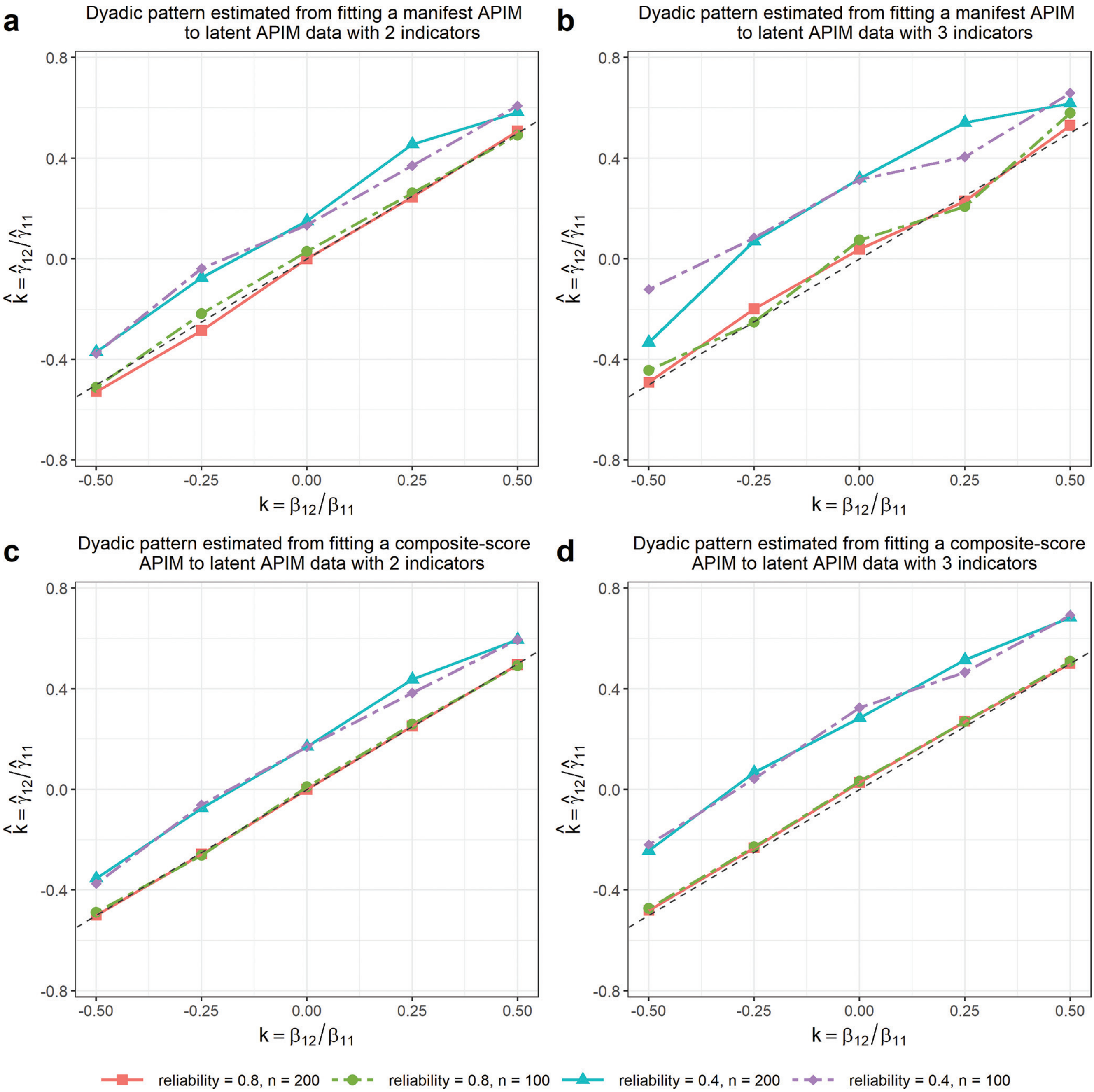
Now we consider situations where variables are not assumed to reflect common factors. Followingly, data sets with two and three indicators were generated from manifest APIMs having different dyadic patterns. The parameter values used in data generation are presented as Tables C-5 to C-6 in the online supplemental materials. Parameter recovery for one of the partner effects (γ_{41}; See Figures 2 and 3 for details) is summarized in Figure 10. Results were comparable for other partner effects as well (not presented).

Panels a and b of Figure 10 show that percent bias of γ_{41} estimates were around $\pm 5\%$ when reliability was relatively high (Cronbach's $\alpha = .8$), regardless of sample size. Manifest partner effect estimates were more likely to be inaccurate when reliability was low (Cronbach's $\alpha = .4$). Estimates were more accurate with larger sample size and higher reliability but were similar for models with 2 and 3 indicators.

Panels c and d of Figure 10 show that power for each partner effect estimate was very low for all conditions, being somewhat higher only when sample size and reliability were the most favorable and moderate dyadic patterns existed. Type I error was maintained to a minimum in general and results were similar for models with 2 and 3 indicators. It was more likely to find at least one statistically significant partner effect estimate among those pertinent to member B when true partner effects existed among manifest variables (See Figure 10e and 10f). With three variables for each member's predictor and outcome, such detection rate

[7] For the manifest APIM, the first partner effect and its corresponding actor effect estimate was used to calculate the dyadic pattern estimate ($\hat{k} = \hat{\gamma}_{12}/\hat{\gamma}_{11}$), because the actor effects and partner effects were simulated symmetrically between the members. Therefore, the resulting dyadic pattern estimates did not depend on which set of partner and actor effect estimates were chosen.

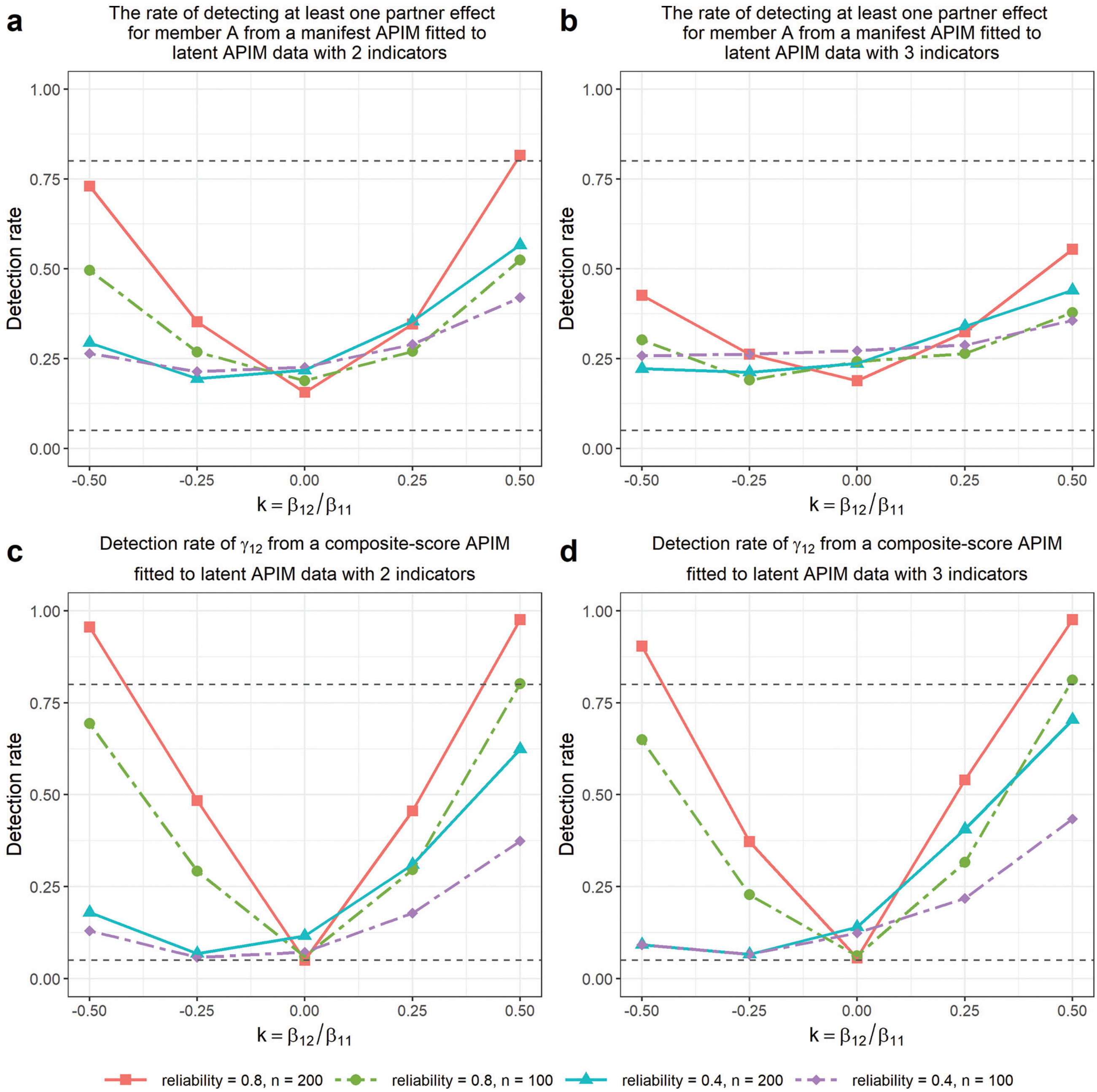
Figure 8
Comparison of Dyadic Pattern Estimates When Fitting the Manifest or Composite-Score APIM to Simulated Latent APIM Data



Note. The x axes present the ratio of partner effects against their corresponding actor effects, or dyadic patterns ($k = \beta_{12}/\beta_{11}$), from the data generating model. The y axes indicate the dyadic patterns calculated by dividing a partner effect from either the manifest APIM (panels a, b) or composite-score APIM (panels c, d) by their corresponding actor effect. For all panels, solid lines indicate high reliability conditions (Cronbach's $\alpha = .8$), whereas dashed lines represent low reliability conditions (Cronbach's $\alpha = .4$). Red and blue lines linking squares and triangles, respectively, indicate conditions with relatively larger sample size ($n = 200$), whereas green and purple lines linking circles and diamonds, respectively, represent conditions with relatively smaller sample size ($n = 100$). The black dashed line $\hat{k} = k$ for all panels indicate the dyadic pattern that would have resulted from fitting a latent APIM to the generated data. See the online article for the color version of this figure.

Figure 9

Detection Rates of Partner Effects When Fitting the Manifest or Composite-Score APIM to Simulated Latent APIM Data



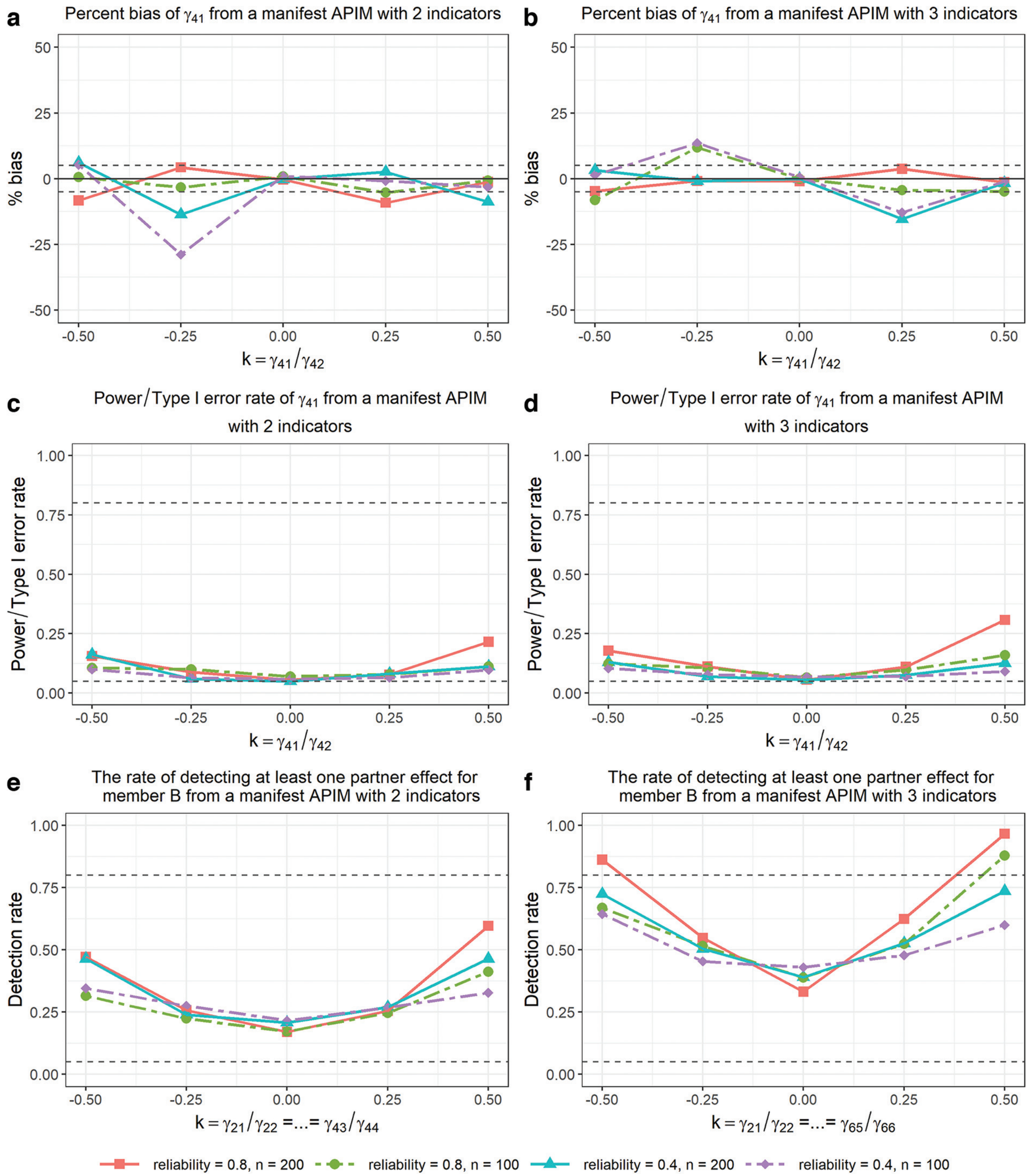
Note. The *x* axes present the dyadic patterns ($k = \beta_{12}/\beta_{11}$) from the data generating model. The *y* axes of panels a and b indicate the rate of detecting statistically significant partner effect related to member A when fitting the manifest APIM to simulated latent APIM data. The *y* axes of panels c and d indicate the rate of detecting a statistically significant partner effect (γ_{12}) when fitting the composite-score APIM instead of the latent APIM. For all panels, solid lines indicate high reliability conditions (Cronbach's $\alpha = .8$), whereas dashed lines represent low reliability conditions (Cronbach's $\alpha = .4$). Red and blue lines linking squares and triangles, respectively, indicate conditions with relatively larger sample size ($n = 200$), while green and purple lines linking circles and diamonds, respectively, represent conditions with relatively smaller sample size ($n = 100$). See the online article for the color version of this figure.

even exceeded .80 when dyadic patterns were distinct and other conditions were favorable. However, the probability of falsely detecting at least one partner effect estimate out of chance when no true partner effects existed was substantial. The fact that this was more of a problem with increased number of variables tells that the manifest APIM, despite its theoretical appeal of being able to analyze multivariate dyadic data simultaneously, has limited performance because of testing its multiple parameters.

Figure 11 depicts the estimated dyadic patterns ($\hat{k}$) for the latent and composite-score APIM fitted to data sets generated by the

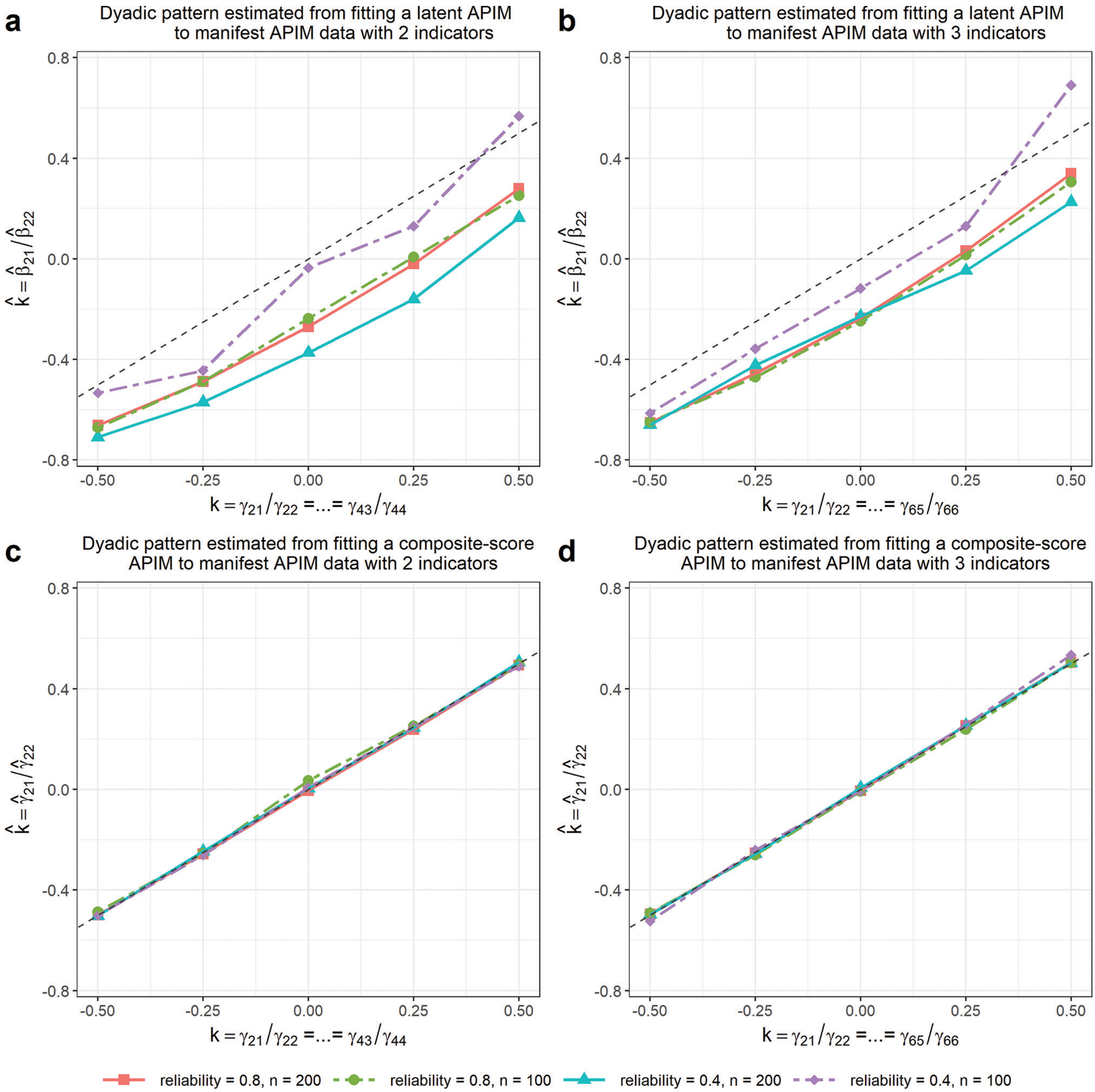
Figure 10

Partner Effect Recovery Results and Detection Rates for Simulated Manifest APIM Data



Note. The x axes present the dyadic patterns ($k = \frac{\gamma_{21}}{\gamma_{22}} = \ldots = \frac{\gamma_{41}}{\gamma_{42}} = \ldots = \frac{\gamma_{2p,2q-1}}{\gamma_{2p2q}}$) from the manifest APIMs that generated the data sets for simulation. The y axes of panels a and b indicate percent bias except when $k = 0$, where they represent bias $\times$ 100 instead of percent bias. The y axes of panels c and d indicate the power of detecting a single partner effect (γ_{41}) when $k \neq 0$ and type I error rate when $k = 0$. The y axes of panels e and f indicate the rate of detecting statistically significant partner effect related to member B when fitting the manifest APIM to simulated manifest APIM data. For all panels, solid lines indicate high reliability conditions (Cronbach's $\alpha = .8$), whereas dashed lines represent low reliability conditions (Cronbach's $\alpha = .4$). Red and blue lines linking squares and triangles, respectively, indicate conditions with relatively larger sample size ($n = 200$), whereas green and purple lines linking circles and diamonds, respectively, represent conditions with relatively smaller sample size ($n = 100$). See the online article for the color version of this figure.

Figure 11
Comparison of Dyadic Pattern Estimates When Fitting the Latent or Composite-Score APIM to Simulated Manifest APIM Data



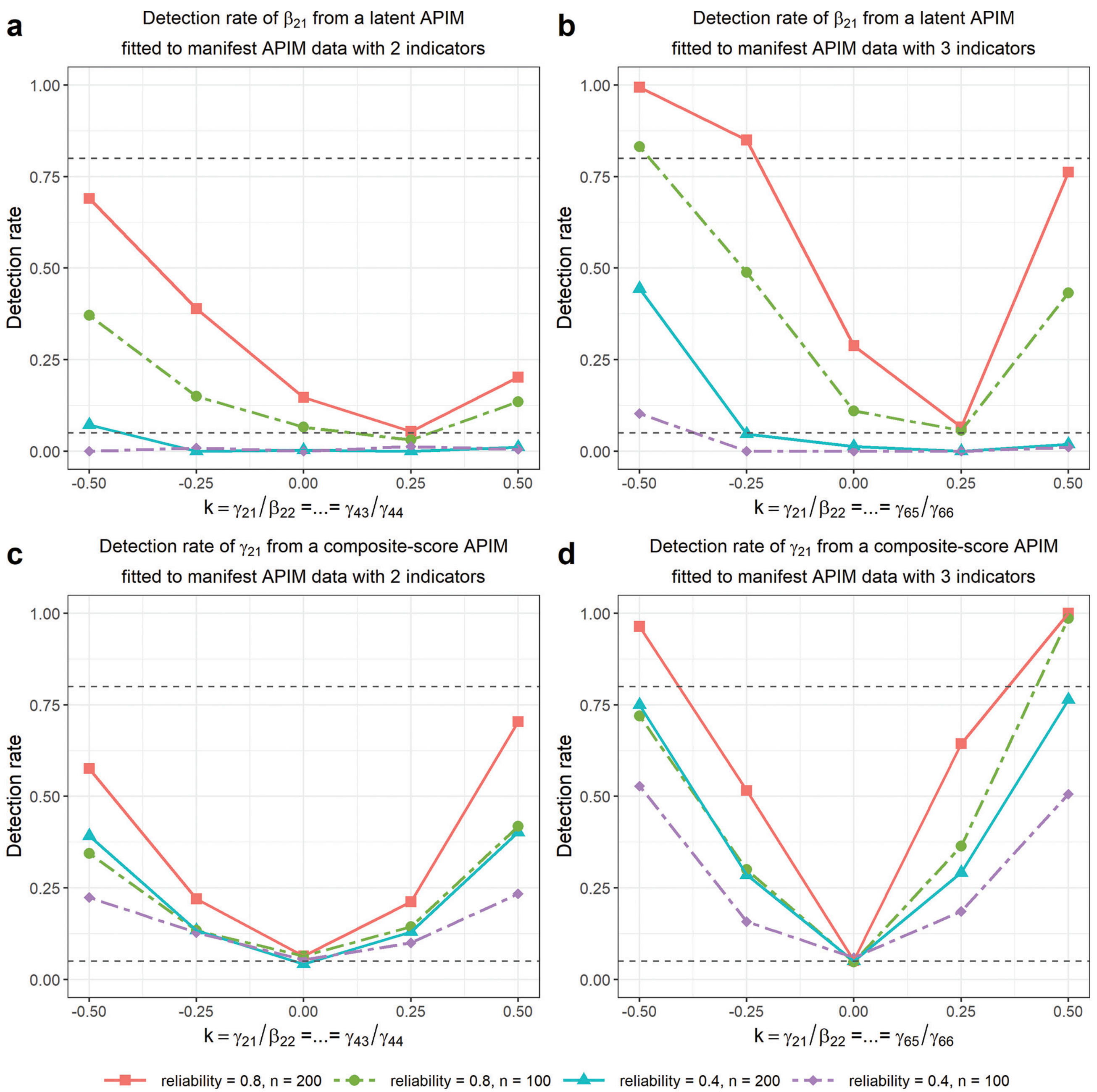
Note. The x axes present the dyadic patterns ($k = \frac{\gamma_{21}}{\gamma_{22}} = \ldots = \frac{\gamma_{41}}{\gamma_{42}} = \ldots = \frac{\gamma_{2p,2q-1}}{\gamma_{2p2q}}$) from the manifest APIMs that generated data sets for simulation. The y axes indicate the dyadic patterns calculated by dividing a partner effect from either the latent APIM (panels a, b) or composite-score APIM (panels c, d) by their corresponding actor effect. For all panels, solid lines indicate high reliability conditions (Cronbach's $\alpha = .8$), whereas dashed lines represent low reliability conditions (Cronbach's $\alpha = .4$). Red and blue lines linking squares and triangles, respectively, indicate conditions with relatively larger sample size ($n = 200$), whereas green and purple lines linking circles and diamonds, respectively, represent conditions with relatively smaller sample size ($n = 100$). See the online article for the color version of this figure.

manifest APIM. Partner effect estimates from the composite-score APIM reflected correct manifest dyadic patterns across all dyadic patterns, regardless of sample size, reliability level, and number of indicators. In contrast, the latent APIM always underrepresented manifest dyadic patterns, except when the true dyadic patterns were moderately positive ($k = \frac{\gamma_{21}}{\gamma_{22}} = \frac{\gamma_{23}}{\gamma_{24}} = \ldots = \frac{\gamma_{2p,2q-1}}{\gamma_{2p,2q}} = 0.5$, where $p = q = 2$ or $p = q = 3$). The opposite directions of bias for the APIMs with or without measurement models aligns with the tendency that the bias caused by applying latent variables inappropriately is in the opposite direction as the bias that comes from not using measurement models when the data stem from reflective constructs (Rhemtulla et al., 2020). The degree of underrepresentation varied according to sample size when reliability was low, whereas it was relatively stable for conditions with high reliability. The degree of underrepresenting original dyadic patterns when they were estimated by the latent APIM was less severe when three indicators were involved, compared with having two indicators in the model.

Figure 12 shows how well the partner effects among manifest variables were detected by fitting the latent and composite-score

Figure 12

Detection Rates of Partner Effects When Fitting the Latent or Composite-Score APIM to Simulated Manifest APIM Data



Note. The x axes present the dyadic patterns ($k = \frac{\gamma_{21}}{\gamma_{22}} = \ldots = \frac{\gamma_{41}}{\gamma_{42}} = \ldots = \frac{\gamma_{2p,2q-1}}{\gamma_{2p2q}}$) from the manifest APIMs that generated data sets for simulation. The y axes indicate the rate of detecting a statistically significant partner effect when fitting the latent APIM (β_{21}) or composite-score APIM (γ_{21}) instead of the manifest APIM. For all panels, solid lines indicate high reliability conditions (Cronbach's $\alpha = .8$), whereas dashed lines represent low reliability conditions (Cronbach's $\alpha = .4$). Red and blue lines linking squares and triangles, respectively, indicate conditions with relatively larger sample size ($n = 200$), whereas green and purple lines linking circles and diamonds, respectively, represent conditions with relatively smaller sample size ($n = 100$). See the online article for the color version of this figure.

APIM. For both models, partner effects distinct from zero were more often found when reliability was high and sample size was relatively large, even though larger sample sizes could make up for low reliability more with composite-score APIMs unlike with latent APIMs. Also, detection rates were higher when more variables were included in each model.

It is noteworthy that detection rates of partner effects with the latent APIM (See Figure 12a and 12b) did not form a symmetric V-shape as with the composite-score APIM detection rates (See Figure 12c and 12d) or power of manifest APIM partner effects (See Figure 10c through 10f). This follows from the latent APIM underreflecting dyadic patterns inside manifest variables (See Figure 11a and 11b). If an effect is estimated without bias, power is naturally higher for stronger effects and converges to type I error rate for weaker effects. However, because the latent APIM returns smaller dyadic patterns than the original manifest dyadic patterns, negative dyadic patterns get detected more easily than positive ones. This is problematic in that the rate of falsely detecting nonexistent manifest partner effects are too high than what is usually acceptable, especially so when reliability and sample size allow for stronger detective power. In contrast, weak positive dyadic patterns between manifest variables do not stand a chance of being detected when a latent APIM is chosen as the method of analysis.

On the other hand, the composite-score APIM produced symmetric detection rates depending on the degree of manifest dyadic patterns, being comparable to the proportion of detecting at least one partner effect per member when fitting the true manifest APIM (See Figure 12c and 12d, Figure 10e and 10f). The composite-score APIM performs superior to the manifest APIM in that it is free from detecting false partner effects when the true dyadic patterns are actor-only ($k = 0$). Therefore, even though fitting a composite-score APIM may result in losing detailed information regarding specific variables and paths among them, the composite-score APIM can be useful in summarizing multivariate dyadic relationships among multidimensional or purely manifest variables, without producing misleading inferences.

Summary of the Simulation Study

In this section, we conducted a simulation study investigating how dyadic patterns in latent constructs or purely manifest variables can be presented differently by the three multivariate extensions of the APIM. Our simulated data sets reflected five characteristic dyadic patterns underlying two or three indicators each for the predictor and outcome of dyad members. Overall, the parameters from the data sets generated in this simulation were well recovered with small bias.

Partner effects from the latent APIM showed reasonable power trends, even though the current simulation conditions act rather as cautionary lower bounds. When dyadic patterns are expected to be less distinct, scale reliability and/or sample size should exceed our presented conditions to ensure sufficient power. Reliability was critical, implying that poorly measured constructs may not work as well as high quality measures just by increasing the sample size or number of indicators. Even for less favorable conditions, the latent APIM did not pose high risks of finding spurious partner effects. Power was more problematic for the partner effects of manifest APIMs, because multiple partial coefficients are smaller in effect sizes and induce multiple testing. In addition, type I error rates were constantly high, making it difficult to distinguish actual partner effects from spurious effects. In that sense, the composite-score APIM showed superior performance to the manifest APIM by having higher detection rates of existing partner effects and minimal type I error rates.

When multivariate dyadic data are assumed to stem from underlying common constructs, overlooking the measurement structure and using models based on manifest variables can produce misleading results by overreflecting latent dyadic patterns. The composite score is not exempt from this phenomenon, making it problematic for applied researchers to just create composite-scores out of multiple-item scales before proceeding to fitting an APIM.

On the other hand, when multiple variables are not reflections of a common factor, such as the components indicating one's socioeconomic status such as education level, occupational prestige, and family income, including measurements models without inspecting substantive theory may produce underreflecting estimates, not agreeing with the true dyadic patterns. Moreover, positive but small dyadic patterns are unlikely to be detected because of such systematic bias. In such cases, the composite score APIM can act as a superior alternative to the manifest APIM. The multiple partial paths that are estimated in the manifest APIM may imply specific relationships between observed variables controlling for each other, but it should be questioned whether the problems in performance would be worth accepting. Given that a thorough evaluation of the measurement structure is not often reported before deciding multivariate analysis methods, the consequences of insufficiently considering measurement models is yet to be discovered.

Real Data Analysis: Relationship Between Married Couples

Data and Motivation for the Example Analysis

In this section, we show how the models we presented in the previous sections can be implemented in an example analysis, using data from the WLS.[8] The WLS tracks 10,317 Wisconsin high school graduates from 1957. Survey data were successively collected from the graduates and their selected siblings, where at one point, spouses were also invited to participate in the study.[9] Although the WLS is a longitudinal data set, data from married couples were collected only for a single wave, making the present study a cross-sectional investigation. In this study, we focus on 6,012 graduates and siblings who (a) participated in the 2004 wave of the WLS, (b) completed at least a part of the telephone interview, (c) were currently married, and (d) whose spouses were heterosexual[10] and participated at least partially in a parallel telephone interview.

Using data from the WLS, we investigate the influence of perceived relationship commitment on happiness among married couples. Relationship commitment is a concept that consists of three positively related but separate components, where the cognitive

[8] Publicly available data of the WLS can be accessed at https://ssc.wisc.edu/wlsresearch/data/. Because our analysis was a secondary data analysis of a publicly available data set not involving identifiable private information about participants, it was not subject to IRB approval.

[9] Spouses of graduates were invited in 2004, followed by the spouses of siblings in 2006.

[10] This was done for the purpose of testing the difference in influences that wives had on husbands and vice versa. One respondent was eliminated from subsequent analyses because both she and her spouse were female.

component represents a long-term orientation for the relationship, the affective component represents psychological attachment to the relationship or the affective bond that develops between partners, and the conative component represents the intention to persist in the relationship (Arriaga & Agnew, 2001). In relationship literature, it is assumed that within a committed relationship, partners would become increasingly susceptible to each other's circumstances and emotions. This creates an emotional interdependence between partners as they become increasingly close and similar to each other, where they have a greater potential for transmitting one's emotion to the other and being disrupted by their partner's positive and negative experiences (Aron et al., 1992; Arriaga & Agnew, 2001; Sels et al., 2020). Consequently, the focus of our example analysis is to investigate the dyadic interdependence that married couples experience in terms of their relationship commitment and emotional positivity, happiness.

As presented in Tables 4 and 5, the WLS contains correlated indicators that can be viewed as manifestations of two constructs, relationship commitment and happiness. For example, the degree that one believes to have similar outlooks on life to that of one's spouse (hereafter *similarity*) can be viewed as the cognitive component of relationship commitment, whereas the degree that one feels close with one's spouse (hereafter *closeness*) can be deemed the affective component. Likewise, the degree that one has been feeling positive emotions recently (hereafter *positive affect*) can be considered as reflecting happiness. Similarly, but not identically, having felt *negative* emotions *less* frequently (hereafter *negative affect*) can show an additional aspect of happiness.

Even though these indicators are conceptualized as reflecting relationship commitment or happiness in common, they are also often used as simple sums, or composite-scores (Aron et al., 1992; McGreal & Joseph, 1993). It should be noted though that variables available within the WLS may not be sufficient enough to cover all three components of relationship commitment as presented by Arriaga and Agnew (2001) or most conventional indicators of happiness scales (e.g., Mattei & Schaefer, 2004; McGreal & Joseph, 1993). Considering such limitations, it should be noted that this example is not to be interpreted as having substantive meaning, but rather as a pedagogical example as to applying APIM to multivariate dyadic data.

The variables from the WLS data can then be used to form comprehensive latent factors for each member as shown in Table 6. The factor reliability estimates in this example are above the low reliability condition in the previous simulation study but less than optimal, with Cronbach's alpha being smaller than .8 (range .465–.639). As we discussed in the Simulation section, having three or more indicators that are valid measures for either relationship commitment or happiness could help in terms of accuracy and power when performing related analyses.

Among the measures presented in Table 4, missing data constitute less than 5% of the total sample. With listwise deletion, 5,875 of 6,012 couples or approximately 97.7% of the total sample would have been available for analysis. We imputed missing values using the variables listed in Table C-9 under the assumption that they were missing at random (Little & Rubin, 2019). The multiple imputation package *mice* (van Buuren & Groothuis-Oudshoorn, 2011) was used within the statistical software R (R Core Team, 2020) with predictive mean matching (Little, 1988) as the algorithm for imputation.[11]

Of 20 imputed data sets, the first dataset was used to explore the best fitting model among manifest or latent APIM models with different sets of constraints. The descriptive statistics of the imputed variables presented in Table 7 show close resemblance to the original variables. After finalizing the best-fitting empirical models, analyses were run on all 20 imputed data sets, pooling results according to Rubin's rules (Rubin, 1987).

Implementation of the Multivariate APIM

To examine the influence of relationship commitment on happiness between married persons, we analyzed the WLS data with a latent APIM with 2 indicators as in Figure 5.[12] By doing so, we decomposed the emotional interdependence arising from relationship commitment into latent interpersonal and intrapersonal effects. Using multivariate dyadic data with two indicators each, we expected to represent the latent constructs (relationship commitment and happiness) better by the common variances contained in multiple indicators, rather than using single manifestations of them. It should be noted that three or more indicators are needed to reflect these constructs close to optimally.

For comparison, a composite-score APIM as in Figure 4 was applied to show the difference in inferences without a latent variable approach. With such a model, unique variances of perceived similarity and closeness are combined into the composite score ($cmm_{comp.H} = sim_H + close_H, cmm_{comp.W} = sim_W + close_W$) together with any shared variance. The same applies to positive and negative affect ($hpp_{comp.H} = posit_H + nonneg_H, hpp_{comp.W} = posit_W + nonneg_W$), rendering the meaning of composite scores distinct from the latent variables defined by the latent APIM. Therefore, the composite-score APIM expresses the dyadic interdependence among married couples in terms of actor and partner effects between composite-scores, which would not necessarily be the same as the dyadic relationship we intended to analyze theoretically. It is not guaranteed that results of such a model would lead to similar inference on relationship commitment and happiness as an analysis of the latent APIM would do.

Models were fit using the package *lavaan* (Rosseel, 2012) within R (R Core Team, 2020).[13] To account for the non-normality of the observed variables in the analyses, maximum likelihood estimation with robust standard errors (Huber, 1967; White, 1980) and robust test statistics asymptotically equivalent to T_2^* (Yuan & Bentler, 2000)[14] was used within *lavaan* (Rosseel, 2012) instead of the conventional maximum likelihood estimation. Based on the results from these models, we will further describe the importance of reflecting the measurement structure of dyadic data within the APIM.

Analysis Results

The latent APIM and nested models with different sets of constraints showed sufficient fit to data as presented in Table 8.

[11] Codes for preparing the WLS data and applying the latent and manifest APIMs can be found in Supplemental Materials B. The analyses were not preregistered.

[12] For a figure specific to the example analysis, please see Figure D-1 in the online supplemental materials.

[13] Example codes can be found in Supplemental Materials B.

[14] This option is called MLR within the statistical software Mplus (Muthén & Muthén, 2017). The R package *lavaan* (Rosseel, 2012) provides similar robust standard errors and test statistics with the argument "estimator = mlr."

Table 4
Description of Variables Used in Analysis

Variable	Indicator names	Survey question	Scale
Similarity	*sim.H* *sim.W*	How similar do you find your outlook on life is with that of your spouse?	1 = not at all similar 2 = not very similar 3 = somewhat similar 4 = very similar
Closeness	*close.H* *close.W*	How close are you with your current spouse?	1 = not at all close 2 = not very close 3 = somewhat close 4 = very close
Positive affect	*posit.H* *posit.W*	How happy have you been during the past four weeks?	1 = so unhappy that life is not worthwhile 2 = very unhappy 3 = somewhat unhappy 4 = somewhat happy 5 = happy and interested in life
Negative affect	*nonneg.H* *nonneg.W*	How often did you feel fretful, angry, irritable, anxious, or depressed in the past four weeks?	1 = almost always 2 = often 3 = occasionally 4 = rarely 5 = never (reverse coded)

Note. Indicators for husbands and wives have suffixes "~.H" and "~.W", respectively.

Because the latent APIM without any constraints in estimating the parameters (hereafter *the full model*) was overidentified with 10 degrees of freedom, its fit to data could be examined by various goodness of fit statistics. Even though the χ^2 test statistic was significantly different from zero, CFI and RMSEA values both suggested reasonable model fit.

Nested models were investigated to test the equivalence between factor loadings, revealing that imposing strictly equal factor loadings for all latent variables ($\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4$) heavily diminished model fit. This implies that factor loadings should be examined as an important source of factor variance rather than being fixed. Therefore, measurement invariance across members should be tested and not just assumed when analyzing dyadic interdependence for dyadic data with latent variables. Parameters other than factor loadings were also tested for equivalence, such as the actor effects for husbands (β_{11}) and wives (β_{22}). Consequently, an empirical model was selected based on goodness of fit statistics and analyzed on all 20 imputed data sets of the WLS. Estimated factor loadings and actor and partner effects are presented in Table 9.

Estimated factor loadings indicated that perceived similarity (sim_H, sim_W) depended relatively more on relationship commitment ($comm_H$, $comm_W$) than perceived closeness did ($close_H$, $close_W$; $\lambda_1 < 1, \lambda_2 < 1$), as did (reverse coded) negative affect ($nonneg_H$, $nonneg_W$) relatively more on happiness ($happiness_H$, $happiness_W$), compared with positive affect ($posit_H$, $posit_W$; $\lambda_3 > 1, \lambda_4 > 1$). Testing for differences among factor loadings showed that factor loadings linking the same construct and indicators did not differ across husbands and wives ($\lambda_1 = \lambda_2, \lambda_3 = \lambda_4$ in Figure D-1 in the online supplemental materials).

Actor effect estimates (β_{11}, β_{22}) illustrated that one's level of happiness was positively related to their relationship commitment. Testing for differences among the actor effects between husbands and wives showed that the amount was not significantly greater for husbands or wives ($\beta_{11} = \beta_{22}$ in Figure D-1). On the other hand, one's evaluation of relationship commitment did not significantly relate to the happiness level of his or her partner as reflected in the insignificant partner effects (β_{12}, β_{21}), which also did not differ across husbands and wives ($\beta_{12} = \beta_{21}$ in Figure D-1). In sum, relationship commitment had a strong positive association with one's own happiness for both husbands and wives, without any partner effects. The standardized actor effect was .399 for husbands and .425 for wives, indicating that married individuals with a 1 *SD* higher relationship commitment tended to experience substantially higher happiness levels of about .4 *SD*.

Even though the latent factors relationship commitment and happiness were separately defined for husbands and wives, it was reasonable enough to believe that married spouses would be

Table 5
Correlation and Covariance of Variables Used in Analysis

Variable	sim_H	$close_H$	$posit_H$	$nonneg_H$	sim_W	$close_W$	$posit_W$	$nonneg_W$
sim_H	0.302	0.087	0.045	0.065	0.082	0.055	0.027	0.040
$close_H$	0.404**	0.155	0.039	0.053	0.060	0.058	0.021	0.037
$posit_H$	0.163**	0.196**	0.256	0.154	0.040	0.018	0.029	0.042
$nonneg_H$	0.136**	0.155**	0.349**	0.757	0.057	0.028	0.038	0.097
sim_W	0.252**	0.257**	0.133**	0.112**	0.351	0.130	0.057	0.098
$close_W$	0.223**	0.327**	0.081**	0.073**	0.488**	0.201	0.046	0.068
$posit_W$	0.086**	0.094**	0.103**	0.079**	0.174**	0.185**	0.311	0.193
$nonneg_W$	0.078**	0.100**	0.089**	0.120**	0.177**	0.163**	0.371**	0.867

Note. Upper-diagonal values are pairwise covariances, lower-diagonal values are pairwise correlations, and diagonal values indicate variances.
** $p < .001$ for correlation coefficients.

Table 6
Structures and Reliability Coefficients of Factors Used in Analysis

Type	Factor (*factor name*)	Indicator	Cronbach's α
Predictor	Relationship commitment—husband ($comm_H$)	sim_H $close_H$	0.553
	Relationship commitment—wife ($comm_W$)	sim_W $close_W$	0.639
Outcome	Happiness—husband ($happiness_H$)	$posit_H$ $nonneg_H$	0.465
	Happiness—wife ($happiness_W$)	$posit_W$ $nonneg_W$	0.493

closely related also for reasons other than their relationship commitment. Therefore, residual covariance was allowed for the same indicators among husbands and wives ($\theta_{\delta_{13}}, \theta_{\delta_{24}}, \theta_{\varepsilon_{13}}, \theta_{\varepsilon_{24}}$). However, such residual covariance terms were either insignificant or minimal. No structure was assumed at the beginning, but the residual covariances between the predictor indicators of husbands and wives ($\theta_{\delta_{13}}, \theta_{\delta_{24}}$) were found to be similar enough so that restricting them to be equal for both similarity and closeness simplified the model without significantly diminishing model fit. See Table C-10 in the online supplemental materials for specific covariance estimates.

The composite-score APIM in Figure D-2 incorporated all indicators as manifest composite scores, without linking them to underlying factors by a measurement model. Consequently, the full model was just-identified without any remaining degrees of freedom. Therefore, goodness of fit for the full model could not be tested with χ^2 based goodness of fit measures, even though the AIC and BIC values were much lower than those of the latent APIM in Table 8. The goodness of fit statistics for nested models of the composite-score APIM are presented in Table 10. Nested models of the composite-score APIM showed nice fit to the data and revealed that actor effects and partner effects did not significantly differ between members. Consequently, this model was analyzed together with the full model on all 20 imputed data sets of the WLS.

The actor effect estimates in Table 11 imply that one's level of positive and nonnegative affect was positively related to their sum of perceived similarity and closeness. Testing for differences among the actor effects between husbands and wives showed that the amount was not significantly greater for husbands or wives ($\gamma_{11} = \gamma_{22}$ in Figure D-2). On the other hand, one's sum of perceived similarity and closeness did not significantly relate to the level of positive and nonnegative affect of his or her partner as reflected in the insignificant partner effects (γ_{12}, γ_{21}), which also did not differ across husbands and wives ($\gamma_{12} = \gamma_{21}$ in Figure D-2).

Even though both the latent APIM and composite-score APIM did not find significant partner effects, it is notable that the dyadic patterns estimated from the two models implied different dyadic relationships. For the latent APIM, estimated dyadic patterns were minimal, indicating an actor-only pattern ($\hat{k}_A = \frac{\hat{\beta}_{12}}{\hat{\beta}_{11}} = \frac{0.017}{0.399} = 0.043$, $\hat{k}_B = \frac{\hat{\beta}_{12}}{\hat{\beta}_{11}} = \frac{0.012}{0.425} = 0.028$). However, the estimated dyadic patterns from the composite-score APIM were meaningfully positive ($\hat{k}_A = \frac{\hat{\gamma}_{12}}{\hat{\gamma}_{11}} = \frac{0.061}{0.205} = 0.298$, $\hat{k}_B = \frac{\hat{\gamma}_{21}}{\hat{\gamma}_{22}} = \frac{0.050}{0.215} = 0.233$), even though they were not statistically significant.

This relates to our findings from the simulation study that omitting measurement models when multivariate dyadic data may reflect underlying common factors could lead to overestimating latent dyadic patterns or underestimating dyadic patterns between manifest variables, especially when reliability is low for the variables involved in the analysis. Although the composite-score APIM's degree of overreflection combined with low detection rates for relatively small effects did not result in statistically significant partner effects, this example analysis exemplifies the importance of carefully incorporating subject matter knowledge into designing measures and choosing analytical methods. In particular, analysis results may be sensitive to the choice of model, if combined with relatively low scale reliability.

Summary of the Example Analysis

Even though we analyzed the same data with identical dyadic interdependence, the results differed depending on the use of

Table 7
Descriptive Statistics of Observed and Imputed Data Sets

		Observed data			Imputed set 1 (n = 6,012)		Imputed set 20 (n = 6,012)	
Variable	Indicator	*N*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Similarity	sim_H	5,962	3.59	0.55	3.59	0.55	3.59	0.55
	sim_W	5,985	3.56	0.59	3.56	0.59	3.56	0.59
Closeness	$close_H$	5,961	3.84	0.39	3.84	0.39	3.84	0.39
	$close_W$	5,981	3.81	0.45	3.81	0.45	3.81	0.45
Positive affect	$posit_H$	5,999	4.80	0.51	4.80	0.51	4.80	0.51
	$posit_W$	6,000	4.80	0.56	4.79	0.56	4.80	0.56
Negative affect	$nonneg_H$	5,997	4.33	0.87	4.33	0.87	4.33	0.87
	$nonneg_W$	5,998	4.09	0.93	4.09	0.93	4.09	0.93

Note. Descriptive statistics of imputed data sets 2 to 19 resulted in almost identical values to those of imputed data sets 1 and 20.

Table 8
Goodness of Fit Statistics for the Latent APIM Submodels (n = 6,012)

Model	Constraints	χ^2 (*df, p*)[a]	CFI	RMSEA	AIC	BIC
Full model	—	19.392 (10, .036)	0.998	0.012	78,291.038	78,465.278
Loading equivalence testing	$\lambda_1 = \lambda_2$	22.804 (11, .019)	0.997	0.013	78,293.574	78,461.112
	$\lambda_3 = \lambda_4$	20.493 (11, .039)	0.998	0.012	78,290.732	78,458.270
	$\lambda_1 = \lambda_2,\ \lambda_3 = \lambda_4$	23.789 (12, .022)	0.997	0.016	78,293.102	78,453.938
	$\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4$	92.837 (13, .000)	0.983	0.032	78,372.157	78,526.292
	$\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = 1$	91.486 (14, .000)	0.983	0.030	78,370.316	78,517.749
Parameter equivalence testing	$\beta_{11} = \beta_{22}$	22.979 (11, .018)	0.997	0.013	78,294.534	78,462.072
	$\beta_{12} = \beta_{21}$	19.292 (11, .056)	0.998	0.011	**78,289.073**	78,456.611
	$c_{x1} = c_{x2}$	21.282 (11, .031)	0.998	0.012	78,291.476	78,459.014
	$c_{y1} = c_{y2}$	28.407 (11, .003)	0.996	0.016	78,299.906	78,467.444
Best fitting empirical model	$\lambda_1 = \lambda_2,\ \lambda_3 = \lambda_4,\ \beta_{11} = \beta_{22},$ $\beta_{12} = \beta_{21}, c_{x1} = c_{x2}$	27.668 (15, .024)	0.997	0.012	78,293.095	**78,433.826**

Note. Models in bold represent the full model without any constraints and a parsimonious empirical model.
[a] Robust χ^2 test statistics are presented instead of standard χ^2 values.

measurement models. The latent APIM enabled describing dyadic relationships in terms of the latent constructs that aligned closer to substantive theory, which in this case were relationship commitment and happiness. Because it grouped relevant indicators into latent factors, the differential effects of individual manifest variables such as the effects of similarity and closeness to positive and negative affect could not be measured. Such research questions would be better understood by fitting a manifest APIM with separate paths for similarity and closeness. However, unless that is the focus of an analysis, the results from a composite-score APIM would be more intuitive and concise, while maintaining low risks of detecting false effects.

Consequently, it is crucial that the variables and their measurement characteristics are well defined in relation to the research question and field of study. The way of forming latent factors needs to be supported from substantive literature and backed up with reliably measured scale indicators. Only then can the strength of association between a factor and its indicators be linked to the intended research questions. In our empirical example, the reliability of the indicators reflecting relationship commitment and happiness was decent at best (See Table 6). This could be partly because the factors were based on only two indicators each. Even though simply adding more indicators would not compensate for weak indicators already included for a given factor (Ledermann & Kenny, 2012), obtaining additional indicators that maintain proper construct validity can boost reliability, resulting in much enhanced model performance.

Relatedly, factor loadings need to be freely estimated and tested further for equivalence in the latent APIM as indicative information to the quality and structure of measurement. Combining indicators equally into composite-scores without such considerations entail the potential to producing misleading inferences. Likewise, applying the latent APIM to multivariate data without appropriate factor structures can lead to wrong conclusions in the opposite direction.

Results of the latent APIM applied to the current example imply that one's evaluation of relationship commitment is highly related to one's own degree of happiness, possibly so much that additional partner effects do not exist. This is a characteristic pattern in terms of dyadic dynamics called the "actor-only pattern" where the ratio of each member's partner effect to actor effect is almost zero ($k_A = \frac{\beta_{12}}{\beta_{11}} = 0, k_B = \frac{\beta_{21}}{\beta_{22}} = 0$; Kenny & Ledermann, 2010). Along with our simulation study in the Simulation section, we advise

Table 9
Summary of Latent APIM Estimates of Factor Loadings and Actor and Partner Effects (n = 6,012)

		Full model				Latent APIM with constraints			
Parameter	Path	Est.	*SE*	*p*	Std. Est.	Est.	*SE*	*p*	Std. Est.
1	$comm_H \rightarrow sim_H$	1	—	—	0.599	1	—	—	0.607
λ_1	$comm_H \rightarrow close_H$	0.800	0.056	<.001	0.675	*0.784*	0.030	<.001	0.675
1	$comm_W \rightarrow sim_W$	1	—	—	0.719	1	—	—	0.687
λ_2	$comm_W \rightarrow close_W$	0.716	0.044	<.001	0.680	*0.784*	0.030	<.001	0.710
1	$happiness_H \rightarrow posit_H$	1	—	—	0.651	1	—	—	0.631
λ_3	$happiness_H \rightarrow nonneg_H$	1.414	0.123	<.001	0.536	*1.496*	0.091	<.001	0.548
1	$happiness_W \rightarrow posit_W$	1	—	—	0.626	1	—	—	0.645
λ_4	$happiness_W \rightarrow nonneg_W$	1.579	0.127	<.001	0.593	*1.496*	0.091	<.001	0.580
β_{11}	$comm_H \rightarrow happiness_H$	0.429	0.048	<.001	0.428	*0.380*	0.030	<.001	0.399
β_{22}	$comm_W \rightarrow happiness_W$	0.335	0.041	<.001	0.407	*0.380*	0.030	<.001	0.425
β_{12}	$comm_W \rightarrow happiness_H$	0.011	0.026	.678	0.014	*0.013*	0.021	.527	0.017
β_{21}	$comm_H \rightarrow happiness_W$	0.009	0.037	.812	0.008	*0.013*	0.021	.527	0.012

Note. Est. = point estimate; Std. Est. = standardized estimate. Numbers in italic indicate parameter estimates with equality constraints.

Table 10
Goodness of Fit Statistics for Composite-Score APIM Submodels (n = 6,012)

Model	Constraints	χ^2 (*df*, *p*)[a]	CFI	RMSEA	AIC	BIC
Full model	—	0.000 (0, –)	1.000	0.000	67,025.750	67,092.770
Actor effect equivalence testing	$\gamma_{11} = \gamma_{22}$	0.601 (1, .438)	1.000	0.000	67,024.618	67,084.931
Best fitting empirical model	$\gamma_{11} = \gamma_{22},\ \gamma_{12} = \gamma_{21}$	0.670 (2, .715)	1.000	0.000	**67,022.678**	**67,076.290**

Note. Models in bold represent the full model without any constraints and a parsimonious empirical model.
[a] Robust χ^2 test statistics are presented instead of standard χ^2 values.

including measurement models within the APIM if multiple dyadic measures are taken with certain underlying constructs in mind.

Discussion

Recommendations for Using Different APIMs for Dyadic Data Analysis

The types of inferences possible with the latent APIM, composite-score APIM, and manifest APIM were discussed, and the parameters and characteristics of the three approaches were compared in detail. Through our analytic and empirical investigations, the effectiveness of the latent APIM became clear, especially for enabling inferences related to latent constructs and psychological theories. However, we acknowledge that alternative models and other approaches may be equally or more suitable for particular contexts. There is a well-known bias and variance (a.k.a. accuracy and precision) trade-off for methods with and without latent variables largely in the SEM literature (Ledgerwood & Shrout, 2011; Liu & Rhemtulla, 2022; Rhemtulla et al., 2020; Rush et al., 2020). Also, less commonly but possibly some observed variables can be treated as causal-formative indicators rather than reflective or effect indicators of unmeasured constructs (Bollen & Diamantopoulos, 2017), provided a theory supports such use of indicators (Hardin, 2017).

In our attempt to provide guidelines for applied researchers in deciding which APIM to use for certain contexts, we list our recommendations below based on theoretical consideration and empirical findings from the simulation study. However, we clarify that these are guiding principles in general, and the optimal decision should not be made without an understanding of the particular context in consideration.

First and foremost, the researcher should investigate the relationship among multivariate dyadic data in relation to psychological theory and literature. The selection of analytic methods and model specifications including the directionality of the cross-sectional association should be guided by subject-matter knowledge and the properties of the measures. If the observed variables are affected by latent constructs and thus these measures are reflective indicators as in the FA, CTT, IRT, and most SEM frameworks (Crocker & Algina, 1986; Embretson & Reise, 2013; Harman, 1976; Kline, 2015), the latent APIM would be appropriate. Otherwise, the composite-score APIM may be suitable, especially when combined scores are interpretable. The manifest APIM is not generally recommended because of its model complexity and low power of detecting moderate partner effects and the high levels of false detection rates when an effect does not exist.

Second, the researchers should check measurement reliability and use scales tested throughout the field if possible, or at least with pilot studies. We highlight that the reliability of the measures is critically important for the trustworthy estimation of dyadic patterns for all types of APIMs, and a large sample size (n = 200) does not really compensate for the low reliability of measures (Cronbach's α = .4).

Third, the sample size and the number of indicators matter, especially for the latent APIM. The latent APIM is not recommended when the sample size is less than 100. It is applicable with two indicators for each construct, but three or more indicators help model specification and interpretation (e.g., comparing factor loadings of multiple indicators) and will likely increase reliability.

Table 11
Summary of the Composite-Score APIM Estimates (n = 6,012)

		Full model				Composite-score APIM with constraints			
Parameter	Path	Est.	*SE*	*p*	Std. Est.	Est.	*SE*	*p*	Std. Est.
γ_{11}	$cmm_{comp.H} \rightarrow hpp_{comp.H}$	0.285	0.023	<.001	0.196	*0.299*	0.016	<.001	0.205
γ_{22}	$cmm_{comp.W} \rightarrow hpp_{comp.W}$	0.313	0.023	<.001	0.225	*0.299*	0.016	<.001	0.215
γ_{12}	$cmm_{comp.W} \rightarrow hpp_{comp.H}$	0.088	0.019	<.001	0.069	*0.079*	0.015	<.001	0.061
γ_{21}	$cmm_{comp.H} \rightarrow hpp_{comp.W}$	0.067	0.023	.004	0.042	*0.079*	0.015	<.001	0.050
ϕ_{12}	$cmm_{comp.H}$ & $cmm_{comp.W}$	0.251	0.013	<.001	0.353	0.251	0.013	<.001	0.353
ψ_{12}	$\zeta_{comp.H}$ & $\zeta_{comp.W}$	0.147	0.019	<.001	0.108	0.147	0.019	<.001	0.108
	$var(\zeta_{comp.H})$	1.251	0.036	<.001	0.945	1.251	0.036	<.001	0.942
	$var(\zeta_{comp.W})$	1.472	0.038	<.001	0.940	1.472	0.038	<.001	0.942
	$var(cmm_{comp.H})$	0.626	0.017	<.001	1.001	0.626	0.017	<.001	1.001
	$var(cmm_{comp.W})$	0.808	0.027	<.001	1.003	0.808	0.027	<.001	1.003

Note. Est. = point estimate; Std. Est. = standardized estimate. Numbers in italic indicate parameter estimates with equality constraints.

Fourth, when the sample size is less than 100, the composite-score APIM can be a viable option. However, the researcher should understand the shortcomings of the composite-score APIM, especially in terms of measurement error and the inability to test the model fit. See the Extending the Traditional APIM to Multivariate Dyadic Data Analysis and Benefits of Having Measurement Models Within the APIM sections for details. The simulation also reveals that the relative size of partner effects compared with actor effects are overestimated when the reliability of the variables is low (.4).

Finally, if there is no reason to believe that multiple indicators reflect common factors or that a linear combination of the variables is meaningful, the researcher can use the traditional APIM in Figure 1 and conduct multiple univariate analyses for different combinations of predictors and outcomes.

Summary, Limitations, and Future Research

Dyadic data contain rich information about dynamic relationships in pairs of people. Owing to the rapid development of data collection, archiving, and sharing techniques and outlets, the volume of dyadic data with multiple indicators has increased, and the trend will likely continue. Whereas multiple responses have often been transformed to composite scores in dyadic data analysis, this article presents multivariate modeling approaches with latent variables and measurement models that allow us to examine various forms of interdependence and directional effects which possibly occur among latent constructs in dyadic research. The measurement model that defines the latent variables accounts for measurement errors, which may reduce the variance of parameter estimates as well as produce less biased structural parameter estimates (Chow et al., 2015; Vij & Walker, 2016). Having two or more indicators for each latent variable with high reliability could enhance the benefits of adopting latent variables within the APIM. The latent APIM is also parsimonious and has positive degrees of freedom to test model fit. In our empirical analysis, the unconstrained latent APIM has 10 degrees of freedom whereas the unconstrained composite-score APIM has zero degrees of freedom. Our empirical study on relationship commitment and happiness also supported that latent actor and partner effects were more intuitive to interpret than without latent variables.

There are a number of limitations in the current study. Although the simulation study considered a variety of conditions involving various dyadic patterns, different levels of reliability, sample size, and the number of indicators, the simulation was limited to symmetric actor and partner effects, factor loadings, and measurement errors for two members in a dyad. It would be interesting to explore when one member's effects are substantially different from or opposite to the other member. The reliability was also set to be consistent across multiple measures, and it would be helpful to know whether the average or minimum reliability matters more for valid inference.

The scope of the current study is limited to a cross-sectional design, whereas many dyadic data analyses involve longitudinal data and the examination of cross-lagged partner effects over time. Therefore, the directionality of the association of interest should be determined through theoretical investigation before applying the analytical methods from the current study. Future research can investigate how more complex dyadic patterns or measurement models would impact the performances of the latent APIM in (intensive) longitudinal dyadic data. It will also be fruitful to develop dyadic methods to account for covariates as well as various interdependence structures in multilevel dyadic data, where dyads are nested within clusters, and between-dyad differences are accounted for in the multilevel dyad models. Finally, the presented multivariate APIM approaches for pairs can be extended to small interactive groups with three or more members (e.g., a therapist and a couple, a guardian and children, a tutor and students) that are prevalent in the fields of psychology and education.

References

Alexandrowicz, R. W. (2015). Analyzing dyadic data with IRT models. In M. Stemmler, A. von Eye, & W. Wiedermann (Eds.), *Dependent data in social sciences research* (pp. 173–202). Springer International Publishing. https://doi.org/10.1007/978-3-319-20585-4_8

Anderson, C., Keltner, D., & John, O. P. (2003). Emotional convergence between people over time. *Journal of Personality and Social Psychology*, *84*(5), 1054–1068. https://doi.org/10.1037/0022-3514.84.5.1054

Aron, A., Aron, E. N., & Smollanm, D. (1992). Inclusion of other in the self scale and the structure of interpersonal closeness. *Journal of Personality and Social Psychology*, *63*(4), 596–612. https://doi.org/10.1037/0022-3514.63.4.596

Arriaga, X. B., & Agnew, C. R. (2001). Being committed: Affective, cognitive, and conative components of relationship commitment. *Personality and Social Psychology Bulletin*, *27*(9), 1190–1203. https://doi.org/10.1177/0146167201279011

Bandalos, D. L. (2018). *Measurement theory and applications for the social sciences*. Guilford Publications.

Bardach, L., Yanagida, T., Schober, B., & Lüftenegger, M. (2019). Students' and teachers' perceptions of goal structures—Will they ever converge? Exploring changes in student-teacher agreement and reciprocal relations to self-concept and achievement. *Contemporary Educational Psychology*, *59*, 101799. https://doi.org/10.1016/j.cedpsych.2019.101799

Bollen, K. A. (1989). *Structural equations with latent variables*. Wiley. https://doi.org/10.1002/9781118619179

Bollen, K. A., & Diamantopoulos, A. (2017). In defense of causal-formative indicators: A minority report. *Psychological Methods*, *22*(3), 581–596. https://doi.org/10.1037/met0000056

Bollen, K., & Lennox, R. (1991). Conventional wisdom on measurement: A structural equation perspective. *Psychological Bulletin*, *110*(2), 305–314. https://doi.org/10.1037/0033-2909.110.2.305

Borsboom, D. (2008). Latent variable theory. *Measurement: Interdisciplinary Research and Perspectives*, *6*(1–2), 25–53. https://doi.org/10.1080/15366360802035497

Brinberg, M., Ram, N., Conroy, D. E., Pincus, A. L., & Gerstorf, D. (2021). Dyadic analysis and the reciprocal one-with-many model: Extending the study of interpersonal processes with intensive longitudinal data. *Psychological Methods*. Advance online publication. https://doi.org/10.1037/met0000380

Chow, C. M., Claxton, S. E., & van Dulmen, M. H. M. (2015). Testing dyadic mechanisms the right way: A primer into moderated actor–partner interdependence model with latent variable interactions. *Emerging Adulthood*, *3*(6), 421–433. https://doi.org/10.1177/2167696815605728

Chow, S. M., Ou, L., Ciptadi, A., Prince, E. B., You, D., Hunter, M. D., Rehg, J. M., Rozga, A., & Messinger, D. S. (2018). Representing sudden shifts in intensive dyadic interaction data using differential equation models with regime switching. *Psychometrika*, *83*(2), 476–510. https://doi.org/10.1007/s11336-018-9605-1

Cohen, P., Cohen, J., Teresi, J., Marchi, M., & Velez, C. N. (1990). Problems in the measurement of latent variables in structural equations causal models. *Applied Psychological Measurement*, *14*(2), 183–196. https://doi.org/10.1177/014662169001400207

Cole, D. A., & Preacher, K. J. (2014). Manifest variable path analysis: Potentially serious and misleading consequences due to uncorrected measurement error. *Psychological Methods*, *19*(2), 300–315. https://doi.org/10.1037/a0033805

Cook, W. L. (1998). Integrating models of interdependence with treatment evaluations in marital therapy research. *Journal of Family Psychology*, *12*(4), 529–542. https://doi.org/10.1037/0893-3200.12.4.529

Crocker, L., & Algina, J. (1986). *Introduction to classical and modern test theory*. Holt, Rinehart and Winston.

De Haan-Rietdijk, S., Gottman, J. M., Bergeman, C. S., & Hamaker, E. L. (2016). Get over it! A multilevel threshold autoregressive model for state-dependent affect regulation. *Psychometrika*, *81*(1), 217–241. https://doi.org/10.1007/s11336-014-9417-x

Decuyper, M., Gistelinck, F., Vergauwe, J., Pancorbo, G., & De Fruyt, F. (2018). Personality pathology and relationship satisfaction in dating and married couples. *Personality Disorders*, *9*(1), 81–92. https://doi.org/10.1037/per0000219

Embretson, S. E., & Reise, S. P. (2013). *Item response theory*. Psychology Press. https://doi.org/10.4324/9781410605269

Finkel, E. J., Simpson, J. A., & Eastwick, P. W. (2017). The psychology of close relationships: Fourteen core principles. *Annual Review of Psychology*, *68*(1), 383–411. https://doi.org/10.1146/annurev-psych-010416-044038

Foran, H. M., & Kliem, S. (2015). Longitudinal analysis of dyads using latent variable models: Current practices and constraints. In M. Stemmler, A. von Eye, & W. Wiedermann (Eds.), *Dependent data in social sciences research* (pp. 203–229). Springer International Publishing.

Galovan, A. M., Holmes, E. K., & Proulx, C. M. (2017). Theoretical and methodological issues in relationship research: Considering the common fate model. *Journal of Social and Personal Relationships*, *34*(1), 44–68. https://doi.org/10.1177/0265407515621179

Garcia, R. L., Kenny, D. A., & Ledermann, T. (2015). Moderation in the actor-partner interdependence model. *Personal Relationships*, *22*(1), 8–29. https://doi.org/10.1111/pere.12060

Gin, B., Sim, N., Skrondal, A., & Rabe-Hesketh, S. (2020). A dyadic IRT model. *Psychometrika*, *85*(3), 815–836. https://doi.org/10.1007/s11336-020-09718-1

Gistelinck, F., Loeys, T., Decuyper, M., & Dewitte, M. (2018). Indistinguishability tests in the actor-partner interdependence model. *British Journal of Mathematical and Statistical Psychology*, *71*(3), 472–498. https://doi.org/10.1111/bmsp.12129

Hardin, A. (2017). A call for theory to support the use of causal-formative indicators: A commentary on Bollen and Diamantopoulos (2017). *Psychological Methods*, *22*(3), 597–604. https://doi.org/10.1037/met0000115

Harman, H. H. (1976). *Modern factor analysis*. University of Chicago Press.

Herd, P., Carr, D., & Roan, C. (2014). Cohort profile: Wisconsin longitudinal study (WLS). *International Journal of Epidemiology*, *43*(1), 34–41. https://doi.org/10.1093/ije/dys194

Hong, S., & Kim, S. (2019). Comparisons of multilevel modeling and structural equation modeling approaches to actor–partner interdependence model. *Psychological Reports*, *122*(2), 558–574. https://doi.org/10.1177/0033294118766608

Hoyle, R. H. (1999). *Statistical strategies for small sample research*. Sage.

Huber, P. (1967). The behavior of maximum likelihood estimates under nonstandard conditions. In L. LeCam & J. Neyman (Eds.), *Proceedings of the Fifth Berkeley symposium on mathematical statistics and probability* (pp. 221–233). University of California Press.

Jöreskog, K. G. (2001). *LISREL 8.50*. Scientific Software.

Kaplan, D. (2009). *Structural equation modeling: Foundations and extensions* (2nd ed.). SAGE. https://doi.org/10.4135/9781452226576

Kenny, D. A. (1996). Models of nonindependence in dyadic research. *Journal of Social and Personal Relationships*, *13*(2), 279–294. https://doi.org/10.1177/0265407596132007

Kenny, D. A., & La Voie, L. (1985). Separating individual and group effects. *Journal of Personality and Social Psychology*, *48*(2), 339–348. https://doi.org/10.1037/0022-3514.48.2.339

Kenny, D. A., & Ledermann, T. (2010). Detecting, measuring, and testing dyadic patterns in the actor-partner interdependence model. *Journal of Family Psychology*, *24*(3), 359–366. https://doi.org/10.1037/a0019651

Kenny, D. A., Kashy, D. A., & Cook, W. L. (2006). *Dyadic data analysis*. Guilford Press.

Kim, H., & Kim, J.-S. (2021). Where the choice of model leads us: An empirical comparison of dyadic data analysis frameworks. In M. Wiberg, D. Molenaar, J. González, U. Böckenholt, & J.-S. Kim (Eds.), *Quantitative psychology: The 85th annual meeting of the psychometric society, virtual* (pp. 439–451). Springer. https://doi.org/10.1007/978-3-030-74772-5_39

Kline, R. B. (2015). *Principles and practice of structural equation modeling*. Guilford Press.

Laurenceau, J.-P., & Bolger, N. (2012). Analyzing diary and intensive longitudinal data from dyads. In M. R. Mehl & T. S. Conner (Eds.), *Handbook of research methods for studying daily life* (pp. 407–422). Guilford Press.

Ledermann, T., & Kenny, D. A. (2012). The common fate model for dyadic data: Variations of a theoretically important but underutilized model. *Journal of Family Psychology*, *26*(1), 140–148. https://doi.org/10.1037/a0026624

Ledermann, T., & Macho, S. (2009). Mediation in dyadic data at the level of the dyads: A Structural Equation Modeling approach. *Journal of Family Psychology*, *23*(5), 661–670. https://doi.org/10.1037/a0016197

Ledgerwood, A., & Shrout, P. E. (2011). The trade-off between accuracy and precision in latent variable models of mediation processes. *Journal of Personality and Social Psychology*, *101*(6), 1174–1188. https://doi.org/10.1037/a0024776

Little, R. (1988). Missing-data adjustments in large surveys. *Journal of Business & Economic Statistics*, *6*(3), 287–296. https://doi.org/10.1080/07350015.1988.10509663

Little, R., & Rubin, D. B. (2019). *Statistical analysis with missing data*. Wiley.

Liu, S., & Rhemtulla, M. (2022). Treating random effects as observed versus latent predictors: The bias-variance tradeoff in small samples. *British Journal of Mathematical and Statistical Psychology*, *75*(1), 158–181. https://doi.org/10.1111/bmsp.12253

Maroufizadeh, S., Hosseini, M., Rahimi Foroushani, A., Omani-Samani, R., & Amini, P. (2018). Application of the dyadic data analysis in behavioral medicine research: Marital satisfaction and anxiety in infertile couples. *BMC Medical Research Methodology*, *18*(1), 117. https://doi.org/10.1186/s12874-018-0582-y

Mattei, D., & Schaefer, C. E. (2004). An investigation of validity of the subjective happiness scale. *Psychological Reports*, *94*(1), 288–290. https://doi.org/10.2466/pr0.94.1.288-290

McGreal, R., & Joseph, S. (1993). The depression-happiness scale. *Psychological Reports*, *73*(3, Pt. 2), 1279–1282. https://doi.org/10.2466/pr0.1993.73.3f.1279

Moorman, S. M. (2016). Dyadic perspectives on marital quality and loneliness in later life. *Journal of Social and Personal Relationships*, *33*(5), 600–618. https://doi.org/10.1177/0265407515584504

Muthén, L. K., & Muthén, B. (2017). *Mplus user's guide* (8th ed.).

O'Muircheartaigh, C., English, N., Pedlow, S., & Kwok, P. K. (2014). Sample design, sample augmentation, and estimation for Wave 2 of the NSHAP. *The Journals of Gerontology. Series B, Psychological Sciences and Social Sciences*, *69*(Suppl. 2), S15–S26. https://doi.org/10.1093/geronb/gbu053

R Core Team. (2020). R: A language and environment for statistical computing. https://www.r-project.org/

Rhemtulla, M., van Bork, R., & Borsboom, D. (2020). Worse than measurement error: Consequences of inappropriate latent variable measurement models. *Psychological Methods*, *25*(1), 30–45. https://doi.org/10.1037/met0000220

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, *48*(2), 1–36. https://doi.org/10.18637/jss.v048.i02

Rubin, D. B. (1987). *Multiple imputation for nonresponse in surveys*. Wiley. https://doi.org/10.1002/9780470316696

Rush, J., Rast, P., & Hofer, S. M. (2020). Optimizing detection of true within-person effects for intensive measurement designs: A comparison of multilevel SEM and unit-weighted scale scores. *Behavior Research Methods*, *52*(5), 1883–1892. https://doi.org/10.3758/s13428-020-01369-5

Schoebi, D., & Randall, A. K. (2015). Emotional dynamics in intimate relationships. *Emotion Review*, *7*(4), 342–348. https://doi.org/10.1177/1754073915590620

Sels, L., Cabrieto, J., Butler, E., Reis, H., Ceulemans, E., & Kuppens, P. (2020). The occurrence and correlates of emotional interdependence in romantic relationships. *Journal of Personality and Social Psychology*, *119*(1), 136–158. https://doi.org/10.1037/pspi0000212

Stas, L., Kenny, D. A., Mayer, A., & Loeys, T. (2018). Giving dyadic data analysis away: A user-friendly app for actor–partner interdependence models. *Personal Relationships*, *25*(1), 103–119. https://doi.org/10.1111/pere.12230

Tabachnick, B. G., Fidell, L. S., & Ullman, J. B. (2007). *Using multivariate statistics* (Vol. 5). Pearson.

van Buuren, S., & Groothuis-Oudshoorn, K. (2011). mice: Multivariate imputation by chained equations in R. *Journal of Statistical Software*, *45*(3), 1–67. https://doi.org/10.18637/jss.v045.i03

van Dulmen, M. H. M., & Goncy, E. A. (2010). Extending the actor-partner interdependence model to include cross-informant data. *Journal of Adolescence*, *33*(6), 869–877. https://doi.org/10.1016/j.adolescence.2010.07.002

Vij, A., & Walker, J. L. (2016). How, when and why integrated choice and latent variable models are latently useful. *Transportation Research Part B: Methodological*, *90*, 192–217. https://doi.org/10.1016/j.trb.2016.04.021

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, *48*(4), 817–838. https://doi.org/10.2307/1912934

Yuan, K.-H., & Bentler, P. M. (2000). Three likelihood-based methods for mean and covariance structure analysis with nonnormal missing data. *Sociological Methodology*, *30*(1), 165–200. https://doi.org/10.1111/0081-1750.00078

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