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MULTILEVEL AUTOREGRESSIVE MODELS FOR LONGITUDINAL DYADIC DATA

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In social and behavioral science, dyadic research has become more and more popular. In case of cross-sectional dyadic data, one can apply the actor-partner interdependence model (APIM). When dyads are measured repeatedly over time, applied researchers are often hesitant to analyze such data due to the statistical complexity. In this paper, we introduce a user-friendly Shiny-application, called the *LDDinSEM*-application. The app automatically fits the lagged dependent actor-partner interdependence model (LD-APIM), a multilevel autoregressive model extension of the APIM within the structural equation modeling (SEM) framework. The application allows the researcher to investigate the effects of an antecedent on an outcome, given the previous outcome. We illustrate the app using an empirical example assessing the actor and partner effects of positive relationship feelings on next day's intimacy in heterosexual couples.

Keywords: Longitudinal dyadic data; Structural equation modeling; Lagged dependent actor-partner interdependence model (LD-APIM); Panel data.

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Psychologists are often interested in the processes underlying social and behavioral phenomena. However, as these phenomena occur in the social context of life, they are often interpersonal by definition (Reis, Collins, & Bersheid, 2000). The most basic social unit of interpersonal interactions is a pair, also called a dyad, such as a married couple, two siblings, or an employer and an employee. It is clear that members of the same dyad are related to one another. For instance, in the context of marital satisfaction, the possibility that the husband's responses are unrelated to the wife's responses is very slim as they inherently report on the same relationship. From a statistical point of view, analyzing such dyadic data can thus be a challenge as most standard statistical procedures assume independency (Gonzalez & Griffin, 1999).

Over the last decade, many dyadic models have been introduced due to the popularity of collecting dyadic data rather than individual data. For instance, the mutual-feedback model to analyze dyads who directly affect each other's score via reciprocal effects (Woody & Sadler, 2005) or the common fate model to analyze dyads who are under the influence of a common theoretical construct (Ledermann & Kenny, 2015). However, the most popular and widely used dyadic model is the actor-partner interdependence model or APIM (Kashy & Kenny, 2000). The APIM is used to analyze intra-personal and inter-personal effects within the dyadic context. For instance, consider the effect of positive feelings about the relationship and the next morning's perception of intimacy within the context of heterosexual couples. It is obvious that the husband's own positive feelings affect his own perception of intimacy (i.e., *the actor effect*), similar for the wife. Yet, one can imagine that the wife's positive feeling will affect the husband's perception of intimacy too (i.e., *the partner effect*), and vice versa. Such effects can simultaneously be estimated by the APIM. Furthermore, the model allows the outcome scores within a dyad to be correlated with one another (i.e., *interdependence*), hereby estimating the (dis)similarity of perceived intimacy between husband and wife.

Due to the complexity of dyadic data and the difficulties that come with implementing these models, applied psychologist often have a hard time fitting such dyadic models. As a result, tutorials and online applications are often used to introduce the researcher to the model and its usage. One of the most cited APIM papers involves a user-friendly guide for fitting the APIM using SAS or HLM (Campbell & Kashy, 2002). Similar tutorials with implementations in other statistical software packages, such as Mplus, also gained quite some interest over the last years (Fitzpatrick, Gareau, Lafontaine, & Gaudreau, 2016). However, the latter tools require a license for the software under consideration. The recently developed *APIM_SEM*-application (Stas, Kenny, Mayer, & Loeys, 2018), which is part of a bigger project called *DyadR* (Kenny, 2017), allows users to fit standard or more complex APIMs for cross-sectional dyadic data without software licenses. All these instances illustrate the need for comprehensive analytic tools.

When considering dyads repeatedly over time, one obtains longitudinal dyadic data (LDD). In order to analyze such data, the dyadic model has to account for additional statistical challenges (Gistelinck & Loeys, 2019). The most prominent issue is the fact that two types of interdependence have to be taken into account now. Like before, the model has to incorporate the correlation between measurements of the two members of a dyad, regardless the time point considered. However, due to the repeated measurements, one has to account for the correlation over time as well, both within and across dyads. The way a person feels today will affect the way he or she will feel tomorrow, the day after, the day thereafter, and so forth. Moreover, it will also affect the emotional status of the person closest to him/her in the upcoming days (Cranford, et al., 2006). Standard multilevel approaches assuming independent residuals fail to account for such *autocorrelation*. Erroneous inference is obtained in case this temporal correlation is ignored (Fitzmaurice, Laird, & Ware, 2011; Singer & Willett, 2003).

Fortunately, there already exist longitudinal dyadic models that tackle these challenges. For instance, one can use dyadic latent growth curve models in case the researcher is interested in simultaneously modeling the developmental processes of each dyad member (Ferrer & McArdle, 2003). However, when a specific trend over time is absent, this model might be less applicable. For instance, when gathering daily or weekly affective measurements, focus often lies on identifying antecedents of the behavior or emotional status within and across dyad members instead, rather than on the evolution over time. To that end, an extension of the APIM toward the longitudinal setting sounds more interesting. Such an extension of the APIM was already proposed by Bolger and Laurenceau (2013) for intensive longitudinal dyadic data, and was further developed in the SEM framework by Gistelinck and Loeys (2019). The model adapts the APIM to incorporate the repeated measurement structure by specifying a complex residual covariance structure. Alternatively, a multilevel autoregressive approach might be interesting for applied researchers (Kuppens, Allen, & Sheeber, 2010) as well. Indeed, as the outcome at a specific time point typically depends on its value at the previous time point, specifying a direct effect for the state-dependency might be more appealing than specifying a residual autocorrelation. Moreover, correlation might not only arise due to state-dependency, but also due to an underlying unobserved trait. In other words, instead of introducing a complex residual covariance structure, it might be more interesting to adapt the APIM to include a lagged dependent variable in order to capture the state-dependency, while adding a random intercept for each dyad member to represent the underlying trait that affects all measurements equally (Rovine & Walls, 2006).

The goal of this article is to introduce the readers to an application called the *LDDinSEM*-application that allows to fit this alternative APIM extension, referred to as the lagged-dependent APIM or LD-APIM. Similar to the *APIM_SEM*-application, we offer the applied psychologist with a simple but comprehensive tool for longitudinal dyadic data modeling. The disadvantage is that this simplicity comes with a cost. As we will explain below, there are a number of model assumptions that need to be made a priori. However, we believe this simple implementation is an ideal first step to break the barrier between understanding and applying a longitudinal dyadic model. Furthermore, given that the model has been imbedded within a free, web-based, point and click interface, it allows the user to experiment with the model and to get familiar with it without the need for specific software. We believe this step is essential for the applied psychologist in order to move on to more complex dyadic models.

The article is organized as follows. First, we will introduce the LD-APIM and discuss what model assumptions are made when this model is fitted. Next, we illustrate how the LD-APIM is easily applied using the *LDDinSEM*-application on an empirical example. We end with a discussion.

The Lagged Dependent Actor-Partner Interdependence Model

As a motivating example throughout this paper we consider a Flemish daily diary study on sexual behavior in 66 heterosexual couples (Dewitte, Van Lankveld, Vandenberghe, & Loeys, 2015). Every morning during three weeks both members of the couple were asked about their sexual and intimate behavior since the last time they had filled out their morning diary (i.e., sexual behavior over the past 24 hours). Every evening the participants were asked to report on their individual, relational, and partner-related feelings and behavior experienced during that day. Here we will only focus on the association between the positive feelings about the relationship and the next morning's perception of intimacy. Positive relationship feelings were computed as the average of nine items on a 7-point Likert scale: the extent to which they felt happy, satisfied, understood, supported, accepted, loved, in love, connected, and close. The amount of intimacy was measured by the amount of kissing, cuddling, and caressing rating from "*not at all*" to "*very frequent*" using a 7-point Likert scale.

Since we consider data from heterosexual couples, it is clear that we are dealing with dyadic data. More specifically, this type of dyads is actually called distinguishable dyads (Olsen & Kenny, 2005). Indeed, one can identify a difference in role for each member of the dyad. In this example, the different roles are defined as "husband" and "wife" as induced by gender. Other examples of distinguishable dyads are trainer and trainee (who gives the training and who is trained), older or younger sibling (age), or supervisor and employee (status). In contrast, indistinguishable dyads are defined as dyads in which no difference in roles can be identified, such as same-sex couples, coworkers, or twins. The LD-APIM implemented in the *LDDinSEM*-application by default assumes distinguishable dyads, and in this paper we will particularly focus on this type, but the app allows to make additional constraints (Gistelinck, Loeys, Decuypere & Dewitte, 2018), making it suitable for both distinguishable and indistinguishable dyads.

In our illustrating example, the couples were measured repeatedly for 21 consecutive days, leading to longitudinal dyadic data. As we assume no life changing events (e.g., an upcoming divorce) during these three weeks of observations, we expect no specific trend in the perceived intimacy of the couples. Moreover, we want to explore the effect of the positive feelings about the relationship on next morning's perception of intimacy. We want to be able to answer research questions like "How does an increase or decrease in one's own positive relationship feelings on a particular day (as compared to his/her average feelings) affect today's perception of intimacy?." To address such research question, we need a model that focusses on predictive effects rather than on the time dynamics of the outcome of interest.

In this paper we therefore propose the following model equations for the LD-APIM:

$$\begin{cases} \mathrm{Y}_{\mathrm{F}ij} = (\mu_\mathrm{F} + \eta_{\mathrm{F}j}) + \rho_\mathrm{F}\mathrm{Y}_{\mathrm{F},i-1,j} + \mathrm{a}_{\mathrm{F(X)}}\,\mathrm{X}_{\mathrm{F}ij} + \mathrm{p}_{\mathrm{MF(X)}}\,\mathrm{X}_{\mathrm{M}ij} + \varepsilon_{\mathrm{F}ij} \\ \mathrm{Y}_{\mathrm{M}ij} = (\mu_\mathrm{M} + \eta_{\mathrm{M}j}) + \rho_\mathrm{M}\mathrm{Y}_{\mathrm{M},i-1,j} + \mathrm{a}_{\mathrm{M(X)}}\,\mathrm{X}_{\mathrm{M}ij} + \mathrm{p}_{\mathrm{FM(X)}}\,\mathrm{X}_{\mathrm{F}ij} + \varepsilon_{\mathrm{M}ij} \end{cases}, \tag{1}$$

with i referring to the time point (i = 2, …, T) and j to the dyad number (j = 1, …, N). A graphical representation of the model can be found in Figure 1. In our motivating example, X represents the positive relationship feelings, while Y corresponds to the perceived intimacy. Here, the F refers to female and M refers to male of the heterosexual couple.

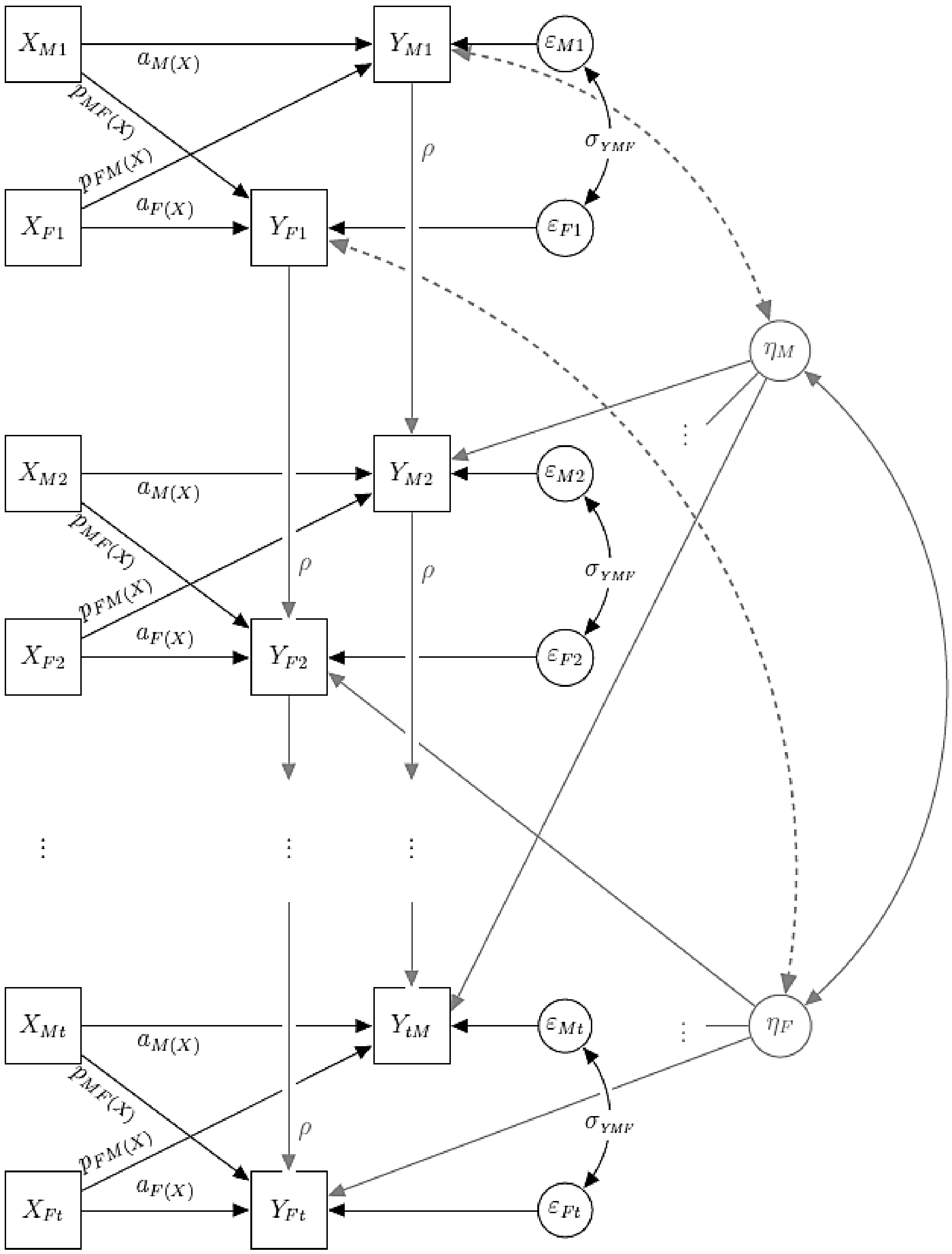


FIGURE 1
A graphical representation of the lagged dependent APIM (LD-APIM).

Considering Equation 1, the LD-APIM can be viewed as half of random intercept cross-lagged panel model (RI-CLPM; Hamaker, Kuiper, & Grasman, 2015) adapted for dyads. It can also be viewed as a dyadic version of an autoregressive latent trajectory model (ALT; Bollen & Curran, 2004) without a linear effect of time but with additional actor and partner effects. It is also clear that the LD-APIM is an extension of the cross-sectional APIM toward the longitudinal setting. On the one hand, there are the parameters a_F and a_M, representing the actor effects for the females and the males, respectively. They correspond to the effect of positive relationship feelings of one dyad member on his/her own perceived intimacy (conditional on the previous perceived intimacy). On the other hand, there are the parameters p_{MF} and p_{FM}, representing the partner effects for the females and the males, respectively. They correspond to the effect of positive relationship feelings of the partner on his/her own perceived intimacy (conditional on the previous perceived intimacy).

However, one should acknowledge *time-averaged* and *time-specific* effects of a time-varying predictor, such as positive relationship feelings. It might indeed be possible that, on average, positive relationship feelings have a positive effect on the perceived intimacy of a person. The better a person feels in his/her relationship, the more he/she will be open to perceive intimacy (i.e., a between-subject effect). However, if the husband/wife feels less positivity toward the relationship on a particular time point, compared to his/her general feelings, the husband/wife might perceive more intimacy as the person might look for affection from his/her spouse (i.e., a within-subject effect). If the researcher ignores this difference, the estimated actor and partner effects would portray a mixture of both effects, leading to deceptive conclusions (Enders & Tofighi, 2007). Moreover, there may be unmeasured common causes of the outcome and the predictor as well. For instance in our illustration, some unmeasured personality traits may affect both the positive relationship feelings and perception of intimacy. If one would opt to make the distinction between a time-averaged and time-specific effect, it has been shown that the latter can be unbiasedly estimated, even in the present of such unmeasured upper level confounders (Talloen, Loeys, & Moerkerke, 2019). Therefore, we strongly recommend splitting up the effect of time-varying predictors into a time-averaged and time-specific component. The former is obtained by calculating the cluster-mean, that is, by calculating the mean value over all time points for each female and male, respectively (i.e., $X_{F.j}$ and $X_{M.j}$). The time-specific component is computed by cluster-mean centering the original predictor variables for each dyad *j* at each time point *i* (i.e., $X_{Fij} - X_{F.j}$ and $X_{Mij} - X_{M.j}$). The extended LD-APIM is written as follows:

$$\begin{cases} Y_{Fij} = (\mu_F + \eta_{Fj}) + \rho_F Y_{F,i-1,j} + a_{F(XA)}\, XA_{Fj} + p_{MF(XA)}\, XA_{Mj} \\ \qquad\qquad + a_{F(XS)}\, XS_{Fij} + p_{MF(XS)}\, XS_{Mij} + \varepsilon_{Fij} \\ Y_{Mij} = (\mu_M + \eta_{Mj}) + \rho_M Y_{M,i-1,j} + a_{M(XA)}\, XA_{Mj} + p_{FM(XA)}\, XA_{Fj} \\ \qquad\qquad + a_{M(XS)}\, XS_{Mij} + p_{FM(XS)}\, XS_{Fij} + \varepsilon_{Mij} \end{cases}, \tag{2}$$

where XA and XS correspond to the time-averaged and time-specific effect of positive relationship feelings, respectively.

As already mentioned, one needs to incorporate two types of interdependency when dealing with longitudinal dyadic data: the interdependency between the dyad members and the interdependency between the different time points within the dyad members. From Equation 2, one can see how the LD-APIM uses a multilevel autoregressive approach for the latter. Conditional on the positive relationship feelings (the variable X), the perceived intimacy of a dyad member at a specific time point (the variable Y_{ij}) is decomposed in a carryover effect (the parameter ρ) of its score at the previous time point (i.e., a state-dependency) and an individual-specific trait ($\mu + \eta_j$). This carryover effect is represented by the autoregressive parameter ρ ($-1 < \rho < 1$) in Equation 2. If the parameter is close to zero, it implies that there is little carryover effect of intimacy from one time point to the other, while an autoregressive parameter close to one, implies opposite. Therefore, the autoregressive parameter is sometimes referred to as a measure of *inertia*. In the model, the individual-specific trait is represented by the intercept μ with white noise η_j, for both males and females. As explained by Gistelinck, Loeys, and Flamant (2020), one should be careful when interpreting this trait. By including the lagged dependent variable in the model, all other regression parameters (including the intercept) should be interpreted as conditional on the outcome score of the previous time point. As a consequence, the parameters $\frac{1}{1-\rho_F}\mu_F$ and $\frac{1}{1-\rho_M}\mu_M$ (and not the intercepts themselves) correspond to the underlying mean perceived intimacy for females and males (conditional on positive relationship feelings), respectively. Note that the model considers the autoregressive parameter, as well as the actor and partner effects, to be fixed rather than random. This may avoid convergence issues that are often inherent to models with many random effects on the one hand, but on the other hand, this may lead to biased standard errors (Jongerling, Laurenceau, & Hamaker, 2015).

In order to account for the correlation between the traits of the dyad members, the upper-level error terms η_{Fj} and η_{Mj} should be allowed to be correlated:

$$\begin{pmatrix}\eta_{Fj}\\ \eta_{Mj}\end{pmatrix} \sim \mathrm{N}\left(\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}\tau_F^2 & \tau_{FM}\\ \tau_{FM} & \tau_M^2\end{pmatrix}\right). \tag{3}$$

It is shown (Gistelinck et al., 2020) that the parameters $\left(\frac{1}{1-\rho_F}\right)^2\tau_F^2$ and $\left(\frac{1}{1-\rho_M}\right)^2\tau_M^2$ correspond to the variability in the trait in females and males, respectively (rather than the random intercept variances themselves). Similarly, one can show that the parameter $\frac{1}{(1-\rho_F)(1-\rho_M)}\tau_{FM}$ equals the covariation between the traits of females and their male partners.

The residuals ε_{Fij} and ε_{Mij} in Equation 2 account for the part that is not predicted by the previous perceived intimacy, nor by the positive relationship feeling of both the individual and his/her partner. In order to acknowledge the correlation between both dyad members at any particular time point, the residuals are allowed to be correlated at each time point i ($i = 1, \ldots, T$):

$$\begin{pmatrix}\varepsilon_{Fij}\\ \varepsilon_{Mij}\end{pmatrix} \sim \mathrm{N}\left(\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}\sigma_F^2 & \sigma_{FM}\\ \sigma_{FM} & \sigma_M^2\end{pmatrix}\right), \tag{4}$$

with σ_F^2 and σ_M^2 the residual variances for females and males, respectively. The parameter σ_{FM} captures the residual covariation and represents the strength of (dis)similarity between the members of a dyad on a time-specific occasion (conditional on the overall interdependency between both dyad members).

The LD-APIM presented above makes several assumptions. First, the model does not assume a specific trend over time for the outcome variable. To be more specific, the model actually assumes *stationarity*. This implies that all model parameters are assumed to be time-invariant: the individual's global perceived intimacy, the actor/partner effects, but also the residual (co)variances, and so forth. However, provided that the user has some knowledge of R-code, this assumption can easily be relaxed using the LD-APIM implementation. As we will show below, the app provides the code from the default model for the users, which allows them to add time-specific indices to the model parameters. In order to provide the user with a simple model to start with, these time-specific indices were not included in the defaults of the *LDDinSEM*-application. Second, the model assumes a first-order autoregressive structure, implying that the perceived intimacy (conditional on the positive relationship feelings and the underlying trait) only depends on its value at the previous time point. However, higher order lagged perceived intimacy scores can be added (Wilkins, 2018). Again, this is easily included in the code generated by the LD-APIM implementation. Including these higher order lagged dependent variables not only complicates the interpretation of the model parameters, it also introduces extra statistical and technical complications. Furthermore, as mentioned before, we did not allow for random slopes, neither for the actor or partner effects, nor for the autocorrelation effect.

Specifying the simple model depicted by Equation 2 with assumptions defined by Equations 3 and 4, is already a tedious task. In order to support researchers in their quest for answers, we constructed a Shiny-application within RStudio (Rstudio, 2017), called the *LDDinSEM*-application. It is a user-friendly and free web application with a point-and-click interface (Chang, Cheng, Allaire, Xie, & McPherson, 2017). The user does not need any software license nor any specialist knowledge on statistical software. Thanks to the application, researchers can upload their data set and specify the LD-APIM appropriate to their research questions. The app then automatically fits the model on the data set using *lavaan* (Rosseel, 2012) behind the scenes. Afterwards, the app provides the user with summary tables for the model parameters, model-based figures of the effects, as well as the original *lavaan* syntax, and the option to download the (transformed) data set. All findings, including tables and figures, are also wrapped into one big summary file, which the user can download.

IMPLEMENTING THE LD-APIM

The following section discusses some technical statistical details with respect to the implementation of the LD-APIM. Readers who are mostly interested in applying the LD-APIM, may move on to the next section which demonstrates how to use the *LDDinSEM*-application.

It is not that straightforward to implement the LD-APIM in standard multilevel software. Even when dealing with individual data rather than dyadic data, Gistelinck et al. (2020) recently showed that fitting a multilevel autoregressive model can be quite challenging, especially when the amount of time points is rather small. Two intertwined statistical issues that arise for this model are the initial conditions problem and the endogeneity problem. As Equation 2 suggests, one needs to define a start-up process for the autoregressive process (Skrondal & Rabe-Hesketh, 2014). If one conditions on the previous outcome score, how can one condition on an unavailable presample response at the first measurement? This is called the initial conditions problem. Within traditional multilevel software, assuming the first outcome variable as exogenous (i.e., predetermined) is common practice (Bollen & Curran, 2004). However, doing so violates the exogeneity assumption within standard regression analysis: residuals are no longer independent from the predictors in the model. Indeed, the underlying trait (reflected by the random intercept) is supposed to affect the outcome variable at each time point, including the first one. Hence, assuming the first outcome variable to be predetermined will not allow for such dependency, while the first outcome variable and the residual will show an intrinsic correlation. This issue is called the endogeneity problem. In case of intensive longitudinal data, both issues are of minor concern (Gistelinck et al., 2020). However, when the amount of time points is relatively small (smaller than 20), erroneous inference is obtained (Achen, 2001). As shown by Gistelinck et al. (2020) in the setting of individual data, the traditional structural equation modeling (SEM) framework easily allows to introduce a correlation between the outcome at the first timepoint and the random intercept. By doing so, we avoid the bias that is introduced when ignoring the endogeneity, while assuming the first outcome variable as predetermined (Allison, Williams, & Moral-Benito, 2017). Other tools for fitting multilevel autoregressive models like dynamic structural equation models (DSEM) in Mplus or mlVAR in R do not appropriately deal with the above issues, and suffer from biased parameter estimators especially when the number of timepoints is small.

Since in many dyadic settings, intensive longitudinal data are not available, we opted to implement our LD-APIM of the *LDDinSEM*-application in the SEM-framework. With longitudinal dyadic data, the amount of dyads typically varies between 60 to 150 dyads (Loeys & Molenberghs, 2013), while the amount of repeated measures often lies between 3 to 20. To deal with the endogeneity and initial conditions issue, we allow the random intercept of the males and females in Equation 2 to correlate with their outcome at the first timepoint respectively, and allow the latter to have their own mean and variance.

Standard SEM software packages assume the data to be structured in the wide format. In case of longitudinal dyadic data, this would imply that the one line of data is considered to contain all information for one dyad, making the line consist of all variables at each time point for both dyad members (i.e., making the data set wide). This is in contrast to a long data format used in standard multilevel software packages, which uses one line of data to contain the information of one dyad member on a particular time point (resulting in a long data set). Another technical detail that hence needs to be addressed within the LD-APIM implementation is the fact that the time-specific components of the predictor sum up to zero. As a result, the design matrix of the model within the SEM framework with data in wide format will no longer be invertible. In order to avoid this issue in the design matrix, one has to replace the effect of the time-specific component at the last time point by the sum of (opposite) effects of the remaining time points. Fortunately, this is easily done within the SEM framework. The use of a wide data format also implies that the LD-APIM will need more time to converge when fitting intensive longitudinal dyadic data.

There are other advantages to implementing the LD-APIM within the SEM software, such as the treatment of missing data. Within multilevel software packages, listwise deletion is often the default to deal with missingness. It removes the entire line of information of a specific time point of a dyad member as soon as one variable is missing. In the SEM software tool *lavaan*, the default is full-information maximum likelihood estimation. In other words, it uses all available information in the dataset to estimate the model parameters. Moreover, the *lavaan* package that we use in the *LDDinSEM*-application is easily combined with other R-packages, such as *semtools*, which allows to perform multiple imputation (Jorgensen, Pornprasertmanit, Schoemann, & Rosseel, 2019).

FITTING THE LD-APIM USING A SHINY-APPLICATION

In our motivating example we are interested in the effect of positive relationship feelings on perceived intimacy. To address this question, we need to acknowledge that these behavior and emotions were repeateadly measured in a close interpersonal context (Dewitte et al., 2015). Although we expect no trend over time, we do want to make a difference between the general behavior (i.e., the trait) of a dyad member and the time-specific behavior (i.e., the state) compared to his/her general behavior. Using the LD-APIM given by Equation 2, we would like to answer the following questions:

(Q1) Do people who have generally more positive relationship feelings, also report a higher perception of intimacy (i.e., $a_{F(XA)}$ and $a_{M(XA)}$)?

(Q2) Do people who have partners with generally more positive relationship feelings, also report a higher perception of intimacy (i.e., $p_{MF(XA)}$ and $p_{FM(XA)}$)?

(Q3) Given yesterday's perception of intimacy, how does an increase or decrease in one's own positive relationship feelings (as compared to his/her average feelings) affect today's perception of intimacy (i.e., $a_{F(XS)}$ and $a_{M(XS)}$)?

(Q4) Given yesterday's perception of intimacy, how does an increase or decrease in one's partner positive relationship feelings (as compared to their average feelings) affect one's own perception of intimacy ($p_{MF(XS)}$ and $p_{FM(XS)}$)?

(Q5) To what extent does yesterday's perception of intimacy affect today's perception of intimacy (i.e., ρ_F and ρ_M) given one's own and one's partner positive relationship feelings?

(Q6) Do women (or men) that generally have a high average perception of intimacy, typically have a male (or female) partner with high average perception of intimacy (i.e., $\frac{1}{(1-\rho_F)(1-\rho_M)}\tau_{FM}$)?

(Q7) If a woman (or man) has a high perception of intimacy on a particular day, will her male partner have a high perception of intimacy that day as well (i.e., σ_{FM}), conditional on positive relationship feelings and perception of intimacy the previous day?

Note that questions (Q1) and (Q2) make comparisons *between* subjects (i.e., between-subject effects), while questions (Q3) till (Q5) address questions *within* subjects (i.e., within-subject effects). As always in regression models, we need to interpret effects conditional on other predictors in the model. In a multilevel model, we can do so at both levels (i.e., the between and within level) separately.

General Lay-Out of the Application

We will fit the LD-APIM using the *LDDinSEM*-application, which can be found on https://fgisteli.shinyapps.io/Shiny_LDD2/. In the application, one can distinguish four tabs at the top (see Figure 2):

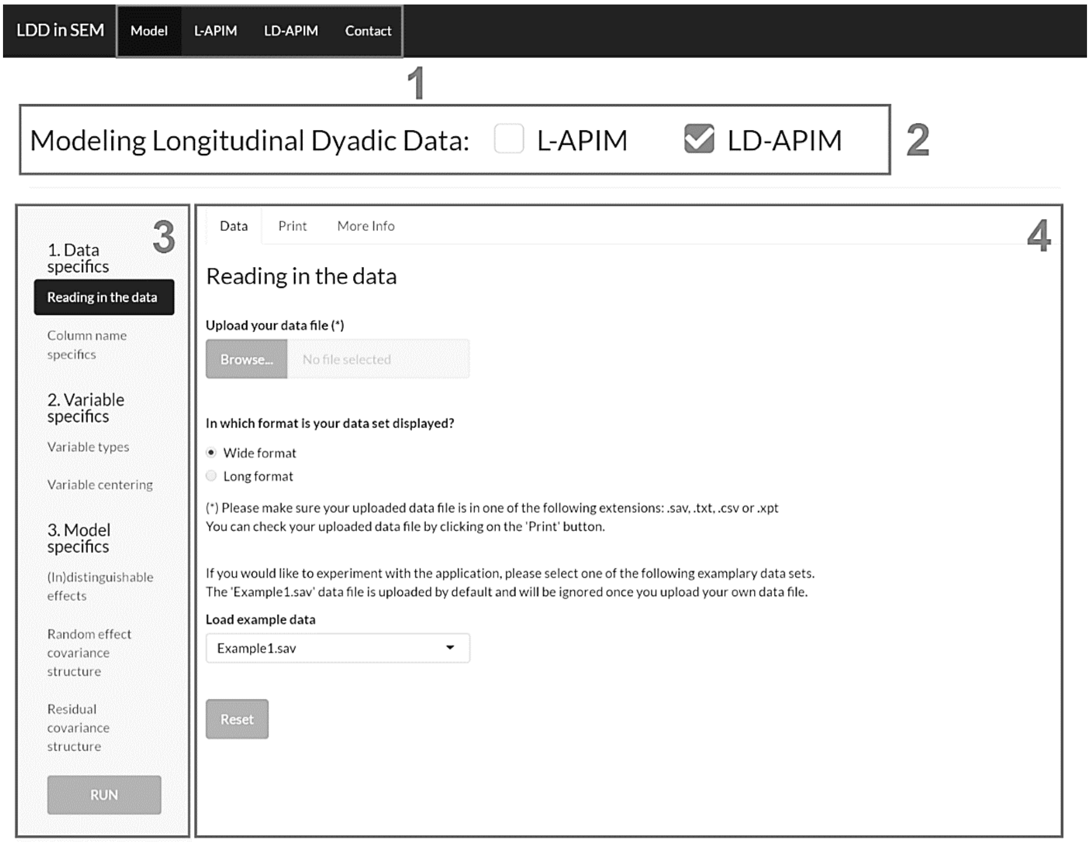


FIGURE 2
The opening page of the *LDDinSEM*-application and its four main areas.

Note. (1) refers to the four main pages of which the app exists (page to fit the model, an information page about the L-APIM, an information page about the LD-APIM and a contact page of the developer; (2) allows the researcher to switch between the L-APIM and LD-APIM; (3) corresponds to the three main steps to fit an L(D)-APIM on LDD; (4) displays the current selected step of the application in the third area. The latter area always consists of at least two tabs: the step itself and a tab with more information about the step in consideration.

(a) "Model," where the user can specify the model for his/her LDD, (b) "L-APIM," an information page about the longitudinal APIM without lagged dependent variables, (c) "LD-APIM," an information page about the lagged dependent APIM, and (d) "Contact," a page with contact information of the developer of the application. While the L-APIM is discussed in Gistelinck and Loeys (2019), we focus here on the implementation of the LD-APIM and how one specifies the latter model in the “Model” tab.

As we want to fit the LD-APIM here, one should tick the button of the LD-APIM in the second row in Figure 2. From the menu on the left, it is clear that the application only needs three steps to implement and fit the LD-APIM: (1) the user uploads the data and adds some information about the data set such that the application gets how the data is structured and what the variable names are: (2) the user specifies the type for all predictor variables in the data and how they should be utilized for the remainder of the analysis; (3) the user specifies the LD-APIM in terms of the mean structure, the random effects covariance structure, and the residual covariance structure. Once these three steps are completed, one can click on the “RUN” button and the app will fit the requested LD-APIM. We will now give more information about these three steps below.

Step 1: Data Specifics

As mentioned above, the first step to fit the LD-APIM is to upload your data set. Researchers can upload their own data set by clicking on the “Browse” button (see Label 1 in Figure 3). In case the user uploaded a wrong data set, it can be removed by clicking on the “Reset” button below (Label 2). The application also provides several example data sets (Label 3) for the user to experiment or reproduce the finding of the tutorials from the “LD-APIM” tab. To reproduce the analysis on positive feelings on perceived intimacy that we will present below, one has to select the “Tutorial1.sav” data file. Although the underlying program *lavaan* assumes the data set to be structured into the wide format (i.e., one line of information for each dyad at all time points), the application allows a long format as input as well (i.e., one line of information for each dyad member at a particular time point). One just needs to indicate the correct structure of the data set (Label 4). One can find more information about the different data formats in the “More Info” tab (Label 5). To check whether the data file is correctly uploaded, take a look at the “Print” tab (Label 6). Our example data are structured in a wide format. The dependent variable perceived intimacy from day one till day 21 can be found in the columns “IntimF1” to “IntimF21” for females and in the columns “IntimM1” to “IntimM21” for males.

The application assumes the variable names to have a specific format: the dyad member and/or time indices are located at the end of the column name with or without specific separation symbols. In our case, the time range goes from 1 to 21 because the couples were interviewed daily for three consecutive weeks (Label 1 at Figure 4). Note that the application allows to restrict the analysis to a particular time range. For example, if the study included a test period which should not be included in the analysis, these time points can be excluded from the time range. However, the application assumes time points to be consecutive and equally spaced, and the data should at least contain 3 time points for the model to be identified. The dyad member indices represent the label that corresponds to the different roles of the dyad members (Label 2). These indices are part of the original variable names and should be reported in the two boxes (random order allowed). In our example, “M” and “F” have to be filled out, referring to males and females, respectively. If one is working with indistinguishable dyads, the labels are necessary for computational matters, but an adapted model can be specified in the third step of the application (see below). At Label 3 in Figure 4, the user has to specify the separation symbols between the variable name and both types of indices. For instance, if column names were constructed as “Intim_5.M,” an underscore “_” and a dot “.” should be filled out in that order. However, in our case no separation symbols are included in column names, so these boxes are left empty.

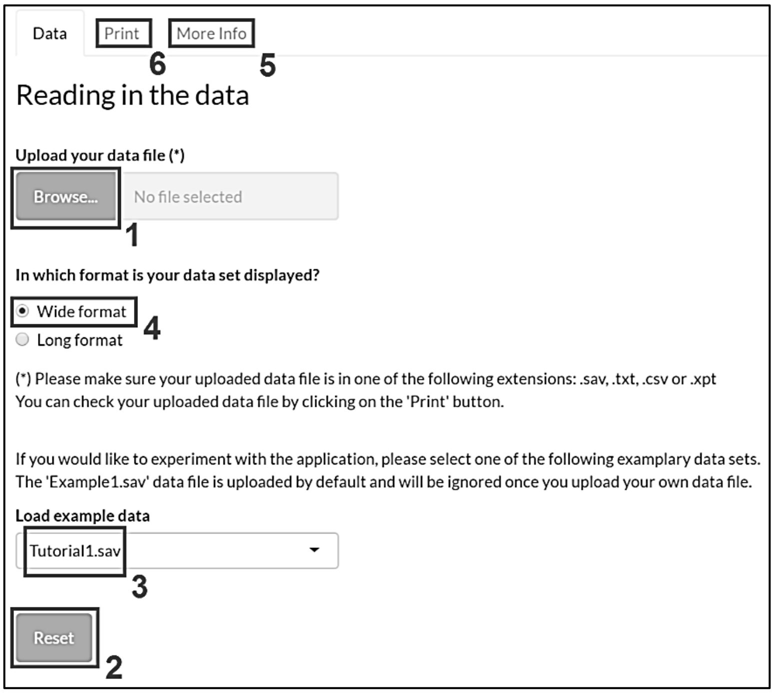


FIGURE 3
The "Reading in the data" page of the *LDDinSEM*-application.

Note. 1 = the "Browse" button to upload the data set; 2 = the "Reset" button to reset the uploaded data; 3 = the example data sets; 4 = the data format of the uploaded/selected data set; 5 = the "More Info" tab with extra information about the different data formats; and 6 = the "Print" tab to check whether the data was correctly uploaded.

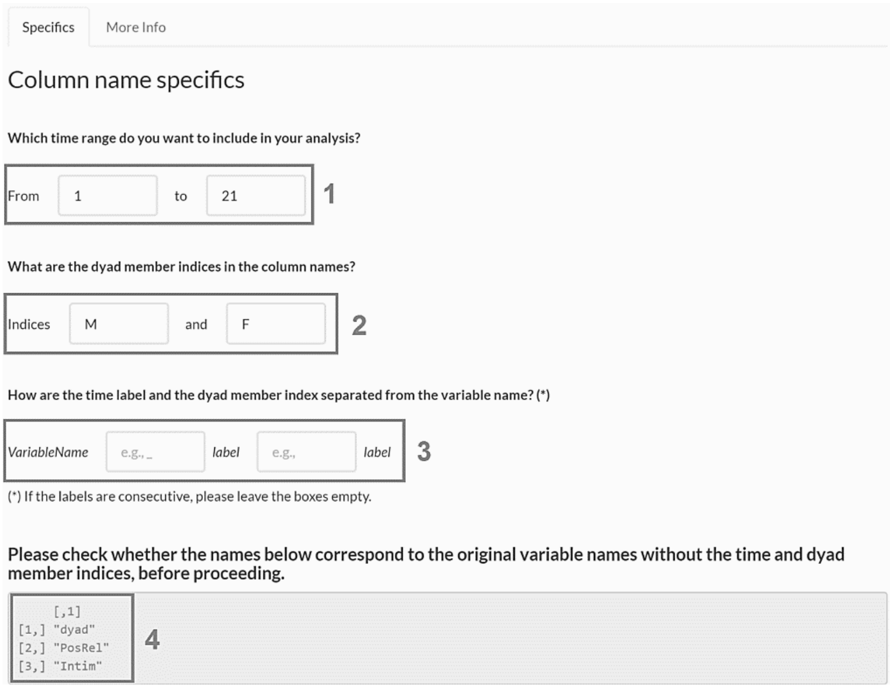


FIGURE 4
The "Column name specifics" page of the *LDDinSEM*-application.

Note. 1 = the time range to include in the analysis; 2 = the labels of the dyad member roles; 3 = the separation symbols in the column names between the variable name and time/dyad member indexes; and 4 = the reconstructed variable names by the application.

Step 2: Variable Specifics

Once the application read in the data correctly, one has to specify which variables to include in the LD-APIM and what type these variables are. When considering LDD data, one can distinguish four different types of dyadic predictors, depending on whether the variable is measured on the dyad- or member-level and whether the variable is time-invariant or time-varying. More specifically, time-constant-dyad variables correspond to time-invariant variables measured on the dyad-level. The values of these variables are the same for both dyad members and are constant over time (e.g., the season in which a short-period study was performed). Overtime-dyad variables correspond to time-varying variables measured on the dyad-level. The values of these variables are the same for both dyad members and change over time (e.g., the amount of hours the couple spent together at each day). Time-constant-member variables differ between both dyad members, but are constant over time (e.g., the age of each dyad member). Overtime-member variables corresponds to time-varying variables measured at the member-level. The values of these variables differ between both dyad members and change over time (e.g., the amount of experienced happiness at each day). It is clear that the predictor *PosRel*, which correspond to the positive relational feelings, represent an overtime-predictor on member level. Obviously, *Intim* coincides with the dependent variable, and should be added at the corresponding place at the “Variable Types” tab.

An important consideration about the time-varying predictor variable needs to be made here. Which specific effect is one interested in when the predictor and outcome are measured at the same timepoints? Is one interested in (a) the temporal association between the predictor and outcome (i.e., the predictor at the previous timepoint affects the outcome at the current timepoint), or (b) the contemporaneous association between predictor and outcome (i.e., the predictor at the current timepoint affects the outcome at the current timepoint), or (c) both associations. Equation 2 seems to suggest option (b) as the time indices for the predictor and outcome are the same. Obviously, this is a matter of labeling: by re-arranging the labels, one can opt for option (a) as well, or combine both (but then two different operationalizations of the same variable would be required). In our example, there is less discussion since predictor and outcome are assessed in the evening and the morning the day after. In addition to the time-specific effects, it is also possible to add between-subject effects.

Before one can tell the application how to include these effects into the model, the application allows for some preprocessing. In the second column of both tables at the “Variable centering” page depicted in Figure 5, the user is allowed to abbreviate the variable names and dyad member indexes (Label 1). As these new labels will be used in the remainder of the application, this option avoids references that are too long. In the third column (Label 2), the user can grand-mean center the variables (except for the outcome variable as the LD-APIM assumes an intercept in the model). In this empirical example, we choose to grand-mean center *PosRel*. In the latter column (Label 3), one can opt to split-up the overtime predictors. As it is possible for the time-specific effect of positive relational feelings to differ from its time-averaged effect, it is advised to differentiate both components. The application will refer to these components as *PosRelS* and *PosRelA* for the time-specific and the time-averaged component, respectively.

Step 3: Model Specifics

In this final step, the LD-APIM must be specified. First, the application asks to describe the mean structure at the “(In)distinguishable Effects” page. With heterosexual couples, we will allow the intercept

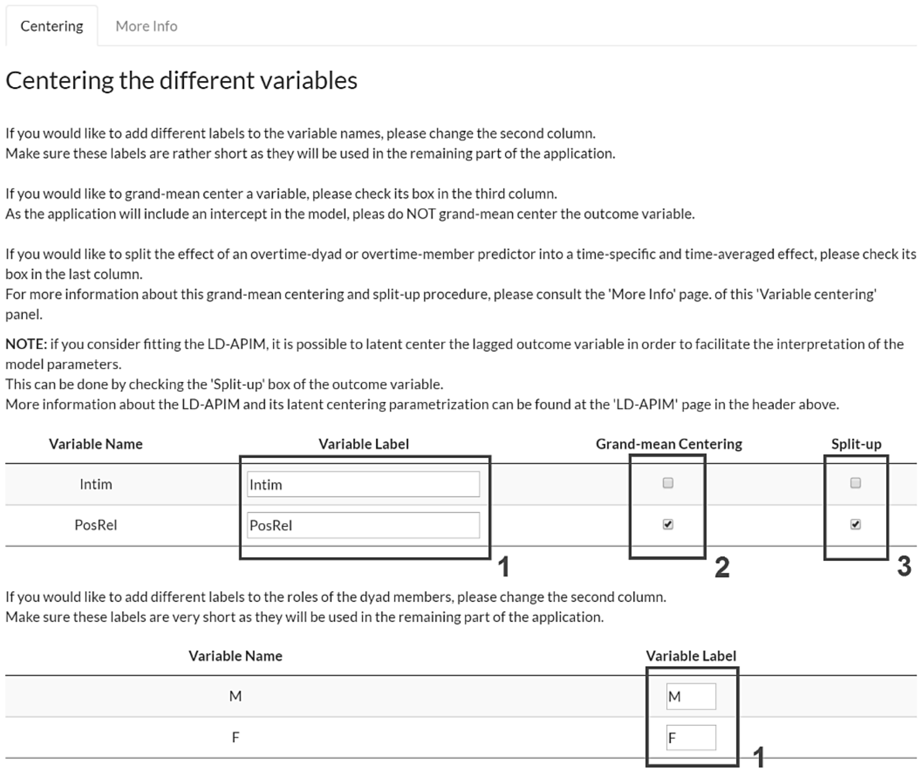


FIGURE 5
The “Variable centering” page of the *LDDinSEM*-application.
Note. This page allows the user to (1) relabel the variables and dyad member indexes; (2) grand-mean center the predictor variables; and (3) split-up the overtime-predictors into a time-averaged and time-specific component.

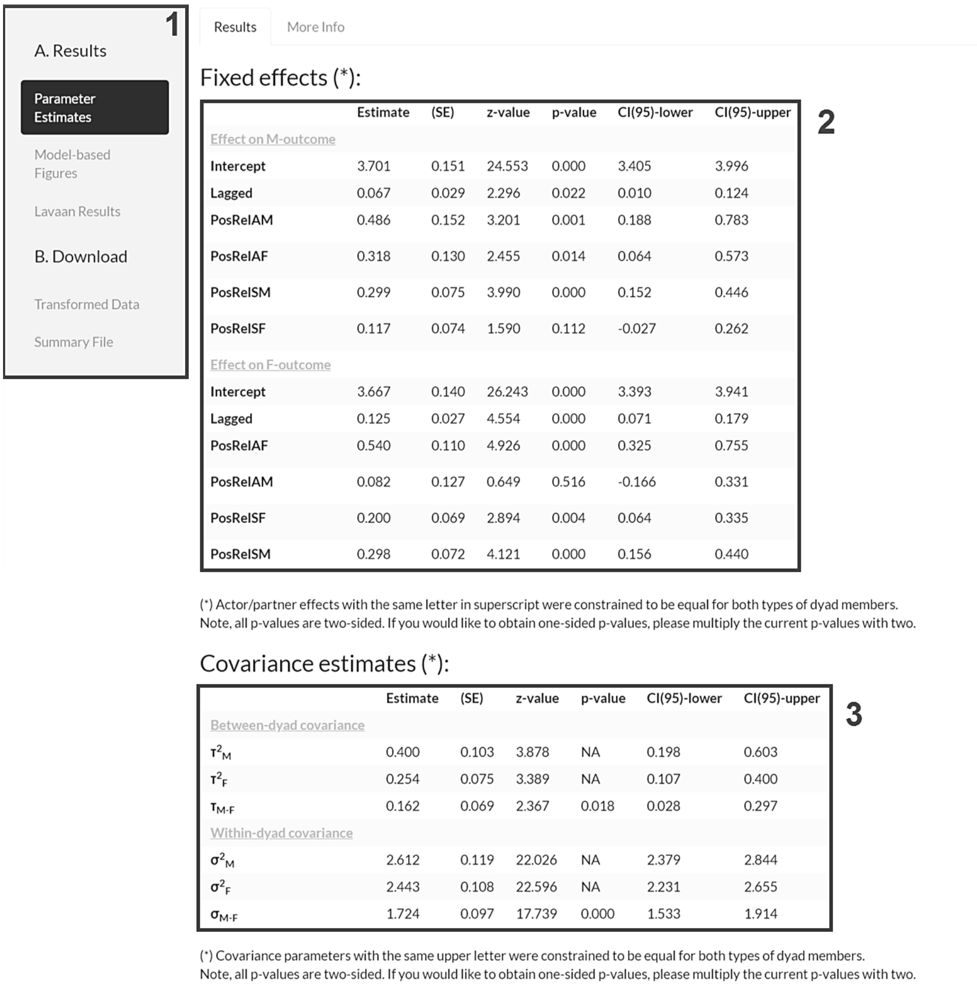
of the model to be different for males and females. With indistinguishable dyads, such as same-sex couples, one might opt these intercepts to be the same. Similar decisions have to be made about the actor and/or partner effects of the overtime/time-constant dyad/member predictors. In our empirical example, we will assume all actor and partner effects of both the time-averaged and time-specific component of *PosRel* to be different for males and females, so all these boxes should be checked. The LD-APIM also contains a lagged outcome variable, for which the effect may differ between men and women as well.

Second, the random effects covariance structure has to be defined at the “Random effect covariance structure” page. As we are working with distinguishable dyads, we allow the variation of these random effects to differ between men and women, and to be correlated. As a result, an unstructured covariance structure is most appropriate. As one can see, one could fix this correlation to zero by choosing for the heterogeneous variance component structure. If dyads are indistinguishable, a compound symmetry or a homogeneous variance component structure might be more appropriate. More information about these different covariance structure can be found in the “More Info” tab of this page.

Third, the user is asked to specify the residual covariance structure at a particular time point. Similar to the random effects covariance structure, four options are available depending on whether you want to allow for different variances for both dyad members, and whether you want to allow the residuals to correlate with each other. In our example, we will assume an unstructured covariance structure. This way, we account for the non-independence between the two dyad members at each time point, while we allow the residual variance to be different for men and women.

RESULTS AND DOWNLOAD

After these three steps, the application is able to fit the LD-APIM. Depending on the complexity of the model and the size of the data set, the running-step might take a few minutes. Once the application has fitted the model, the results will be displayed in two parts (see Label 1 in Figure 6). The first part depicts the results of the model estimation, while the second part contains different download options.



Fixed effects (*):

	Estimate	(SE)	z-value	p-value	CI(95)-lower	CI(95)-upper
Effect on M-outcome						
Intercept	3.701	0.151	24.553	0.000	3.405	3.996
Lagged	0.067	0.029	2.296	0.022	0.010	0.124
PosRelAM	0.486	0.152	3.201	0.001	0.188	0.783
PosRelAF	0.318	0.130	2.455	0.014	0.064	0.573
PosRelSM	0.299	0.075	3.990	0.000	0.152	0.446
PosRelSF	0.117	0.074	1.590	0.112	-0.027	0.262
Effect on F-outcome						
Intercept	3.667	0.140	26.243	0.000	3.393	3.941
Lagged	0.125	0.027	4.554	0.000	0.071	0.179
PosRelAF	0.540	0.110	4.926	0.000	0.325	0.755
PosRelAM	0.082	0.127	0.649	0.516	-0.166	0.331
PosRelSF	0.200	0.069	2.894	0.004	0.064	0.335
PosRelSM	0.298	0.072	4.121	0.000	0.156	0.440

(*) Actor/partner effects with the same letter in superscript were constrained to be equal for both types of dyad members.
Note, all p-values are two-sided. If you would like to obtain one-sided p-values, please multiply the current p-values with two.

Covariance estimates (*):

	Estimate	(SE)	z-value	p-value	CI(95)-lower	CI(95)-upper
Between-dyad covariance						
τ^2_M	0.400	0.103	3.878	NA	0.198	0.603
τ^2_F	0.254	0.075	3.389	NA	0.107	0.400
$\tau_{M\text{-}F}$	0.162	0.069	2.367	0.018	0.028	0.297
Within-dyad covariance						
σ^2_M	2.612	0.119	22.026	NA	2.379	2.844
σ^2_F	2.443	0.108	22.596	NA	2.231	2.655
$\sigma_{M\text{-}F}$	1.724	0.097	17.739	0.000	1.533	1.914

(*) Covariance parameters with the same upper letter were constrained to be equal for both types of dyad members.
Note, all p-values are two-sided. If you would like to obtain one-sided p-values, please multiply the current p-values with two.

FIGURE 6
The opening page of the *LDDinSEM*-application after hitting the "RUN" button.
Note. 1 = extended menu with the results and download section; 2 = the fixed parameter estimates; and 3 = the covariance parameter estimates of the LD-APIM.

Parameter Estimates

As Figure 6 shows, the first page in the results section displays the parameter estimates of the LD-APIM for both dyad members. The first table corresponds to the mean structure parameters estimates: the upper part for the first type of dyad member (in our case the males), and the bottom part for the second type of dyad member (in our case the females). In case of indistinguishable dyads, this separation is still made using the arbitrary labels from the "Data Specifics" step, but some model parameter estimates might have been fixed to be equal for both dyad member roles. This will be indicated by an identical superscript at the end of the parameter. The table contains, next to the point estimate, the standard error (*SE*), the corresponding z-value, *p*-value and the 95%-confidence interval (i.e., CI(95)-lower and CI(95)-upper). Note that all *p*-values mentioned in this table are two-sided.

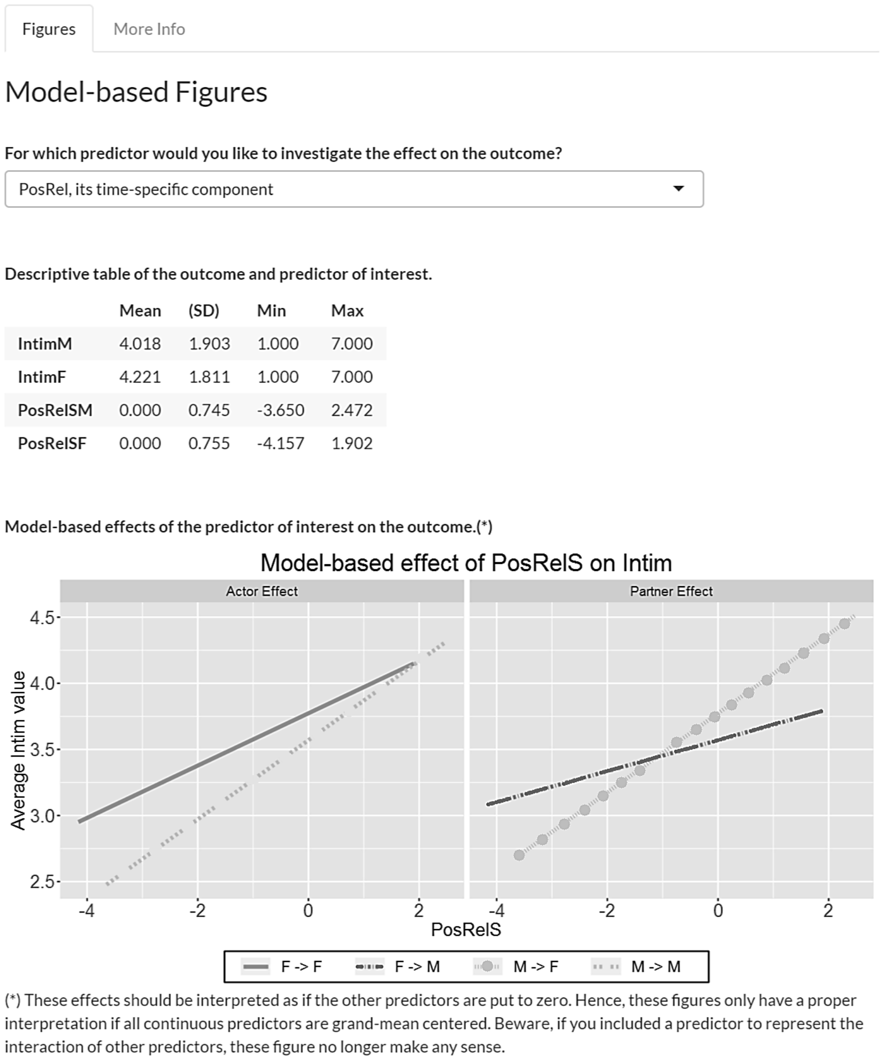
Based on the first table, we can address the first five research questions. The effect of *PosRelAM* on the male outcome and the effect of *PosRelAF* on the female outcome are both positive (0.49 and 0.54, respectively). Men and women who report more positive feelings on average thus report more perceived intimacy, given the average partner positive feelings 0. Similarly, the effect of *PosRelSM* on the male outcome and the effect of *PosRelSF* on the female outcome are positive (0.30 and 0.20, respectively). For both men and women, an increase in the positive relationship feelings on a specific day is associated with higher perceived intimacy on the next day, given the perceived intimacy the day before and the time-specific partner positive feelings 0. This also illustrates that the general positive relationship feelings have a larger effect on the perceived intimacy than the time-specific effect. Nevertheless, the latter still has a significant effect on perceived intimacy. The effect of *PosRelAF* on the male outcome is equal to 0.32, which means that men whose wives report more positive relationship feelings, report more intimacy too, given the average men's feelings 0. However, no such significant time-averaged partner effect was found for females. This shows that on general, females tend to be less affected by the general positive relationship feelings of their husbands. However, as the effect of *PosRelSM* on the female outcome is 0.30 and highly significant, wives are affected by their husband, but on a time-specific level. If a husband reports more positive relationship feeling, more than he would show on general, his wife will report more perceived intimacy (given her level of intimacy from the day before) (Q4). Contrary, such a significant time-specific effect has not been found for males (i.e., the effect of *PosRelSF* on the male outcome). As the parameter *Lagged* equals 0.067 and 0.125 for males and females respectively, it is clear that there is a significant carryover effect for perceived intimacy from one day to the other, although rather moderate in size (Q5). The difference in magnitude also suggest that wives tend to be more steadfast in their feelings over time than their husbands. As mentioned with the introduction of the model, due to the (non-centered) autoregressive effects in the LD-APIM, one should be careful when interpreting the intercept parameters.

Now, the average perceived intimacy across time for males and females correspond to $\frac{1}{1-\rho_M}\mu_M = \frac{3.70}{1-0.07} = 3.97$, and $\frac{1}{1-\rho_F}\mu_F = \frac{3.67}{1-0.13} = 4.19$, respectively.

The second table at the bottom of the page contains the covariance parameter estimates. The upper part of the table contains the random effects covariance parameters, while the lower part of the table contains the residual covariance parameters. Similar to the first table, the point estimate, the standard error (*SE*), z-value, *p*-value and 95%-confidence interval (i.e., CI(95)-lower and CI(95)-upper) are included in the table for each covariance parameter. Again, the reported *p*-values are two-sided. Based on this table, we can answer the last two research questions. The random intercept variances represent temporal stability and indicates that 95% of the average perceived intimacy (conditional on positive relational feelings) lies between $\frac{\mu_M - 1.96\,\tau_M}{1-\rho_M} = \frac{3.70 - 1.96\sqrt{0.40}}{1-0.07} = 2.64$ and $\frac{\mu_M + 1.96\,\tau_M}{1-\rho_M} = \frac{3.70 + 1.96\sqrt{0.40}}{1-0.07} = 5.30$ for males, and between 3.06 and 5.32 for females. The correlation of the average perceived intimacy between males and females of a dyad is $\frac{\tau_{MF}}{\tau_M * \tau_F} = \frac{0.16}{\sqrt{0.40 * 0.25}} = .51$ 0. The correlation of the daily fluctuations between males and females has a magnitude of $\frac{\sigma_{MF}}{\sigma_M * \sigma_F} = \frac{1.72}{\sqrt{2.61 * 2.44}} = .68$ 0. Hence, when one dyad member perceives a lot of intimacy on a specific day, so will the other dyad member, conditionally on all other predictors in the model.

Model-Based Figures and *lavaan* Results

On the "Model-based Figures" page (see Figure 7), the user can select for which predictor a model-based figure needs to be displayed. A small descriptive table is also presented for both the outcome and the selected predictor. At the bottom of the page, the effect itself is plotted in a figure. It is clear from this plot that both the actor and partner effects of the time-specific positive relational feeling have a positive effect on perceived intimacy for both the females and the males. However, the partner effects have a higher impact on females than on males.


Figures More Info

Model-based Figures

For which predictor would you like to investigate the effect on the outcome?

PosRel, its time-specific component

Descriptive table of the outcome and predictor of interest.

	Mean	(SD)	Min	Max
IntimM	4.018	1.903	1.000	7.000
IntimF	4.221	1.811	1.000	7.000
PosRelSM	0.000	0.745	-3.650	2.472
PosRelSF	0.000	0.755	-4.157	1.902

Model-based effects of the predictor of interest on the outcome.(*)

(*) These effects should be interpreted as if the other predictors are put to zero. Hence, these figures only have a proper interpretation if all continuous predictors are grand-mean centered. Beware, if you included a predictor to represent the interaction of other predictors, these figure no longer make any sense.

FIGURE 7
The "Model-based Figures" page of the *LDDinSEM*-application after hitting the "RUN" button.

For those researchers who are familiar with R and/or *lavaan*, we also provided a page with more technical results, see the "Lavaan Results" page. In the first tab, the model specification of the LD-APIM within *lavaan* is included. We encourage the user to copy/paste this syntax within RStudio and experiment with the model. For instance, if the user wants to allow the intercept to be time-varying, one can simply change the label of the intercept to be different for each time point. For the sake of completeness, we also provided the original *lavaan* output and table. The latter was used to compute the summary tables of the "Parameter estimates" page.

Transformed Data and Summary File

Before the user can truly experiment with the model, he/she also needs the data set used to fit the model. These can be found at the first page within the "Download" section. This transformed data set differs from the original uploaded data set with respect to: (a) reshaping in case the data set was not structured in the wide format; (b) relabeling as the user might have relabeled all variable names; (c) indexing as the column names have been adapted to correspond to the model syntax of the LD-APIM from the application; (d) centering as predictors could be grand-mean centered; and (e) split-up as we allowed the user to split-up overtime variables into a time-averaged and a time-specific component.

We also provided a summary file with all the results at the "Summary File" page. More specifically, the file, which can be downloaded as a pdf, a Word-doc, or a webpage, contains: (a) the changes to the original data set as mentioned above; (b) the LD-APIM expressed in equations and a general graphical representation of the LD-APIM (i.e., not adapted to the particular model expressed by the equations); (c) the tables with the parameter estimates; and (d) all model-based figures.

Discussion

This paper presented a free web-based Shiny-application that allows applied researchers to fit the LD-APIM. The latter is an extension of the cross-sectional APIM toward the longitudinal setting. The goal of the paper was to introduce dyadic researchers to an easy tool that allows them to explore their longitudinal dyadic data. As the latter type of data often frightens researchers by the statistical complexity it embodies, we hope that this application will help them. Moreover, we hope it introduced them to the wealth of dyadic research question that can be addressed.

Like any tool, there are features that can be improved, or additional elements that could make the tool even more user-friendly. One disadvantage of the current app entails the fact that one has to perform calculations in order to obtain a correct estimate of the grand underlying mean of the outcome variable. This can be avoided by centering the outcome variable. However, using the observed cluster-mean to center the outcome variable will introduce Nickell's bias in the autoregressive parameter (Nickell, 1981). As shown by Asparouhov, Hamaker, and Muthén (2018), latent centering can be used to avoid such bias. As the SEM framework allows for latent variables, it might be interesting to reconsider the implementation of the LD-APIM in the application using latent centering instead. It would also allow researchers to include latent outcome variables and latent predictors too. Moreover, it would enable us to resolve the measurement error introduced by the manifest centering approach in the LD-APIM. Indeed, by using the observed cluster-mean to center predictors into a time-averaged and time-specific effect, we actually introduced Lüdtke's bias into the time-averaged actor and partner effects (Lüdtke, et al., 2008). By using latent centering for the predictors, such bias is avoided (Asparouhov et al., 2018). In fact, both Nickell's and Lüdtke's bias has been resolved in the Bayesian DSEM implementation of Mplus (Muthén & Muthén, 2012). Unfortunately, DSEM is primarily developed in order to deal with intensive longitudinal data. The approach for the initial conditions problem within DSEM leads to bias when the amount time points is rather small (Gistelinck et al., 2020). Moreover, extending DSEM to deal with dyadic data might not be straightforward.

Next, it needs to be stressed that several modeling choices are already made for the user in the app. While that might be convenient for the user, the risk is that no careful consideration is given on their plausibility for the user's specific data. As already mentioned one needs to think about the temporal and contemporaneous associations that one is interested in, about how reasonable it is to assume fixed rather than random actor and partner effects, and so forth. Within the *LDDinSEM*-application, we assume the variables to be assessed for both dyad members simultaneously at equally time distances. It would be interesting to consider other implementations that do not assume such a discrete time model. For instance, it might be good to investigate a possible implementation of the LD-APIM within R-packages such as the *ctsem* (Driver, Oud, & Voelkle, 2017), which allow a continuous time design.

Lastly, we only considered the LD-APIM in the context of continuous outcome variables. It has already been shown how the cross-sectional APIM can be adapted for binary and count outcomes (Loeys, Cook, De Smet, Wietzker, & Buysse, 2014; Spain, Jackson, & Edmonds, 2012) within the multilevel modeling framework. As suggested by Josephy, Loeys, and Rosseel (2016), diagonally weighted leased squares can be used within the SEM framework in order to allow for categorical outcomes as well. However, further investigation is needed to confirm its performance in the context of longitudinal dyadic data. Despite the limitations and assumptions that we make in the defaults of the application, we hope that the *LDDinSEM*-application will inspire dyadic researchers to perform longitudinal dyadic data analysis.

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