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Disentangling between- and within-person variation in relationship science

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Abstract

Objective: This article provides an overview of the Cross-Lagged Panel Model (CLPM), Random-Intercept Cross-Lagged Panel Model (RI-CLPM), and Latent Curve Model with Structured Residuals (LCM-SR), highlighting the major issues of the CLPM for relationship science, and discusses dyadic extensions of those three models.

Background: Understanding interdependencies among people and constructs is a central interest in relationship science. Addressing such research questions requires complex designs ideally using data collected at multiple measurement occasions of multiple constructs from at least two persons (e.g., both partners of a couple). The Cross-Lagged Panel Model (CLPM) has been widely used to analyze such data, however, particularly during the last decade, it has been pointed out that the CLPM confounds between- and within-person variation. As a consequence, alternative models such as the Random-Intercept Cross-Lagged Panel Model (RI-CLPM) and the Latent Curve Model with Structured Residuals (LCM-SR) were proposed that aim to disentangle between- and within-person variation and, hence, allow conclusions regarding within-person dynamics.

Method: As an illustrative example, we apply dyadic extensions of the CLPM, RI-CLPM, and LCM-SR to investigate the dynamic interplay between depression and relationship satisfaction in a sample of 1699 mixed-gender couples surveyed in the German Family Panel.

Results: While the CLPM indicated a reciprocal relationship between depression and satisfaction, the RI-CLPM and LCM-SR indicated a unidirectional association flowing from depression to satisfaction.

Conclusion: We discuss how findings like this can foster theory-building and, ultimately, strengthen relationship science.

KEYWORDS

depression, development, interpersonal relationships, longitudinal research, research methodology

INTRODUCTION

Relationship science is inherently concerned with interdependencies. Such interdependencies may occur at a dyadic level between, for example, members of a couple, mother and child, grandfather and grandchild, or two siblings, but can also involve more than two persons as in the case of interdependencies among both parents and their child(ren), or between a group of friends. To further complicate issues, most, if not all, research questions are concerned with more than one variable. For example, in recent issues of the *Journal of Marriage and Family*, studies have investigated associations between fathers' work schedules and parenting (Zilanawala & McMunn, 2023), couple's personality traits and experiences of partner violence (Kanemasa et al., 2023), or couple's job loss and fertility (Di Nallo & Lipps, 2023). Finally, these bivariate (or even multivariate) associations are often investigated longitudinally, that is, over a longer period of time involving multiple measurement occasions.

The complex questions raised in relationship science involving multiple actors, multiple constructs, and multiple time points require tailored analysis methods. For a long time, the cross-lagged panel model (CLPM; Biesanz, 2012) has been used as the primary analysis tool for investigating interdependencies among persons and constructs across the fields of psychology. However, in the last decade, criticism against the CLPM has reignited and led to the development of alternative models that provide other opportunities. In the present article, we will discuss the limitations of the CLPM with a particular focus on their relevance for relationship science. Furthermore, we will explain two alternative models that have been developed during the last decade—the random-intercept (RI) CLPM (Hamaker et al., 2015) and the latent curve model with structured residuals (LCM-SR; Curran et al., 2014)—and discuss their potential for relationship science. Crucially, we will illustrate how those models can be extended to incorporate multi-actor data. We will draw on the interplay between relationship satisfaction and depression as an illustrative example throughout the paper. The association between these constructs has been examined in various studies using the CLPM (for reviews, see Goldfarb & Trudel, 2019; Whisman et al., 2021), with new studies still being conducted (e.g., Choi & Jung, 2021; Morgan et al., 2018). We will demonstrate how CLPM and its alternatives could be adopted to provide different insights into this association.

STATISTICAL MODELS FOR INVESTIGATING INTERDEPENDENCIES IN RELATIONSHIP SCIENCE

In the following sections, we briefly introduce three models developed to investigate reciprocal influences between two (or more) variables over time. It should be noted that these models were, at least partly, inspired by other models and modeling approaches such as fixed-effects regression analysis (Allison, 2009) or multilevel modeling (Snijders & Bosker, 2012). In this article, we will not compare the CLPM, RI-CLPM, and LCM-SR to those other models; such comparisons, however, can be found in other sources (e.g., Hamaker et al., 2015; Mund & Nestler, 2019; Orth et al., 2021). A conceptual comparison between the models discussed in this article can be found in Table 1. The content of Table 1 will be further discussed in the following sections as we introduce each model.

TABLE 1 Conceptual overview of and comparison between the cross-lagged panel model, random-intercept cross-lagged panel model, and latent curve model with structured residuals.

			Interpretation			
Model	**Typical research question**	**Analysis level**	**Autoregressive effect**	**Cross-lagged effect**	**Key features**	**Measurement occasions**
Cross-Lagged Panel Model	Are higher scores on depression (relative to others) are predictive of future relative changes in relationship satisfaction?	Unclear	Stability of inter-individual differences in X/Y	Effect of scores in X on residual change in Y	Stable between-person differences are not modeled; cross-lagged effects commingle between- and within-person processes	≥2
Random-Intercept Cross-Lagged Panel Model	Is higher depression than usual associated with subsequent lower-than-usual relationship satisfaction?	within and between	Stability of deviations from person-specific mean in X/Y	Effect of a deviation from person-specific mean in X/Y on subsequent deviation from person-specific mean in Y/X	Individuals vary around person-specific mean; cross-lagged effects reflect within-person processes; no between-person differences in mean-level changes over time	≥3
Latent Curve Model with Structured Residuals	Is higher depression than usual associated with subsequent lower-than-usual relationship satisfaction?	Within and between	Stability of deviation from person-specific developmental trajectory of X/Y	Effect of deviation from person-specific trajectory of X/Y on subsequent deviations from person-specific trajectory of Y/X	Individuals vary around a person-specific developmental trajectory; cross-lagged effects reflect within-person processes; between-person differences in mean-level trends are assumed	≥4

Cross-Lagged panel model

In many fields of psychology, including relationship science, the CLPM is a very common approach for investigating associations between multiple variables over time. Specifically, the CLPM is used to examine to what extent higher scores on one variable (relative to other persons) are associated with relative changes in another variable over time. In most cases, the primary interest of researchers employing the CLPM is on the autoregressive and the cross-lagged effects. The autoregressive effects provide information on the rank-order stability of the included variables, whereas the cross-lagged effects indicate to what extent prior scores of one variable x (e.g., depression) relate to subsequent scores of the other variable y (e.g., relationship satisfaction). As the autoregressive and cross-lagged effects are estimated simultaneously, the cross-lagged paths are often interpreted in terms of residualized change (Biesanz, 2012; Hertzog & Nesselroade, 2003). Specifically, when predicting variable y at time point t by variable x at a previous time point $t-1$, y_{t-1} is controlled for—hence, with its prior levels partialed out, y_t resembles a residualized score (Castro-Schilo & Grimm, 2018; Cohen et al., 2003). In Figure 1, we display a typical CLPM involving four measurement occasions; in general, however, the model can be estimated with a minimum of two measurement occasions.

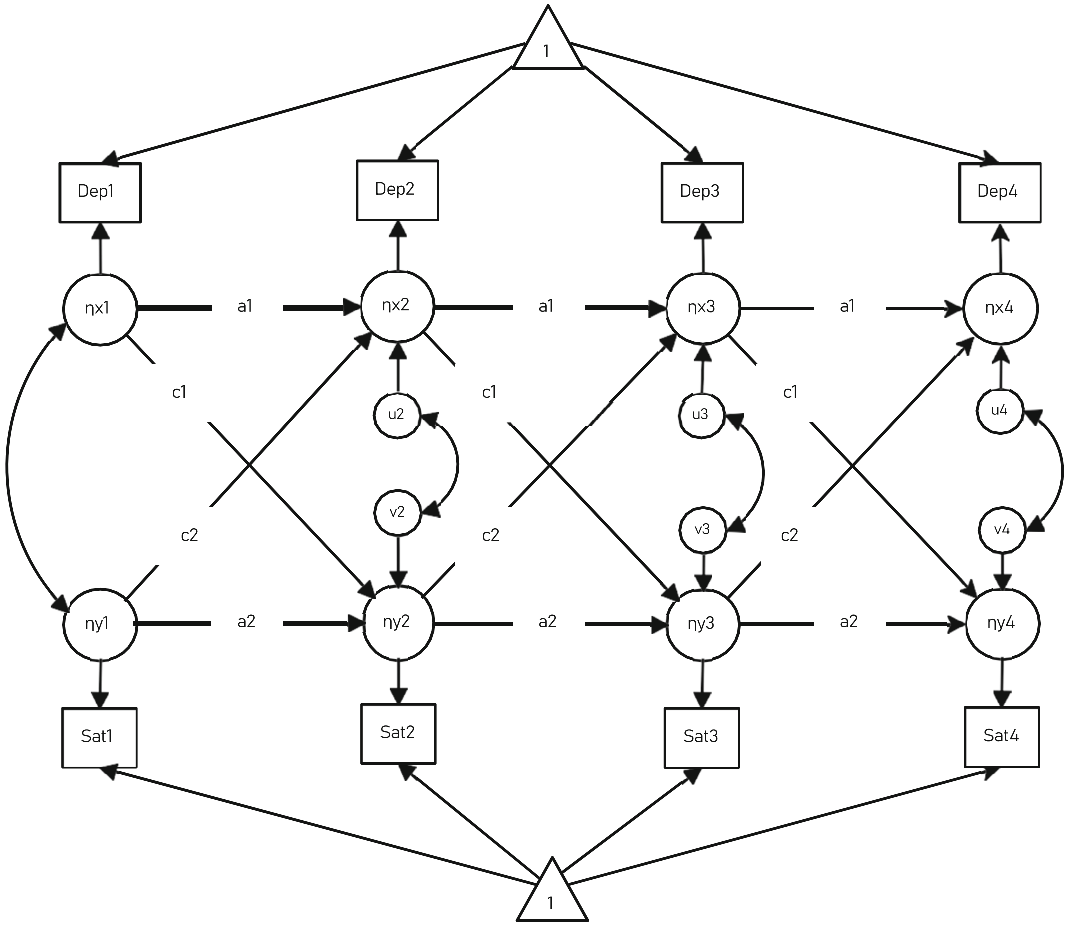

FIGURE 1 Cross-Lagged Panel Model. Cross-Lagged Panel Model for four measurement occasions. Dep: Depression; Sat: Satisfaction; ηx and ηy denote (pseudo-) latent variables for depression (x) and relationship satisfaction (y)

The CLPM can be a valuable analysis model for various research questions surrounding individual (and interpersonal) development over time (Lüdtke & Robitzsch, 2021, 2022; Orth et al., 2021; but see Hamaker, 2023; Lucas, 2023, for a contrasting view). However, the CLPM has been criticized for several reasons (Allison, 2009; Berry & Willoughby, 2017; Hamaker, 2023; Hamaker et al., 2015; Lucas, 2023). We will focus on two of them that are particularly relevant for relationship science. First and foremost, the CLPM has been criticized for commingling within- and between-person sources of variance which can make the results of the model difficult to interpret. To illustrate, in cross-sectional studies, there is only variation between persons (e.g., some people are more depressed than others). In longitudinal studies, however, there is variation within persons (e.g., a specific person is more depressed at time point t than at the previous time point $t-1$) in addition to the differences between persons that may be preserved over time (Anusic & Schimmack, 2016; Fraley & Roberts, 2005). The CLPM does not distinguish between these two sources of variation, as it assumes that all individuals fluctuate around a common group mean for each variable. Thus, when the CLPM is used to examine the associations between depression and relationship satisfaction, it does not explicitly take into account that there are temporally stable differences between individuals in both depression (Goldstein et al., 2022; Hopwood et al., 2013) and relationship satisfaction (Bühler & Orth, 2022). Instead, these between-person differences are contained in the estimates of the autoregressive and cross-lagged paths together with the within-person differences (Berry & Willoughby, 2017; Hamaker, 2023; Hamaker et al., 2015; Lucas, 2023).

Second, in the CLPM, one does not model a specific form of mean-level change over time (e.g., such as a linear trend) and also no between-person differences in these mean-level changes. However, not modeling such changes and the between-person differences in these trends when they are present may potentially distort the results of the statistical analyses (Curran et al., 2014; Usami, Murayama, & Hamaker, 2019; Wang & Maxwell, 2015). In our example, mean-level trends have been documented for both relationship satisfaction (Bühler et al., 2021) and depression (Sutin et al., 2013), raising concerns about relying on the CLPM to model their longitudinal dynamics.

Taken together, despite its utility and large impact on many research fields, including relationship science, results of the CLPM may be difficult to interpret or even lead to erroneous conclusions. In the last decade, however, some alternative models have been developed to address the limitations of the classical CLPM.

Random-Intercept CLPM

The RI-CLPM (Hamaker et al., 2015) was suggested to disentangle within- and between-person sources of variation as estimated in the CLPM. The model assumes that, for each variable, each individual has a unique and relatively stable mean score around which the individual fluctuates over time. For example, each person is supposed to have a specific trait-like level of depression and, likewise, a specific trait-like level of relationship satisfaction. In a longitudinal study, a mean score of depression or relationship satisfaction across multiple measurement occasions may be akin to such trait-like levels. At each measurement occasion, a person may deviate from their specific mean score (e.g., lower depression than usual), while still scoring higher than others in the sample. That is, there are stable between-person differences to the extent that individuals have consistently higher scores *than others* on certain variables, but these individual scores may deviate more or less from the person-specific mean at each measurement occasion. In the RI-CLPM, this idea of a person-specific mean score is implemented by including a latent intercept factor for each variable across all time points (see Figure 2)—note that for modeling those random intercept factors, at least three measurement occasions are required. In our example, the intercept factor of relationship satisfaction would reflect the assumption that some

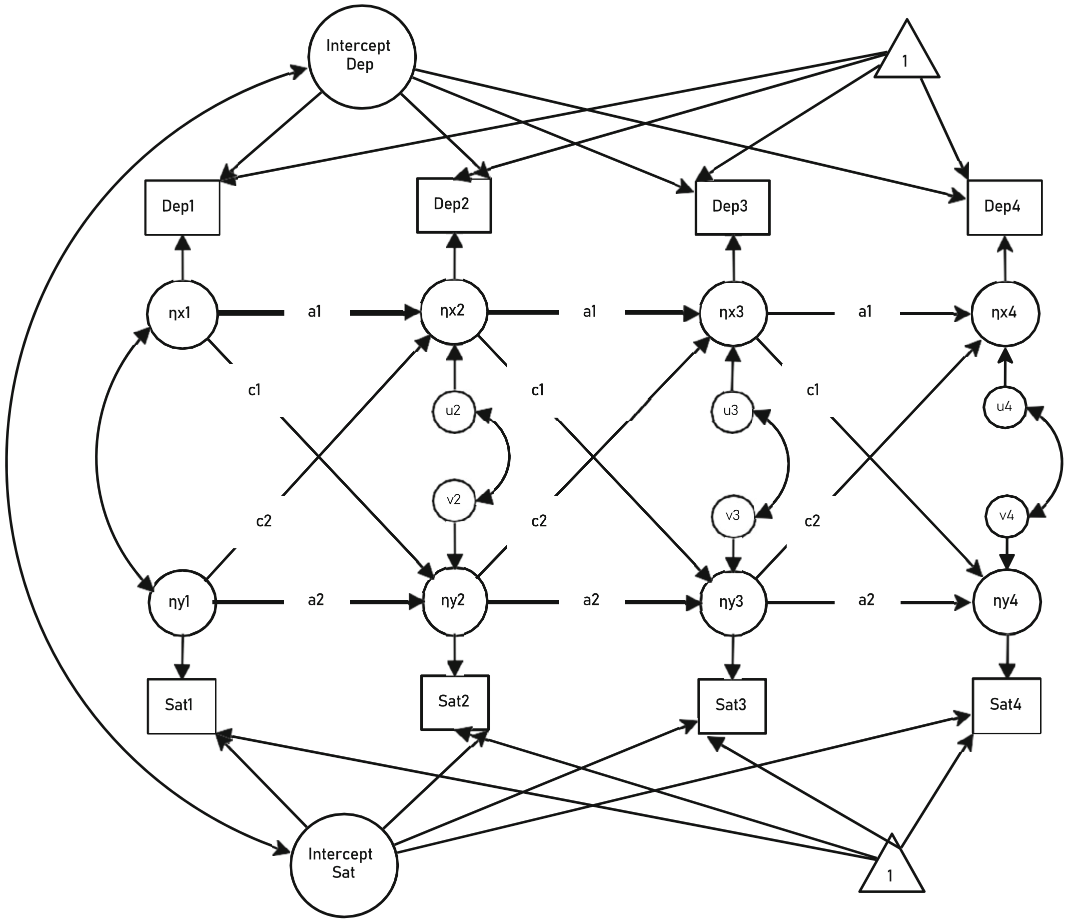

FIGURE 2 Random-Intercept Cross-Lagged Panel Model. Random-Intercept Cross-Lagged Panel Model for four measurement occasions. Dep: Depression; Sat: Satisfaction; ηx and ηy denote (pseudo-) latent variables for depression (x) and relationship satisfaction (y), respectively.

individuals tend to be generally more satisfied with their relationships *than other individuals* (i.e., between-person differences).

Through the inclusion of the random intercept factors, stable between-person differences are separated from the variables in the model. This approach is similar to person-mean centering in the context of multilevel modeling (Allison, 2009; Nestler & Humberg, 2024; Wang & Maxwell, 2015). As a consequence, the autoregressive and cross-lagged paths in the model purely pertain to within-person associations. Put differently, the autoregressive effects now provide information on the *within-person* stability of the variables, instead of containing information on the between-person rank-order stability of those variables as in the CLPM. Likewise, the cross-lagged paths in the RI-CLPM capture within-person associations controlled for the between-person associations. Regarding our example, these paths indicate to what extent a deviation above or below the person-specific mean in depression at a given point in time is associated with a subsequent deviation from the person-specific mean in relationship satisfaction, thereby controlling for previous deviations from the person-specific mean in relationship satisfaction (i.e., path $c1$ in Figure 2; Hamaker et al., 2015). The correlations between depression and relationship satisfaction within one time point reflect within-person associations as well and indicate the association between deviations from the person-specific mean in depression and deviations from the person-specific mean in relationship satisfaction at the same measurement occasion.

Several add-ons to the RI-CLPM have been introduced during the last years. For example, the model has been extended to incorporate latent variables, (dichotomous) moderators, and time-invariant variables as predictors or outcomes of within-person dynamics (Mulder & Hamaker, 2021). In addition, Speyer et al. (2023) have demonstrated how more complex moderation analyses involving interactions at the within-person level or across the within- and between-person levels can be implemented using the RI-CLPM. Recently, Mulder (2023) proposed a strategy for conducting power analyses specifically for the RI-CLPM, promoting its appropriate utilization.

Taken together, the RI-CLPM can be considered a flexible tool suitable for many research questions pertaining to within-person associations between two variables over time. Hence, it should be kept in mind that the RI-CLPM is not a replacement for the CLPM, as both address very different research questions (see Table 1; Hamaker, 2023; Hamaker et al., 2015; Orth et al., 2021) and tap into different causal processes (Lüdtke & Robitzsch, 2021). Thus, the choice of the model depends on the research questions to be investigated (Hamaker, 2023). For example, when researchers are interested in disentangling the two sources of variation because their research question or theoretical framework pertains to within-person dynamics, then the RI-CLPM may be favored over the CLPM. When the research focus does not require disentangling between- and within-person variation, then the CLPM might be chosen (Hounkpatin et al., 2018; Lucas, 2023; Lüdtke & Robitzsch, 2021, 2022; Orth et al., 2021).

Latent Curve Model with Structured Residuals

The LCM-SR (Berry & Willoughby, 2017; Curran et al., 2014) considers stable between-person differences in the included variables as well as developmental trends. This is done by not only incorporating random intercept factors as in the RI-CLPM, but also slope factors for each variable capturing mean-level changes over time (see Figure 3). Thus, in addition to the person-mean centering achieved through the inclusion of random intercepts, the data are additionally detrended (Berry & Willoughby, 2017; Wang & Maxwell, 2015). As a consequence, the LCM-SR can be considered as consisting of two parts: a between-person part that is basically reflecting a LCM and a within-person part pertaining to within-person dynamics in the form of autoregressive and cross-lagged effects. Running this model generally requires at least four measurement occasions.

The growth curve in the model captures between-person differences in initial levels (the latent intercept factors) and development (latent slope factors) of the variables. For this part of the model, it is important to find a growth curve that describes the time trends in the data adequately, as the adequacy of the parameter estimates depends on the correct specification of the growth curves (Voelkle, 2008). To this end, any linear or nonlinear form known from classical growth modeling may be implemented (Bollen & Curran, 2006; Grimm et al., 2017; Nestler et al., 2015; Ram & Grimm, 2007). It is also possible that different growth curves are required for the included variables (Berry & Willoughby, 2017).

The interpretation of the growth curve portion of the LCM-SR is the same as for classical growth models (Bollen & Curran, 2006; Grimm et al., 2017): The variance of the intercepts represents the amount of between-person differences in the variables at the onset of the observation period (e.g., some people are generally more depressed than others). The mean and the variance of the slope factors reflect developmental trends over time (e.g., depressive symptoms decrease on average) and between-person differences in these developmental trends (e.g., some individuals decrease more strongly in depression than others), respectively.

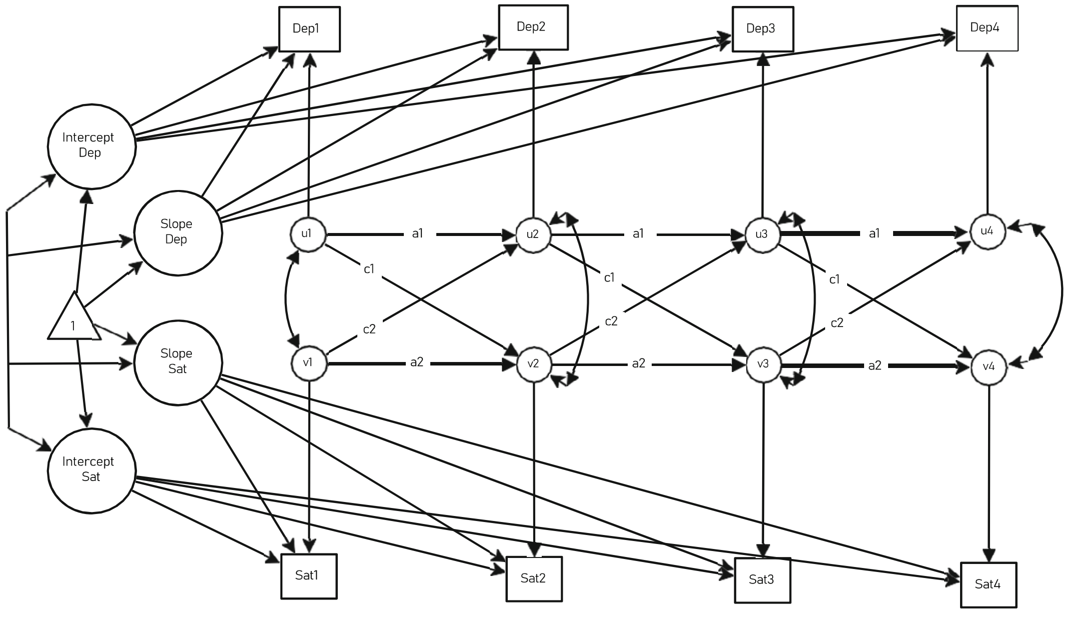

FIGURE 3 Latent Curve Model with Structured Residuals. Latent Curve Model with Structured Residuals for four measurement occasions. Dep: Depression; Sat: Satisfaction.

The within-person part of the LCM-SR, as in the RI-CLPM, consists of autoregressive and cross-lagged relationships between residuals. These residuals reflect time-point specific deviations from the person-specific mean *and* the person-specific growth trajectory. Regarding our example, a negative cross-lagged path between depression and satisfaction (i.e., path $c1$ in Figure 3) in the LCM-SR would indicate that a person scoring higher on depression than could be expected from their developmental trajectory tends to score lower on relationship satisfaction at the next measurement than could be expected from the person-specific trajectory.

The LCM-SR is a flexible statistical tool that can be tailored to very specific research questions. For example, it is possible to incorporate latent variables, predictors and outcomes of growth trajectories, moderator, and mediation variables (Curran et al., 2014). On the downside, however, the LCM-SR appears prone to nonconvergence in some applications (Orth et al., 2021; Scott, 2021) and requires thoughtful model building and step-by-step testing (see workflow proposed by Curran et al., 2014). We note again that the LCM-SR is not a direct replacement of the CLPM but instead has been developed to address specific research questions; so the selection of this model, similar to the RI-CLPM, should primarily be guided by theoretical considerations (Hamaker, 2023).

At the heart of all three models is the question of the dynamic interplay between two (or more) constructs over time (c-paths depicted in Figures 1–3). We have already discussed that the meaning of those effects is different across the three models (see also Table 1). Furthermore, several studies conducted during the last decade have shown that the significance of such reciprocal effects between variables can be largely influenced by the chosen modeling approach in a way that cross-lagged effects are more likely to occur in the CLPM compared to the RI-CLPM and/or the LCM-SR (Berry & Willoughby, 2017; Etherson et al., 2022; Kim et al., 2022; Masselink et al., 2018; Mund et al., 2021; Mund & Nestler, 2019; Oh et al., 2020;

Orth et al., 2021; Shi et al., 2023), even when cross-lagged effects do not exist in the data (Hamaker et al., 2015; Lucas, 2023; Usami, Todo, & Murayama, 2019). Despite these differences in the interpretation of the model parameters, we note that the CLPM, RI-CLPM, and LCM-SR are actually closely related such that the CLPM is nested in the RI-CLPM and the LCM-SR (e.g., Hamaker et al., 2015; Nestler & Humberg, 2024). Specifically, when there are no stable between-person differences (i.e., the intercept variance is zero), the RI- CLPM reduces to the CLPM. Similarly, when there are neither stable between-person differences nor developmental trends over time (i.e., the intercept and slope variance as well as the slope factor mean is zero), then the LCM-SR match the CLPM.

MULTI-ACTOR NATURE OF RELATIONSHIP SCIENCE

In addition to investigating interdependencies among two (or more) variables over time, investigating interdependencies among people is at the core of relationship science. While it is easy to *assume* interdependencies and reciprocal influences between couples, siblings, or parents and their children, it can be difficult to translate those assumptions to statistical models (Carr & Springer, 2010). In the last years, several approaches have been developed to take into account interdependencies within social interactions (e.g., Eichelsheim et al., 2010; Kenny et al., 2006; Nestler et al., 2015).

The most influential model to investigate influences between two (or more) individuals is the actor-partner-interdependence model (APIM; Kenny, 2018; Kenny et al., 2006). In short, one feature of the APIM that makes it particularly appealing for relationship science is its ability to differentiate between *actor*- and *partner*-effects.

Actor effects describe to what extent a characteristic (e.g., depression) of one person influences another characteristic (e.g., relationship satisfaction) *of this person*. Partner effects, on the other hand, indicate to what extent a characteristic (e.g., depression) of one person influences another characteristic (e.g., relationship satisfaction) *of another person*. Put differently, actor effects indicate intrapersonal effects, whereas partner effects pertain to interpersonal associations (Kenny et al., 2006; Nestler et al., 2015).

The CLPM has already been extended to incorporate dyadic data, even regarding the interplay between depression and relationship satisfaction (e.g., Choi & Jung, 2021; Morgan et al., 2018). By contrast, despite the growing use of the RI-CLPM and the LCM-SR, they have mostly been used in the case of a single person. In fact, we are aware of only one application of a dyadic LCM-SR, that considered the interplay between conflict communication and relationship satisfaction (Johnson et al., 2022). However, extending the RI-CLPM and LCM-SR to incorporate dyadic (or more complex) data structures is straightforward. The models depicted in Figures 2 and 3 describe the case in which the associations between two variables are observed over time for one individual. To incorporate a dyadic data structure, the models as depicted in Figures 1–3 need to be implemented separately for each person of the dyad (e.g., one RI-CLPM for women, one separate model for men). These models are then connected by introducing the partner effects within a construct (e.g., one person's satisfaction at a time point predicts the other person's satisfaction at the following time point) and across constructs (e.g., one person's satisfaction at a point in time predicts the other person's depression at the following time point). Furthermore, correlations between the residuals of the variables at different time points are included in the model to control for any dyadic dependencies not accounted for by other components in the model. In the following section, we provide an example of such a dyadic extension of the RI-CLPM and the LCM-SR; the corresponding R code for these models can be obtained from https://osf.io/4d32a/.

EMPIRICAL EXAMPLE: DEPRESSION AND RELATIONSHIP SATISFACTION BRIEF RESEARCH BACKGROUND

The interplay between depression and relationship satisfaction has been the focus of research for decades (for reviews, see Goldfarb & Trudel, 2019; Whisman et al., 2021). It has been argued that, on the one hand, high-quality partner relationships may function as a buffer against psychological ill-being. Indeed, relationship satisfaction has been shown to be associated with higher overall well-being (Proulx et al., 2007) and health, including a lower mortality risk (Robles et al., 2014). Consequently, being confined in an unsatisfactory and unfulfilling relationship may give rise to psychological distress (Umberson et al., 2006). Depression, on the other hand, is highly prevalent in contemporary Western societies (Bromet et al., 2011; Kessler & Bromet, 2013; Shorey et al., 2022) and may, hence, also operate as a stressor threatening relationship functioning and, consequently, relationship quality.

Different theories have been proposed to understand the association between depression and relationship satisfaction (e.g., Beach et al., 1990; Coyne, 1976; Hammen, 1991), and several empirical studies have been conducted to examine these ideas for the case of single individuals (Goldfarb & Trudel, 2019; Whisman et al., 2021). Arguably, less attention has been paid to understanding *dyadic* associations, and especially with attention to disentangling between-person differences in depression and relationship satisfaction from their within-person associations. For example, the marital discord model (Beach et al., 1990) focuses on how poor relationship functioning may serve as a risk factor for depression; in testing this idea, one may consider the key theoretical argument to concern within-person associations (e.g., how experiencing more or less satisfaction *than usual* may be associated with more or less depression *than usual*) and also dyadic processes (e.g., one's atypical level of satisfaction is associated with the partner's atypical levels of depression; see Beach et al., 2003). Further, in applying the marital discord model to understand the within-person dynamics, one may be particularly concerned with accounting for overall changes in depression (Sutin et al., 2013) and relationship satisfaction (Bühler et al., 2021) over the years. Testing these ideas requires models that can incorporate such complexity.

In general, there seem to be two larger traditions in investigating the interplay between depression and relationship satisfaction. The first tradition employs multilevel models to examine the association between relationship satisfaction and depression and typically draws on data with shorter-term intervals (e.g., daily, weekly, monthly; Biesen & Smith, 2022; Poyner-Del Vento & Cobb, 2011; Tolpin et al., 2006; Whisman et al., 2011; Whitton et al., 2008). The second tradition draws on models such as the CLPM and has been favored especially when using data with longer time intervals (e.g., multiple months, years; Barton et al., 2022; Choi & Jung, 2021; Morgan et al., 2018).

The benefit of multilevel models is that they can disentangle between- and within-person sources of variation in a straightforward fashion by, for example, using a person-mean centered predictor variable (Snijders & Bosker, 2012; Wang & Maxwell, 2015). Hence, they achieve already much of the models discussed in this paper. However, standard multilevel models allow to examine effects on one outcome variable only (i.e., they are univariate models) and therefore do not allow to estimate dependent bidirectional effects. Also, estimating and interpreting the effects of lagged variables (including the decision of how to center them; Falkenström et al., 2022) or including actor and partner effects is challenging in this setting. Thus, studies that have employed multilevel models so far examined the association between depression and relationship satisfaction for individuals only (i.e., no partner effects) and did not investigate the reciprocal, dynamic interplay between depression and relationship satisfaction.

Studies using the CLPM as the main analytic tool, however, are not able to disentangle between- from within-person sources of variation and has also rarely been implemented in a dyadic setting. In two of the few dyadic studies in which cross-lagged associations have been examined over time, depression and relationship satisfaction were related bidirectionally both within (i.e., actor effects) and across partners (i.e., partner effects; Choi & Jung, 2021; Morgan et al., 2018). However, only one study so far has investigated within-person associations between relationship satisfaction and depression separate from their between-person associations (using RI-CLPM; Barton et al., 2022).

When the two sources of variation were disentangled, it was found that lower relationship satisfaction than usual is cross-sectionally associated with higher scores on depression than usual. In contrast, no significant association was found between the two constructs over time (i.e., no $c1$- or $c2$-paths according to Figure 2). However, this study invoked individual data and did not consider dyadic associations. Further, no study so far has accounted for developmental trends of depression and relationship satisfaction in examining their cross-lagged associations. In the following, we demonstrate how a dyadic RI-CLPM and LCM-SR can be employed to address such gaps in the literature in examining the association between depression and relationship satisfaction and compare the results against a dyadic version of the CLPM.

Sample

We used data from Waves 2 (conducted in 2009) to 6 (conducted in 2013) from the German Family Panel pairfam (Huinink et al., 2011). In 2008, pairfam started to assess 12,402 individuals representative of the German population regarding a wide variety of constructs related to family life, career trajectories, social relationships, and several aspects of personality and well-being. Yearly interviews were conducted with the participants until 2022. In addition to the anchor participants, their partners were assessed upon agreement via paper-pencil questionnaires. The last assessment wave of pairfam was conducted in 2022.

We included participants in the analysis who (a) participated with their partner (i.e., provided data for the estimation of partner effects) and (b) were together at W2 and W3 (i.e., provided data for the estimation of longitudinal autoregressive and cross-lagged effects). In this way, we extracted data from 1699 mixed-gender couples which we used in all analyses. Differences between the included and excluded participants are summarized in Supplemental Table S1. At the first measurement occasion selected for the present study, the average age was 31.98 years (SD = 6.24) for women and 32.80 years (SD = 5.88) for men, respectively. On average, the couples have been together for 9.4 years (SD = 6.09). Monthly household income averaged 2964.64€ (≈3241 USD; SD = 1476.40€).

Measures

Depression was measured using the Dysthymia-subscale of the State–Trait Depression Scale (Spaderna et al., 2002). The scale contains five items (e.g., "I am sad") that respondents answered using a 4-point frequency rating scale ranging from 1 (*almost never*) to 4 (*almost always*).

Relationship satisfaction was measured using a single item ("Overall, how satisfied are you with your relationship?"). Respondents answered this question using a Likert-type rating scale ranging from 0 (*very dissatisfied*) to 10 (*very satisfied*).

Data analysis

We implemented a dyadic CLPM, a dyadic RI-CLPM, and a dyadic LCM-SR. Estimation was conducted using the package lavaan, version 0.6.12 (Rosseel, 2012) in R 4.1.1 (R Core

Team, 2021). We used a robust maximum likelihood estimator and full information maximum likelihood to accommodate missing data (Enders, 2010). The syntax for all models is available at https://osf.io/4d32a/.

Results

In the following, we display the key results of the analysis. The complete results including 95% confidence intervals of the parameters and standardized estimates are available at https://osf.io/4d32a/.

Dyadic CLPM

In the dyadic CLPM, we constrained the autoregressive effects, cross-lagged effects, and time-point-specific correlations between depression and relationship satisfaction to be equal over time. The constraints on the autoregressive and cross-lagged paths were introduced because we assumed stationarity of the associations between relationship satisfaction and depression; that is, we did not expect neither the autoregressive nor the cross-lagged paths to change over time. We note that this is an assumption that can be tested empirically and is not necessary to fit the models. In fact, with measurement occasions very far apart or stretching over multiple developmental periods or when certain life transitions occur between time points, stationarity may not hold. To investigate the appropriateness of such constraints, a model with those constraints can be tested against a model without those constraints via a χ^2-difference test. Furthermore, we also constrained the autoregressive effects, cross-lagged effects, and time-point-specific correlations between depression and relationship satisfaction to be equal for women and men, as we had no reason to expect gender-specific differences in those parameters based on previous studies. Again, this is a modeling decision that can be tested and that is not essential for fitting the model. If researchers expect those paths to be different across genders, those restrictions do not have to be imposed. Finally, we constrained the actor and partner effects to be the same for women and men. This fully constrained model did not fit the data well (see Table 2); however, a fully unconstrained model without any restrictions whatsoever did not fit well either ($\chi^2 = 1064.467$, df $= 96$, CFI $= 0.864$, RMSEA $= 0.077$, SRMR $= 0.087$). Thus, we decided to use the more parsimonious constrained model in the following for ease of interpretation.

The correlations between all variables are displayed in the left portion of Table 3. The associations between depression and relationship satisfaction were statistically significant both

TABLE 2 Model fit indices of the dyadic cross-lagged panel model, dyadic random-intercept cross-lagged panel model, and dyadic latent curve model with structured residuals.

Index	Cross-Lagged Panel Model	Random-Intercept Cross-Lagged Panel Model	Latent Curve Model with Structured Residuals
χ^2	1144.673	159.598	191.436
df	173	160	151
p_{χ^2}	<0.001	0.029	0.014
CFI	0.865	0.995	0.994
RMSEA	0.057	0.011	0.013
SRMR	0.090	0.035	0.031

Abbreviations: CFI, comparative fit index; df, degrees of freedom of the χ^2-test; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual.

TABLE 3 Correlations between depression and satisfaction in the dyadic cross-lagged panel model, the dyadic random-intercept cross-lagged panel model, and the dyadic latent curve model with structured residuals.

	Cross-Lagged Panel Model			Random-Intercept Cross-Lagged Panel Model			Latent Curve Model with Structured Residuals		
Parameter	*r*	*S.E.*	*p*	*r*	*S.E.*	*p*	*r*	*S.E.*	*p*
Between-person correlations[a]									
Within partners									
Depression W ↔ Satisfaction W	−.308	0.030	<.001	−.435	0.033	<.001	−.449	0.066	<.001
Depression M ↔ Satisfaction M	−.276	0.028	<.001	−.381	0.036	<.001	−.388	0.060	<.001
Int Depression W ↔ Slo Depression W	—	—	—	—	—	—	−.299	0.153	.051
Int Depression W ↔ Slo Satisfaction W	—	—	—	—	—	—	.053	0.156	.733
Int Satisfaction W ↔ Slo Satisfaction W	—	—	—	—	—	—	−.039	0.502	.938
Int Satisfaction W ↔ Slo Depression W	—	—	—	—	—	—	.263	0.284	.355
Slo Depression W ↔ Slo Satisfaction W	—	—	—	—	—	—	−.582	0.826	.481
Int Depression M ↔ Slo Depression M	—	—	—	—	—	—	−.116	0.114	.308
Int Depression M ↔ Slo Satisfaction M	—	—	—	—	—	—	−.147	0.326	.652
Int Satisfaction M ↔ Slo Satisfaction M	—	—	—	—	—	—	.142	0.714	.842
Int Satisfaction M ↔ Slo Depression M	—	—	—	—	—	—	.045	0.109	.677
Slo Depression M ↔ Slo Satisfaction M	—	—	—	—	—	—	−.217	0.558	.698
Between partners									
Depression W ↔ Depression M	.213	0.029	<.001	.265	0.036	<.001	.251	0.033	<.001
Depression W ↔ Satisfaction M	−.188	0.026	<.001	−.224	0.034	<.001	−.220	0.035	<.001
Satisfaction W ↔ Satisfaction M	.311	0.028	<.001	.514	0.034	<.001	.533	0.067	<.001
Satisfaction W ↔ Depression M	−.161	0.026	<.001	−.287	0.034	<.001	−.285	0.044	<.001
Within-person correlations[b]									
Within partners									
Depression W ↔ Satisfaction W	—	—	—	−.213	0.040	<.001	−.187	0.063	.003
Depression M ↔ Satisfaction M	—	—	—	−.180	0.040	<.001	−.181	0.057	.002
Between partners									
Depression W ↔ Depression M	—	—	—	.105	0.043	.014	.111	0.045	.014

(Continues)

TABLE 3 (Continued)

Parameter	Cross-Lagged Panel Model			Random-Intercept Cross-Lagged Panel Model			Latent Curve Model with Structured Residuals		
	r	*S.E.*	*p*	*r*	*S.E.*	*p*	*r*	*S.E.*	*p*
Depression W ↔ Satisfaction M	—	—	—	−.136	0.036	<.001	−.142	0.037	<.001
Satisfaction W ↔ Satisfaction M	—	—	—	.197	0.038	<.001	.191	0.040	<.001
Satisfaction W ↔ Depression M	—	—	—	−.065	0.040	.106	−.070	0.043	.101

Note: *S.E.*: standard error; W: women; M: men; Int: intercept; Slo: slope. *N* for all models is 1699 mixed-gender couples.
[a]For the RI-CLPM and the LCM-SR, this is the correlation between latent intercept factors.
[b]Within-person correlations are not present in the CLPM.

TABLE 4 Selected results of the dyadic cross-lagged panel model and the dyadic random-intercept cross-lagged panel model for the interplay between depression and relationship satisfaction.

Parameter	Cross-Lagged Panel Model			Random-Intercept Cross-Lagged Panel Model		
	b	*S.E.*	*p*	*b*	*S.E.*	*p*
Autoregressive paths[a]						
Depression → Depression	0.627	0.012	<.001	0.213	0.027	<.001
Satisfaction → Satisfaction	0.409	0.017	<.001	0.100	0.024	<.001
Cross-lagged actor effects[a]						
Depression → Satisfaction	−0.356	0.045	<.001	−0.179	0.076	.019
Satisfaction → Depression	−0.007	0.002	.001	−0.005	0.003	.108
Cross-lagged partner effects (*within-construct*)[a]						
Depression A → Depression B	0.045	0.010	<.001	0.060	0.019	.002
Satisfaction A → Satisfaction B	0.104	0.012	<.001	0.042	0.017	.015
Cross-lagged partner effects (*cross-construct*)[a]						
Depression A → Satisfaction B	−0.159	0.042	<.001	−0.241	0.074	.001
Satisfaction A → Depression B	−0.004	0.002	.032	−0.005	0.003	.068

Note: *b*: Unstandardized regression weight, *S.E.*: standard error. *N* for all models is 1,699 mixed-gender couples.
[a]Parameters are constrained to be equal between partners.

within partners and across partners. Thus, in general, higher depression of one partner was associated with higher depression of the other partner as well as with lower relationship satisfaction of oneself and the other partner. Higher satisfaction of one partner was associated with higher satisfaction and lower depression of the other partner, respectively.

The key parameters of the CLPM are displayed in the left portion of Table 4. Regarding autoregressive effects, we observed high stability for both depression and relationship satisfaction over time. The cross-lagged actor effects indicated that higher depression at one time point predicted lower relationship satisfaction at the subsequent time point and vice versa. To determine whether the cross-lagged effects are significantly different from each other, we conducted a series of χ^2-difference tests where we compared the results of the model presented in Table 4 to a model in which the cross-lagged actor effects were set equal. This comparison indicated that the cross-lagged effects of depression on satisfaction were larger than the reverse path ($\Delta\chi^2 = 61.75$, $\Delta df = 1$, $p < .001$).

Regarding partner effects, the within-construct partner effects indicated that higher depression of one partner at a given point in time was predictive of higher depression of the other partner at the following measurement occasion. Similarly, the results indicated that higher satisfaction of one partner predicted higher satisfaction of the other partner at the following occasion. Cross-construct partner effects indicated that higher depression of one partner predicted lower satisfaction of the other partner at the subsequent time point. Likewise, higher satisfaction of one partner tended to be associated with lower depression of the other partner at the following measurement occasion. As with the actor effects, the cross-lagged partner effects of depression on satisfaction were larger than the cross-lagged partner effects of satisfaction on depression ($\Delta\chi^2 = 14.42$, $\Delta df = 1$, $p < .001$). Taken together, the results obtained in this analysis converge very well with previous studies particularly in the sense that they suggest a reciprocal relationship between depression and relationship satisfaction over time (Choi & Jung, 2021; Morgan et al., 2018).

Dyadic RI-CLPM

In the dyadic RI-CLPM, we constrained the autoregressive effects, cross-lagged effects, and time-point-specific correlations between depression and relationship satisfaction to be equal over time and across gender. Furthermore, we constrained the actor- and partner effects to be the same for women and men. As in the CLPM, these constraints were imposed because we did not expect those parameters to differ across time and gender; in other applications, however, it may be necessary to estimate those paths freely (e.g., if gender differences are expected, if measurement occasions are far apart). The fully constrained model fit the data very well (see Table 2).

Correlations between the key variables are displayed in the middle portion of Table 3. As can be seen, at the between-person level (i.e., correlation between the latent intercept factors), depression and satisfaction were negatively correlated both within and across partners. Depression was positively correlated across partners, as was relationship satisfaction. Thus, as in the CLPM, the pattern indicates that individuals with higher scores on depression than others have lower relationship satisfaction than others and have partners with higher scores on depression and lower scores on satisfaction than others. A very similar pattern emerged at the within-person level with one exception: the within-person correlation between one partner's satisfaction and the other partner's depression was no longer statistically significant.

The key results of the RI-CLPM are displayed in the right portion of Table 4. As in the CLPM, the autoregressive effects indicated high stability for both depression and satisfaction. Note, however, that, in the case of the RI-CLPM, the autoregressive effects pertain to within-person stability. The cross-lagged actor effects indicated that deviations from a person's average level of depression at one time point predicted lower relationship satisfaction than usual at the subsequent time point. Unlike in the CLPM, the reverse path from satisfaction to depression did not reach statistical significance; furthermore, the path from depression to satisfaction was significantly larger than the reverse path ($\Delta\chi^2 = 5.36$, $\Delta df = 1$, $p = .02$).

The within-construct partner effects indicated that deviations from one partner's average level of depression were predictive of deviations from the other partner's depression as well.

Likewise, when one partner was more satisfied than usual with the relationship, the relationship satisfaction was higher than usual as well for the other partner at the next measurement occasion. Regarding cross-construct partner effects, the results indicated that when one partner scored higher on depression as usual at one time point, the other partner reported lower relationship satisfaction than usual at the following measurement occasion. On the other hand, deviations from one's average levels of satisfaction at one time point were not associated with deviations from the partner's average score of depression at the following measurement occasion. Again, the path from depression to satisfaction was substantially stronger than the path from satisfaction to depression ($\Delta\chi^2 = 11.25$, $\Delta df = 1$, $p < .001$).

In summary, the results of the RI-CLPM propose a different pattern than the results of the CLPM. Specifically, while the CLPM suggested a reciprocal relationship between depression and relationship satisfaction, the results of the RI-CLPM indicate that, when accounting for between-person differences in the two constructs, a unidirectional relationship exists. That is, deviations from one's average level of depression are associated with subsequent deviations from both one's own and the partner's usual levels of relationship satisfaction, but the same does not hold true for the other direction. In this sense, the results of our analysis also differ from the results reported by Barton et al. (2022) obtained with an individual RI-CLPM (i.e., no dyadic data), Specifically, Barton et al. (2022) only found cross-sectional associations between depression and satisfaction, whereas longitudinal associations have not been found.

Dyadic LCM-SR

The dyadic LCM-SR required some tweaks to fit properly. Starting with the growth curves, changes in depression of both women and men were adequately captured by linear growth curves. Relationship satisfaction of men was also adequately described by a linear growth curve, whereas women's relationship satisfaction was best described by a nonlinear growth curve. Specifically, we fitted a latent basis growth curve model in which the first slope loading was set to 0 and the last slope loading was set to 1 (Ram & Grimm, 2007). In this way, the mean of the slope represents the change in relationship satisfaction that occurred between the first and last measurement occasion considered in the study. Furthermore, despite significant mean-level decreases in depression and relationship satisfaction for women and men, the variance of the respective slope factors was very small. To avoid estimation problems (i.e., inadmissible parameter estimates such as negative variances), we constrained correlations between all slope factors and between slope and intercept factors across gender to be zero. That is, while we allowed a correlation between women's intercept of satisfaction and women's slope of depression, for example, no correlation was allowed between women's intercept of satisfaction and men's slope of depression, for example. Thus, we assume that there are no correlated changes between women's and men's depression and relationship satisfaction. Finally, the autoregressive and individual cross-lagged effects had to be estimated freely for women and men, whereas the within- and cross-construct partner effects could be constrained to be equal across gender. The model specified in this way showed a very good fit to the data (see Table 2).

The correlations between variables in the model are displayed in the right portion of Table 3. The estimates are all very close to those from the dyadic RI-CLPM and the pattern is identical. Thus, individuals with higher scores on depression than others have lower relationship satisfaction than others and have partners with higher scores on depression and lower scores on satisfaction than others. The same pattern emerged at the within-person level with the exception that one partner's satisfaction was not associated with the other partner's depression.

The key results of the LCM-SR are displayed in Table 5. Whereas depression showed high within-person stability for both women and men, the within-person autoregressive path for satisfaction was only significant for men. This finding indicates that women's deviations from their average trajectory of relationship satisfaction are less stable compared to men's deviations. That is, women seem to return faster to their average trajectory than men. The cross-lagged actor effects indicated that deviations from women's average trajectories of depression at one time point predicted lower relationship satisfaction than could be expected based on their average trajectory at the subsequent time point. As in the RI-CLPM, the path from satisfaction to depression did not reach statistical significance. For men, however, neither cross-lagged actor effect reached statistical significance, indicating that deviations from men's average trajectories of depression or relationship satisfaction were not related with the deviations from the average trajectory of the other variable over time.

TABLE 5 Selected results of the dyadic latent curve model with structured residuals for the interplay between depression and relationship satisfaction.

Parameter	Women *b*	Women *S.E.*	Women *p*	Men *b*	Men *S.E.*	Men *p*
Autoregressive paths						
Depression → Depression	0.186	0.043	<.001	0.148	0.049	.003
Satisfaction → Satisfaction	0.055	0.036	.125	0.111	0.046	.021
Cross-lagged actor effects						
Depression → Satisfaction	−0.272	0.113	.016	0.027	0.149	.855
Satisfaction → Depression	−0.005	0.005	.274	−0.004	0.005	.456
Cross-lagged partner effects (*within-construct*)[a]						
Depression A → Depression B	0.065	0.020	.001	0.065	0.020	.001
Satisfaction A → Satisfaction B	0.044	0.017	.013	0.044	0.017	.013
Cross-lagged partner effects (*cross-construct*)[a]						
Depression A → Satisfaction B	−0.263	0.073	<.001	−0.263	0.073	<.001
Satisfaction A → Depression B	−0.006	0.003	.057	−0.006	0.003	.057

Note: *b*: Unstandardized regression weight; *S.E.*: standard error. *N* is 1699 mixed-gender couples.
[a]Parameters are constrained to be equal between partners.

The partner effects could all be constrained to be equal for women and men. Similar to the RI-CLPM, the within-construct partner effects indicated that deviations from one partner's average trajectory of depression were predictive of deviations from the other partner's average trajectory of depression at the subsequent measurement occasion. Likewise, when one partner was more satisfied with the relationship than could be expected based on their average development, the relationship satisfaction was higher than could be expected for the other partner at the next measurement occasion. Regarding cross-construct partner effects, the results indicated that when one partner scored higher on depression than could be expected based on their average trajectory, the other partner reported lower relationship satisfaction than could be expected at the following measurement occasion. As in the RI-CLPM, the association between one partner's satisfaction and subsequent depression of the other partner did not reach statistical significance and was significantly weaker than the association between one partner's depression and subsequent relationship satisfaction of the other partner ($\Delta\chi^2 = 23.76$, $\Delta df = 1$, $p < .001$).

In summary, the results of the LCM-SR by and large converge with those obtained with the RI-CLPM. That is, the LCM-SR indicated a unidirectional relationship between depression and satisfaction in that one partner's depression was associated with the other's satisfaction, whereas the reverse path was not substantial. We note, however, that it was necessary to tweak the LCM-SR to achieve proper convergence (Orth et al., 2021; Scott, 2021). To this end, we had to introduce some constraints (e.g., no correlated changes; different growth trajectories for relationship satisfaction) and relax others (e.g., different actor effects for women and men). As a consequence, the comparability between the LCM-SR and the other models is impaired. Furthermore, in applications with a truly substantive focus, the feasibility and interpretability of such modeling decisions should be weighed carefully.

DISCUSSION

Questions regarding the interplay between multiple constructs within and across multiple actors over time are essential in relationship science. Yet, investigating such questions requires tailored research designs and specific analysis tools. While the CLPM has been the dominant analysis model for a long time, alternative models such as the RI-CLPM (Hamaker et al., 2015; Mulder & Hamaker, 2021) and the LCM-SR (Curran et al., 2014) were proposed during the last decade that may prove useful for relationship science. The value added of the RI-CLPM and LCM-SR over the CLPM is that by disentangling between- and within-person variation they can be used to examine within-person dynamics that are at the core of many theories in relationship science (Berry & Willoughby, 2017; Johnson et al., 2022). As a consequence, models like the RI-CLPM and the LCM-SR allow researchers to translate theories to appropriate statistical models or to gain a new perspective (i.e., a within-person perspective) on established frameworks and findings. However, despite their promise, modeling approaches such as the RI-CLPM and the LCM-SR have not yet been adopted widely in relationship science. To enable their more frequent use, we demonstrated the mechanics of the CLPM, RI-CLPM, and LCM-SR using the example of the interplay between depression and relationship satisfaction. Guided by different theoretical perspectives, many studies have examined the relationship between depression and relationship satisfaction over time and between partners, some finding reciprocal associations. (Choi & Jung, 2021; Goldfarb & Trudel, 2019; Morgan et al., 2018; Whisman et al., 2021). When examining this link from a within-person perspective, however, the evidence for a reciprocal relationship seems mixed. For example, earlier studies using multilevel models to disentangle between- and within-person sources of variation have found bidirectional associations between depression and relationship satisfaction (Biesen & Smith, 2022), no relationship between both domains (Whitton et al., 2008), unidirectional effects of relationship satisfaction on subsequent depression (Poyner-Del Vento & Cobb, 2011), or unidirectional effects of depression on relationship satisfaction (Tolpin et al., 2006; Whisman et al., 2011). Regarding the models presented in this article, Barton et al. (2022) have shown no longitudinal association between depression and relationship satisfaction using the RI-CLPM and our illustrative analysis suggested a unidirectional relationship flowing from depression to satisfaction. The CLPM, similar to previous studies (Choi & Jung, 2021; Morgan et al., 2018) indicated a bidirectional interplay between depression and relationship satisfaction. Thus, the results converge with similar comparisons in showing that the CLPM seems to overestimate bidirectional associations (Berry & Willoughby, 2017; Etherson et al., 2022; Kim et al., 2022; Lucas, 2023; Lüdtke & Robitzsch, 2022; Masselink et al., 2018; Mund et al., 2021; Mund & Nestler, 2019; Oh et al., 2020; Orth et al., 2021; Shi et al., 2023; Usami, Todo, & Murayama, 2019). It is worth noting, though, that the CLPM did not fit the data well, indicating that its parameters might be biased. Of course, our example and previous studies differed in multiple aspects such as sampling strategies, characteristics of the couples, measurements, and time frames in addition to the analytic models, posing a challenge in making direct comparisons or drawing a definitive conclusion. Indeed, a full understanding of such a complex phenomenon that can vary across temporal, cultural, and relational contexts requires attention to multiple factors, with modeling techniques being just one of them.

Regarding sampling strategy, for the present analysis, we included couples who were together at least two measurement occasions per requirements of the statistical model. The decisions to consider (a) dyadic data from (b) couples in relatively established relationships may have led to the inclusion of overly satisfied couples. This decision was guided by the requirements of the statistical models in the sense that (a) data from at least two measurement occasions are necessary to estimate autoregressive and cross-lagged effects and (b) data from both members of the couple are necessary to estimate partner effects. However, some studies have shown that people who participate as a couple in a study are, on average, more satisfied with their relationship than individuals who participate without their partner (Barton et al., 2020; Park et al., 2021). In this study, such patterns were present as well, although particularly regarding relationship duration and age (see Supplemental Table S1). Thus, due to the requirements of model fitting, we apparently oversampled older couples with, accordingly, longer relationships, whereas younger individuals with shorter relationships were underrepresented. This selection may have impacted the results. For example, in relatively stable circumstances as in the case of rather settled relationships, cross-lagged and partner-effects might be lower than in new, unfamiliar, or developing contexts such as newly formed relationships where partners still need to adapt to each other (Mund & Neyer, 2021; Neyer et al., 2014). That said, we note that a recent study also observed similar evidence for a unidirectional elationship (depression predicting later relationship quality but not vice versa) in younger, dating couples (Joosten et al., 2022). Given the data requirements for different models, we suggest that researchers pay particular attention to the characteristics of the analyzed sample when interpreting and generalizing the results. Conducting a direct test of whether and how the analytic sample is unique (e.g., comparing those included vs. excluded from the analyses) should be encouraged whenever possible as it can provide valuable insights in this regard.

Regarding measures, our global indicators of depression and relationship satisfaction did not tap into specific aspects of depression (e.g., dysthymia, rumination, lack of motivation) and satisfaction (e.g., partner support, positive communication, affection), and thus may have been limited in providing more nuanced insights into the association between the two constructs. For example, while Barton et al. (2022) found no reciprocal associations between depression and overall relationship satisfaction, a bidirectional relationship was found between depression and partner support.

Regarding the time interval, we investigated the one-year lags implemented in the pairfam data. This is a typical time lag that has been used in other studies employing the CLPM as well (Choi & Jung, 2021; Morgan et al., 2018). Classical research on within-person dynamics employing multilevel models, in contrast, usually build on much shorter time intervals such as days or weeks (Biesen & Smith, 2022; Poyner-Del Vento & Cobb, 2011; Tolpin et al., 2006; Whisman et al., 2011; Whitton et al., 2008). As a consequence, studies extending over such different time periods can well lead to different results (Dormann & Griffin, 2015; Gollob & Reichardt, 1987; Voelkle et al., 2012). This points to the more general issue of developing more specific theoretical considerations regarding the time span over which (reciprocal) effects are thought to unfold. As of yet, theoretical frameworks on the interplay between depression and relationship satisfaction, but also regarding the interplay between other domains, do not provide clear guidance whether the assumed relationships unfold over days, months, and/or years. Thus, basically any time frame could be used to investigate the theoretical assumptions. In case of the absence of reciprocal effects over 1 year, for example, it would be easy to conclude that the theory is incorrect, although it might work very accurately over shorter (or longer) time periods. Thus, with a strengthened theoretical background, it would become possible to develop studies that are better suited to capture the expected effects and to employ statistical models that can examine the assumed causal processes (Hamaker, 2023; Lerner et al., 2009).

It is important to note, though, that results obtained by applying novel modeling strategies do by no means invalidate findings from other studies in which other models have been employed. It is crucial to keep in mind that different models address different research questions and are not directly comparable (Lucas, 2023; Lüdtke & Robitzsch, 2021, 2022; Orth et al., 2021; Usami, Todo, & Murayama, 2019). Which model is the most appropriate is, thus, not a question that can be answered unequivocally—rather, the choice of a statistical model always needs to be guided by theoretical considerations (Hamaker, 2023). Put differently, if there is no interest in within-person effects, then neither the RI-CLPM nor the LCM-SR may be appropriate candidate models; instead, researchers have many other options such as the CLPM, Dynamic Panel Models (Lucas, 2023), "classical" LCMs (Bollen & Curran, 2006) and many others (for comparisons between some of those models, see Grimm, 2007; Grimm et al., 2017; Hounkpatin et al., 2018).

In fact, the development and use of new analytical models highlights that, to fundamentally advance our understanding of the interplay between two (or more) constructs over time and across two (or more) actors, great precision is needed when translating theoretical perspectives into empirical investigations and proper statistical models (Hamaker, 2023). Ideally, decisions about which models will be applied and if/which models will be compared in a substantive study should be preregistered in future research. Specifically, preregistration of modeling approaches is helpful because each statistical model taps into different research questions and is based on a specific set of assumptions (Hamaker et al., 2015; for the models relevant to the present manuscript, see Table 1; for more detailed discussions and comparisons, see Lüdtke & Robitzsch, 2022; Orth et al., 2021; Usami, Murayama, & Hamaker, 2019). When researchers conclude that a specific theory should be tested with a specific model, this modeling approach should be preregistered, along with criteria for determining model fit and alternative models, which can help minimize researcher degrees of freedom. Similarly, when researchers assume that it is necessary to investigate a theory over a specific time frame, the chosen time frame should be preregistered to foster transparency concerning whether the predictions derived from the theory were accurate or not (for the respective time frame). In this way, preregistration provides stricter tests of underlying theories.

In addition to introducing the general idea behind within-person models, another aim of the present article was to demonstrate the flexibility and adaptability of such models. Specifically, we showed that the RI-CLPM and the LCM-SR can be extended to incorporate multi-actor data as easily as the classical CLPM (Choi & Jung, 2021; Morgan et al., 2018). In this way, it is possible to combine the unique perspective of within-person models with the power of modeling approaches like the APIM (Kenny, 2018; Kenny et al., 2006) in order to reflect the multi-actor nature of relationship science. We have focused on dyadic data from distinguishable dyads (i.e., mixed-gender couples) in the example, but the models can be further extended to incorporate more complex constellations such as triadic data or data from indistinguishable dyads. At the same time, though, it should be clear that with increasing complexity of the models, the requirements regarding sample size and number of measurement increases. For example, while the CLPM works already with two measurement occasions, at least three and four measurement occasions are required for the RI-CLPM and the LCM-SR, respectively.

New statistical models are no panacea. They all come with their own set of prerequisites, advantages, assumptions, and limitations, and there is always a trade-off in model selection between using model-specific benefits and at the same time accepting shortcomings of the models (Lüdtke & Robitzsch, 2021; Usami, Murayama, & Hamaker, 2019; Usami, Todo, & Murayama, 2019). Nevertheless, the advances in statistical modeling of complex interdependencies among constructs and actors that have been made in the last decade enrich the toolbelt of relationship researchers immensely and provide researchers with a range of modeling options that can best reflect both the theory and data, ultimately helping to advance relationship science.

CONCLUSION

The last decade has brought about numerous advances in modeling complex relationships between people and constructs. These advances may foster relationship science, because the newly developed modeling strategies match the within-person perspective inherent in many theories of the field and, hence, allow a more accurate testing of those theories. By employing models such as the RI-CLPM or the LCM-SR, relationship researchers may gain a deeper understanding of within-person dynamics that, ultimately, may feed back into the development of new theories or revisions of existing ones.

CONFLICT OF INTEREST STATEMENT

The authors reported no conflicts of interest.

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