Models for Dyadic Data

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Humans are social animals, and most human experience unfolds in a social context. Indeed, many of the problems addressed in clinical psychology can only be understood by taking into consideration the interdependence of two (or more) people within their social system. For example, social anxiety, depression, violence and aggression, psychopathic and narcissistic behaviors, eating disorders, and marital satisfaction, are manifest in and shaped by the social context in which they exists (Girard et al., 2017; Sbarra & Wishman, 2013). Clinical interventions for childhood and developmental problems typically require working with the child's social environment, including teachers, parents, and other people who shape the daily lives of children.

The most basic social system is that of two individuals, or a *dyad*. Despite its simplicity, many forms of complex social interactions take place in the context of an interactive dyadic system—for example, the bond between a child and her mother, a romantic relationship between two partners, or the relationship between a patient and therapist. In this chapter, we describe models for analyzing data from such dyadic systems. This chapter begins by defining key characteristics of dyadic systems and then identifies clinical research questions related to dyadic systems and processes that unfold over time. We use these questions to select models and illustrate data analytic techniques.

Why do we need models for dyadic data?

The key statistical concept underpinning dyadic research is *non-independence*. This term means that the members of a dyad are associated in such a way that the assumption of independence in standard analyses does not hold (Kenny, 1996; Kenny & Judd, 1986; Kenny, Kashy, & Cook, 2006). Other terms such as interdependence (Gonzalez & Griffin, 1997;

Thorson, West, & Mendes, 2017) or linked scores (Kenny et al., 2006) are used to refer to the same broad idea. Non-independence can be understood from both a conceptual and a statistical standpoint. Conceptually, non-independence means that the behavior of one unit in a dyadic system is best explained by also taking into consideration the behavior of the other unit. For example, the meaning of a six-month old baby's crying or gazing at his caregiver is not fully grasped unless also observing the concurrent behavior of his caregiver (e.g., smiling back to the child, feeding him, soothing him). Likewise, the caregiver's behavior is better explained—and might be understood only—by also observing the child's behavior. Similarly, an individual's adherence to, and progress in, therapy can only be understood in the context of her interactions with the therapist.

From a statistical standpoint, non-independence manifests in a non-zero correlation between the scores of the dyad members. The requirement for independent observations is one of the key assumptions for ANOVAs, t-tests, linear regression, and other models based in the general linear model; in the case of correlated data from two members of a dyad, the independence assumption is violated. Consequently, these models cannot be used for analyzing dyadic data because the corresponding inferential statistics (*T*, *F* or regression coefficients) have biased standard errors and decreased degrees of freedom, leading to either too conservative or too liberal significance tests. This, in turn, leads to higher rates of Type 1 and Type 2 error (Kenny et al., 2006).

In our description of models, we refer to specifications that pertain to distinguishable dyads. A dyad is *distinguishable* or *nonexchangeable* when there is at least one variable that allow establishing differences between the members (Gonzalez & Griffin, 1997; Kenny et al., 2006). For example, heterosexual couples are potentially distinguishable because one can measure differences between men and women. Different age siblings or therapist-client dyads are also distinguishable (Bolger & Laurenceau, 2013). In contrast, same-sex couples or twins are indistinguishable if there is no clear factor establishing a difference between the members of the dyad. Although this distinction is not necessary, some researchers have used structural equation models for distinguishable dyads, and multilevel models for indistinguishable dyads (Nestler, Grimm, & Schönbrodt, 2015). However, this is not always the case (e.g., Baucom et al., 2015). Methods for evaluating distinguishability are beyond the scope of this chapter and are available in the literature (Gonzalez & Griffin, 1997; Kenny, Kashy, & Bolger, 1998; Ledermann & Macho, 2014).

Key research questions in clinical psychology related to dyadic systems:

Outcomes vs. process research

Understanding modeling approaches for dyadic data, or any other data, requires a context in which research questions can be stated and models selected accordingly. In clinical psychology, one possible framework is to outline questions about dyadic systems that distinguish between *outcomes* of a process and the *process* itself. One example of clinical research in dyads focused on *outcomes* would be a study of the characteristics of a counselor that are associated with client's perceived working alliance (Kivlighan, Clements, Blake, Arnzen, & Brady, 1993). One example of research focused on *processes* would be a study examining how the counselor's behavior and the client's perception of working alliance change over time. Here, the study would focus on understanding how the two trajectories can be described, whether or not they are related, and what factors can explain different features of the change.

In the next section, we illustrate a number of clinical research questions that can be considered as related to outcomes, and describe a statistical model typically used to address them. In the following section, we illustrate a variety of questions focused on processes, and describe statistical models that can be used to address them. Table 1 provides a list of the models covered in this chapter, examples of research questions addressed by each them, and data features suited to such models.

INSERT TABLE 1 HERE

Importantly, the models we describe below may be used flexibly to study dyadic outcomes and processes ranging from laboratory-based psychophysiological investigations to prospective epidemiological studies. Moreover, such processes – and potential changes in the processes – can operate at multiple levels, in multiple dimensions, and multiple time metrics (e.g., minutes, days, years).

Models for studying outcomes

Studies focusing on outcomes typically have either cross-sectional or pre-post designs. In the first case, all the variables are measured at a single occasion. In the second case, dyadic change in the relevant variables (e.g., symptoms) is measured before and after an intervention. Ideally, these two measures are taken as part of a randomized control trial, so the difference in the change of control and treated group can be attributed to the intervention. Regardless of the specific research design and question, these pre-post studies also take an outcomes approach, largely because they focus on whether the intervention is associated with differences in the total amount of change in the outcome variable.

In both cases, the research takes an *outcomes approach* because the goal is to explain individual differences in the outcome variable of interest by exploring its associations with one or more of covariates and predictors, without characterizing the processes that led to that outcome or investigating how those associations unfolded over time. Some other examples of questions focusing on outcomes in cross-sectional studies are include: What type of spouse support is associated with higher marital satisfaction in patients with cancer (Hagedoorn et al., 2000)? What features of the family´s environment and expressed emotion help explaining inpatients' eating disorders (Medina-Pradas, Navarro, López, Grau, & Obiols, 2011)? Is expressed emotion of parent and child related to child obsessive–compulsive disorder symptoms (Przeworski et al., 2012)? All of these studies are dyadic in nature because the outcome variable (marital satisfaction, therapy working alliance, eating disorders, etc.) is part of a system of inter-connected constructs, and evaluating the association between those constructs requires gathering information about both members in the dyad.

Some examples of questions from pre-post studies are: In couple therapy, what styles of couple alliance predict couple outcomes (Anker, Owen, Duncan, & Sparks, 2010)? What coping strategies protect infertile couples from depression over a failed insemination attempt (Berghuis & Stanton, 2002)? What characteristics of counselor and client are associated with psychotherapy working alliance (Kivlighan, Marmarosh, & Hilsenroth, 2014)? When treating children with social anxiety problems, under what conditions is it beneficial to involve their parents in therapy (Garcia-Lopez, Díaz-Castela, Muela-Martinez, & Espinosa-Fernandez, 2014)? Most of the clinical questions in a dyadic cross-sectional or pre-post studies are and can be addressed with the Actor-Partner Interdependence Model, or APIM (Kenny et al., 2006), which is described below.

The Actor-Partner Interdependence Model (APIM)

When studying dyadic systems, researchers focusing on outcomes often use the Actor-Partner Interdependence Model (APIM; Kenny, 1996; Kenny et al., 2006). For example, in couples with one member affected by cancer, Hagedoorn and collaborators (2000) applied the model to study the extent to which marital satisfaction was explained by the adoption of a supportive style termed *active engagement* by the non-affected partner (this style entails engaging the patient in discussions, inquiring how the patient feels, asking about help and information, and using other constructive problem solving methods). Here, we use this topic to illustrate how the APIM can address questions about dyadic outcomes–although their study used a more complex version of the model involving more, and slightly different, variables.

Figure 1 depicts the most basic form of an APIM for this research question. X represents the active engagement of the caregiver, as perceived by the caregiver (Xc) and the patient (Xp). Yc and Yp represent marital satisfaction of each member of the couple. The effect of each individual's perception on his or her own satisfaction is called *actor effect* (a), whereas the effect on the partner's satisfaction is called *partner effect* (p): a_c and a_p are the actor effects of the caregiver's and patient's perceptions on their own marital satisfaction, whereas p_{cp} and p_{pc} are the influences of each member of the dyad on their counterpart's satisfaction. Two error terms, e_{Yc} and e_{Yp}, are typically included to account for the variance of the outcome variables that are not explained by the actor or partner effects.

This model typically includes a covariance between Xc and Xp, and another covariance between e_{Yc} and e_{Yp}. The former accounts for the association between the initial states of both elements of the dyad, often called *compositional effects* (Kenny et al., 2006). The latter accounts for the relation between the final states that are not explained by the model.

INSERT FIGURE 1 HERE

The APIM allows quantifying and comparing the interpersonal and intrapersonal effects for both members of the dyads, and testing hypotheses about their statistical significance: Is the patient's satisfaction explained by the perception of partner's active engagement? Is it explained by the partner's self-perception of active engagement? Which of these two has a greater influence? One approach to evaluate hypotheses such as these is to constrain some of the model parameters. This implies restricting the values that one or several parameters can take, and evaluating whether model fit decreases as a consequence of such restriction. For example, to test a hypothesis positing a symmetrical relation, one could constrain the two partner effects (p) to have the same value. If one of the partners exerts a stronger influence than the other, the model fit will be significantly degraded by this constraint, and the hypothesis of symmetrical relation will be formally rejected. Similarly, if we hypothesize that the relationship is non-reciprocal, we may constrain one of the partner effects to zero, while freely estimating the other, and evaluate the increase of misfit through nested models comparison. Note that a cross-sectional design without experimentation (i.e., an observational study) can only show relations among constructs but provides no information about potential causal links between them.

The APIM can also be applied in pre-post designs. For example, Marmarosh and colleagues studied the relation between the attachment style of therapists and clients at the beginning of psychotherapy (predictive variable X) and the working alliance reported by each one after 3 weeks (criterion variable Y) (Marmarosh et al., 2014). The interpretation of the actor and partner effects is analog to the cross-sectional example detailed above, and similar hypotheses could be tested formally. It is also possible to include more than one predictive variable at time 1, so several actor and partner effects are evaluated. For example, Marmarosh and colleagues (2014) included two different attachment styles (avoidance and anxiety) for both clients and therapists, plus the interaction between the styles of clients and therapists, resulting in a more complex APIM. In their study, they found a negative interaction between therapists' and clients' initial attachment styles, which significantly predicted later clients-perceived alliance: the effect of therapists' anxiety on clients-perceived alliance was different depending on whether the clients themselves had high or low levels of anxiety. Applying a pre-post design ensures that the predictive variable antecedes the outcome. However, a proper experimental design–with random assignment to different conditions–would provide better evidence for attributing causality.

If the same variables are measured at both occasions, the APIM described here is equivalent to an auto-regressive cross-lagged model with two time points (Nestler et al., 2015). The stability and cross-lagged coefficients are equivalent to the actor and partner effects, respectively. In the context of psychotherapy, this model is sometimes termed a repeated measures (RM) APIM (cf. Baucom, Dickenson, et al., 2015; Crowell et al., 2014; Perry et al., 2017). Extending the model to further include additional occasions allows testing whether the actor and partner effects can explain the longitudinal interrelations –i.e., whether the processes are interdependent over time (Laurenceau & Bolger, 2005). This leads to an auto-regressive model with more than two occasions. We describe these models later in the chapter.

APIMs can be used to address a number of different questions in clinical psychology. Some examples involve health behavior in couples (Butterfield & Lewis, 2002; Franks, Wendorf, Gonzalez, & Ketterer, 2004), attachment styles and relationship dependence on behaviors under stress (Campbell, Simpson, Kashy, & Rholes, 2001), outcomes in couple's therapy (Cook & Snyder, 2005), relations among aggression, victimization, anxiety and depression in couples (Lawrence, Yoon, Langer, & Ro, 2009), and health-related quality of life in children with cystic fibrosis and their caregivers (Driscoll, Schatschneider, McGinnity, & Modi, 2012), among others. Lederman, Macho and Kenny (2011) provide a discussion on how the APIM can be extended to account for mediation effects.

Models for studying processes

Dynamic processes in dyads

Whereas some studied focus on outcomes, other types of studies focus on psychological processes as they unfold over time. We refer to this as *process approach* or *process research* (cf. Goldfried, Greenberg, & Marmar, 1990; Kopta, Lueger, Saunders, & Howard, 1999; Laurenceau, Hayes, & Feldman, 2007). In this approach, questions relate to change and its underlying mechanisms. For example, Laurenceau et al. (2007) defined three sets of questions relevant to change in psychotherapy. The first question pertains to the course –and shape– of change, including: a) comparing the observed trajectory with the theoretically predicted pathway; b) evaluating whether the individual trajectories are well represented by the group trajectory; c) identifying sections of the trajectory with higher rates of change and studying what factors explain them (e.g., some researchers have found periods of rapid improvement during depression treatment, interspersed with periods of symptom stability or exacerbation. What variables explain these periods?); and d) finding differences between responders and non-responders (e.g., did the non-responders show an improvement, but then returned to the initial level? How can this pattern be explained?).

The second type of question that can be answered using a process approach relates to moderators of change. Moderators may change the effect of the causal variables in the study. In the context of psychotherapy, for example, client's age and sex may differentially predict treatment development. Process research often focuses on identifying moderators that are associated with changes of interest (e.g., Is the course of change the same for younger and older couples?). The third question focuses on the mediators of change. A mediator is a variable that is changed by the intervention and causes later changes in the relevant outcome (e.g., Is a reduction in OCD behavioral symptoms preceded by a reduction of caregivers' overprotective behaviors, which follow from the intervention itself?).

A process approach is, in principle, more involved, with efforts to reveal mechanisms underlying changes in the dyads. Such processes typically involve complex interrelations among multiple variables. Any attempt to identify interrelations will require a number of factors, including: a) rich data that represent the multivariate nature of the process as well as their time dependency, and b) models that can uncover such dynamics at the appropriate level of analysis and time-scale resolution (e.g., minutes, days, weeks) (Nesselroade & Boker, 1994).

Any system of human interrelations is dynamic, inasmuch as it unfolds over time. Hence, a dynamic approach is required for studying and understanding many clinical problems. A dynamic model is a set of equations that expresses the time dependency of the system. For example, a dynamic model can include a function describing the changes in a system as a function of its previous state (Hamaker, Zhang, & Maas, 2009). A dynamic model applied to dyadic systems includes at least two processes–one for each member of the dyad– and must account for the existence of both between- and within-person influences (Ferrer & Steele, 2014, 2012; Levenson & Gottman, 1983). For instance, if one is interested in emotional valence in a system composed of two romantic partners, the valence for one of them at the present moment is likely related to his or her own previous valence (intra-individual influence), as well as to the previous state of the partner (inter-individual influence). A model to describe a dyadic system must account for both self and partner effects (Felmlee & Greenberg, 1999). Dynamic models allow not only describing the present state as a function of previous states, but also present rate and direction of change.

In clinical psychology research, as in any other field, matching theory to methods is vital. To study dyadic processes we need models able to characterize and differentiate processes within- and between people, and within- and between dyads. In this respect, to answer specific hypotheses, model selection must be guided by one's theory about the phenomenon. In the remainder of this chapter we focus on models for dyadic data that are suited to capture features of dynamic processes in dyads.

Latent growth curve models (LGC)

Latent growth curve (LGC) modeling is a technique used to characterize changes in a process over time (Ferrer & McArdle, 2003; McArdle & Epstein, 1987; Meredith & Tisak, 1990; Rao, 1958). Here, we focus on a bivariate LGC specification and illustrate how it can be used to address clinical research questions involving dyads. Suppose a researcher would like to study the effect of an upcoming stressful event on a person's emotions and those of his or her partner. This was the topic addressed by Thompson and Bolger (1999) in their study of daily stress among examinees of the Bar Examination to obtain a lawyer license and their partners. In a scenario like this, several questions would be pertinent that involve both dyad members. For example, focusing on the emotional effects of the examination, one could be interested in: a) the trajectory of the examinee's anxiety as the date of the exam approaches, b) the trajectory of the partner's dissatisfaction with the relationship, and, c) the potential relation between these two processes. Given a number of measurement occasions on both variables, a bivariate LGC model could be applied to address these questions. Figure 2 depicts a path diagram of such a model (top panel) and trajectories in variables *X* and *Y* from a sample of 100 couples (bottom panel).

INSERT FIGURE 2 HERE

In the LGC model of figure 2, *X* represents the examinee's self-reported anxiety and *Y* represents the partner's dissatisfaction with the relationship. Both variables are measured at four occasions. At each occasion, the observed scores for each process ($Y_{[t]}$ and $X_{[t]}$) are a function of two latent variables: an intercept (y_0 and x_0) and a slope (y_s and x_s) of the growth trajectory, for each variable. The latent intercept has loadings of the same value –usually 1– on all occasions. The latent slope has loadings that define the shape of the curve over time. For example, if the trajectory is expected to increase linearly and the observations are equally spaced in time, the loadings could be fixed to 0, 1, 2, 3. Other values for the slope's loadings allow different specifications for the trajectory; for example, it is possible to fix only the first and last loading to 0 and 1, and freely estimate the rest, so the model can capture any shape of change (i.e., *Latent Basis Growth Model*; McArdle & Epstein, 1987; Meredith & Tisak, 1990). If the first slope loading is fixed to zero, the latent intercept represents the value of the process at the initial occasion.

This model allows estimation of the means of the two latent variables (μ_0 and μ_s), which capture the mean intercept and slope for the whole sample. If the slope loadings are specified with increasing values, a positive slope represents an increase in the average trajectory, and vice versa. Because the model also yields estimates of the variances in the latent variables, it is possible to capture between-individual differences in both initial level and rate of change. The covariance between the intercept and slope (σ_{0s}) captures the relation between the initial state and the growth for the sample. In Figure 2, the covariances between the two latent intercepts (σ_{00}) and between the two latent slopes (σ_{ss}) are also estimated. The first parameter represents the relation between the initial values in the examinees' anxiety and their partners' dissatisfaction. The second parameter captures the relation between the rates of growth of both processes. To accommodate further associations between the partners' processes, other parameters can be included in the model. For example, the covariance between one person's intercept and the partner's slope would represent the association between, say, the examinee's anxiety at the initial assessment and increases (or decreases, depending on the slope valence) in the partner's dissatisfaction with the relationship. To account for the non-independence between both partners' scores, the unique variance of the scores for each individual are typically allowed to covary. This covariance accounts for any interdependence between the processes that are not related to the bivariate growth.

Although we describe standard uses of the LGC models, alternative specifications can be used to capture other forms of associations between both dyad members. For example, Ledermann and Macho (2014) described a LGC model for *common fate effects*, defined as variables affecting both members of the dyad equally (Kenny et al., 2006; Ledermann & Kenny, 2012). In Ledermann and Macho's model, the scores from the two members of a couple were regressed on the same latent variable or process at each time point. Therefore, it was assumed that they are different expressions of the same unobserved construct. In their study, the scores represented negative sentiments about the relationship expressed by each member of the couple, whereas the common latent process was the negative affect in the dyad. Then, a single LGC model was specified to describe the trajectory of the latent process for the dyad. Because this model specifies a measurement structure for the latent process, *measurement invariance* tests are required to ensure that the construct is the same across measurement occasions (measurement invariance, also called *factorial invariance,* is a statistical procedure for formally testing whether the relations between a set of observed and latent variables are constant over time, or across different groups. See Bollen & Curran, 2006; Ferrer, Balluerka, & Widaman, 2008; Ledermann & Macho, 2014; Meredith, 1993). Other specifications of multivariate processes are also possible in the context of LGC models (McArdle, 1988).

One general limitation of most LGC models for dyadic interactions is that all variability not related to the within- or between-person influences goes to the residuals, without further partitioning. One relatively recent technique suited to overcome this criticism about residuals is the mixed-effects location scale model (Hedeker, Mermelstein, & Demirtas, 2008; Rast, Hofer, & Sparks, 2012), an extension of the mixed-effects model that allows partitioning the residuals. In the context of dyadic data, this model was used to characterize daily emotional ups and downs of couples as a function of individual and partner effects. In addition, the within-person variance over time was explained by factors outside the dyad (e.g., weather), which permeated the daily ups and downs in affect (Ferrer & Rast, 2017).

Bivariate LGC models for dyadic data allow the identification of growth in each variable as well as the relationship between the changes in both variables. But such a relation, expressed by the covariance between slopes, is not time-dependent, thus overlooking possible interrelations between the variables over time. It is also possible to specify a LGC with direct cross-lagged associations between the observed scores of both individuals (Bollen & Curran, 2006; Curran & Bollen, 2001). These parameters would capture time-lagged influences between the two processes, beyond those modeled by the growth process. Whereas the latent slope in this model captures smooth (typically linear) change over time, the addition of time-lagged parameters allows describing time-specific features of change. These parameters can be constant over time, or time-specific, representing discrete periods in the data. Typically, however, a dyadic LGC is specified to model associations between the changes in dyadic processes through the covariances between latent intercepts and slopes. If a main interest is in examining time-lagged influences and sequences between the processes, other models exist that focus more specifically on such relations (Ferrer & McArdle, 2003; McArdle, 2009). We describe these models in the next sections.

Latent change score models (LCS)

Latent change score models (McArdle, 2001, 2009; McArdle & Hamagami, 2001) are a general framework to model the change in a process as well as its time-related sequences. As such, they subsume LGC models as one particular specification. However, whereas the standard LGC model includes parameters capturing information about the whole trajectories, LCS models typically combine those parameters with additional time-lagged effects, which capture time-specific sequences of influences. Here we provide a conceptual overview of this family of models through one clinical example, and we explain how to interpret the main results. More extended descriptions and applications are available elsewhere (e.g., Ferrer et al., 2007; Ferrer & McArdle, 2003, 2010; McArdle & Hamagami, 2001).

There is a large literature suggesting that child and adolescent psychopathology is associated with features of parents and family environment. For example, there is a strong association between depressive symptoms in mothers and anxiety in their adolescent daughters (Garcia-Lopez et al., 2014). Suppose we want to describe the longitudinal trajectory of both processes and to study the dynamic interrelations between these two constructs in a sample of adolescents. We could hypothesize that higher levels of mothers' depressive symptoms would lead to subsequent increases in their adolescent daughters' anxiety, but high anxiety in daughters would not be associated with increases in mother's depressive symptoms. A LGC model would capture whether the initial state and the growth of each process are related, but would not provide information about the order in which these processes influence each other. A potential model to address this question is a dyadic LCS model (Ferrer & McArdle, 2003, 2010, McArdle, 2001, 2009; McArdle & Hamagami, 2001).

Suppose we recruit a sample of mother-daughter dyads and measure mothers' depression and daughters' anxiety every two weeks during four months, leading to nine assessments in total. A potential bivariate LCS specification to examine questions from these data is depicted in Figure 3 (path diagram in top panel, trajectories for 100 dyads in bottom panel). Here, *X* and *Y* represent mothers' depressive symptoms and daughters' anxiety, respectively. In the standard LCS model, a latent variable representing changes is specified for each process at each repeated occasion. This latent variable captures the changes in the latent scores of a process between one occasion and the next.

INSERT FIGURE 3 HERE

At each occasion, the latent process is a function of the initial unobserved level, y_0 and x_0, plus the accumulation of changes up to that occasion. Various specifications for the unobserved changes Δ_y and Δ_x are possible, depending on one's hypothesis of change. In Figure 3, these changes are a function of three elements: a) an additive component (y_s and x_s), b) the latent levels of the same process at the previous occasion (i.e., self-feedback, β_y and β_x), and the latent levels of the other process at previous occasion (i.e., coupling, γ_y and γ_x). All three parameters capture a relevant feature of the trajectory, and therefore they must be interpreted together.

Let us assume the hypothesis that mothers' depressive symptoms (*X*) lead to changes in daughters' anxiety (*Y*), but not the other way around. Support for this hypothesis data would be represented by the γ_y coupling parameter being different from zero, but not γ_x. Additionally, the self-feedback effects (β_y and β_x) would indicate the time-lagged influence of each process on itself, whereas the mean of each of the additive components (i.e., the means of y_s and x_s) would indicate the presence of a constant influence in the changes at each occasion, and the magnitude of such influence. As in a dyadic LGC model, the LCS model captures the variability in the latent initial states and the additive components of the processes (quantified by the variances of y_0, x_0, y_s and x_s) as well as the linear relations among them (quantified by the covariances between those four latent variables). Dyadic LCS models have been applied, to study depressive symptoms in spouses (Kouros & Cummings, 2010), relation between marital satisfaction and self-rated health (Proulx & Snyder-Rivas, 2013), effects of intimate safety, acceptance and activation on marital satisfaction (Hawrilenko, Gray, & Córdova, 2016) and the effect of self-directed interventions on couples' communication (Bodenmann, Hilpert, Nussbeck, & Bradbury, 2014), among others.

Finally, the dyadic LCS model could be extended to include additional processes. Suppose that, in addition to examining mothers' depressive symptoms and daughters' anxiety, we are interested in mothers' expressed emotion and its interplay with the other two processes. This new variable could be included in a model where different patterns of lagged influences among the three processes could be evaluated. Because each additional process can lead to a large number of additional parameters, the model becomes more complex. Hence, we recommend relying on theory for model specification and selection of paths to be examined. For examples of such multivariate systems, see Ferrer & McArdle (2004) and McArdle, Hamagami, Meredith, & Bradway (2000).

Time series analysis

The models described above (APIM, LGC, and LCS) are typically applied in scenarios with relatively large sample sizes. The goal is often to characterize the relevant aspects of change at the group level. In contrast, the term "*time series analysis*" is commonly used in situations with fewer dyads –one is enough– and a relatively long string of data points of the same process per case. Researchers using these methods are typically interested in characterizing the idiosyncratic features of change in each of the dyads under study. Some examples of time series include the hourly stock market value of a given company or the daily temperature of a specific location. In psychological research on dyads, time series are applied primarily applied to the study of emotion, affect, and intensively sampled psychophysiological data (Ferrer & Zhang, 2009; Gottman & Notarius, 2000; Levenson & Gottman, 1983). A critical feature of time series is the self-dependency of the data points. This dependency indicates the degree to which the state of the system at any given moment is correlated with itself at previous times. Time self-dependency can be quantified through the autocorrelation (ACF) and partial autocorrelation (PACF) functions. The former refers to the correlation between two given scores separated for a particular time lag k. For example, an autocorrelation of order one, represents the correlation between adjacent scores (Ferrer & Zhang, 2009). The *partial autocorrelation*, on the other hand, represents the dependence between the scores at times t and $t+k$ after accounting for all the intermediate occasions.

Another key concept in time series processes is that of stationarity. Conceptually, stationarity indicates that the statistical characteristics of the process do not change over time. Therefore, any particular window of time is equally representative of the whole process. For most time series models, weak stationarity is required (Ferrer & Zhang, 2009), implying that: a) the mean levels of the variables in the process do not change (i.e., there is no increase or decrease over time), b) the variances and covariances between the different variables are constant at any particular measurement occasion, and, c) the pattern of lagged dependency only changes as a function of interval length. When a series is not stationary due to trends or seasonal components, it is common to pre-process the data to remove these components before applying any model. A number of methods have been proposed for detecting and analyzing non-stationarity (Bringmann et al., 2017; Cabrieto, Tuerlinckx, Kuppens, Grassmann, & Ceulemans, 2017). For more information about general properties of time series, see Bisgaard & Kulahci (2011) and Shumway & Stoffer (2011).

Auto-regressive models. The auto-regressive (AR) models described here are mathematically equivalent to a Repeated Measures APIM, and also to a LCS model without the latent additive components (x_s and y_s). For example, the classic cross-lagged panel model is an application of AR models applied to repeated measures panel data. In general, however, AR models are a class of models typically used in time series where a long string of data is available. In the context of dyadic research, an important goal of AR models is to describe the idiosyncratic features of each dyad. Figure 4 depicts a path diagram of an AR model (top panel), and the observed scores over 95 days for three different couples (bottom panel). This figure represents a bivariate auto-regressive model for the two members of a couple. The variables Y and X could denote, say, the anxiety of the female and male, respectively, in each dyad. At any time t, the female's anxiety in the relationship Y_t is a function of both her own anxiety at the previous time $Y_{t\text{-}1}$ as well as that of her partner at the previous occasion $X_{t\text{-}1}$. The first influence is typically termed the auto-regressive (AR) coefficient, stability or inertia (Gottman, Swanson, & Murray, 1999; Hamaker et al., 2009) of the process, and is captured by the parameters β. The second influence is the cross-lagged-regression (CL), or partner's effect, captured by the parameter γ_x or γ_y, for the female and male, respectively. Together, these parameters define an auto-regressive model of order one (AR1). The residuals in the processes (d_y and d_x) are typically termed innovations or shock variables and account for the variance in the process not explained by previous states. Such shocks can also be specified so they predict the system at future occasions. In this case, the model becomes an auto-regressive moving-average model, ARMA.

INSERT FIGURE 4 HERE

For simplicity and parsimony, the values of the AR and CL parameters are often constrained to be equal across occasions. But such a constraint can be relaxed in order to account for potential influences of lags greater than one or to test for differences in the parameters across various segments in the data. As noted previously, if an APIM is applied to more than two measures, and the actor and partner influences are constrained to be equal over time, the resulting RM-APIM is equivalent to the auto-regressive model described here (Nestler et al., 2015; Perry et al., 2017).

AR models allow answering questions pertinent to dyadic interactions. Examples of such questions are: Are both individuals in the dyad equally influenced by their own previous states? Are the partner effects the same? Does the model lose its predictive value if one of the partner effects is constrained to be zero–e.g., from male to female? By adding AR and CL parameters of higher order (e.g., lag 2, lag 3) it is possible to evaluate the time-dependency of the model: How many previous measures are needed to explain the state of the system at any given time?

The basic AR model described here can be extended in different ways. For example, Gottman and collaborators (Gottman, Murray, Swanson, Tyson, & Swanson, 2002) proposed a set of dynamic functions –linear and non-linear– that allows the auto-regressive components in the model to capture different patterns of partners' influence. They used these equations to describe dynamic affect changes in couples' interactions and to predict later marriage success. Recent developments of this framework (Hamaker et al., 2009) allow comparing competing models and evaluating which one is better for each particular couple (Madhyastha, Hamaker, & Gottman, 2011).

Dynamic factor analysis (DFA). When studying many psychological phenomena, researchers must account for the fact that the observed scores are not perfect measures of the processes under study –i.e., there is error of measurement. To deal with this issue, multiple observed variables are often used to represent a latent factor representing the unobserved *process*. One model that can accommodate the resulting multivariate time series is the dynamic factor analysis (DFA. Engle & Watson, 1981; McArdle, 1982; P. C. Molenaar, 1985). DFA integrates features of factor analysis and time series analysis into a single model that captures the measurement structure of a latent variable as well as its time dependency.

The basic specification of a DFA model allows addressing questions such as: Which of the observed indicators is contributing more strongly to the latent process? How do the latent processes in the dyad influence each other and themselves over time? Are they influenced by their own previous states or by those of the partner? For how long can such influences be detected? Or, said differently, how long until such influences dissipate? DFA has been primarily used to study fluctuations of emotions over time. For example, it has been applied to examine the change in emotional states of patients with Parkinson disease (Chow, Nesselroade, Shifren, & McArdle, 2004; Shifren, Hooker, Wood, & Nesselroade, 1997), the different patterns of emotional evolution after a romantic breakup (Sbarra & Ferrer, 2006), or the changes in anxiety in patients following psychotherapy (Fisher, Newman, & Molenaar, 2011).

In dyadic data, DFA has been predominantly used to study the interrelations between the emotional ups and downs of both dyad members. For example, Ferrer and Nesselroade (2003) used it to examine the structure and dynamics of affect in a husband and wife couple. One interesting finding from that study is that the husband's negative affect on a given day influenced the wife's negative affect one day later, while at the same time inhibiting her positive mood. Ferrer and Widaman (2008) applied DFA to a large sample of dyads to investigate similar questions of structure and dynamics. Some findings of particular relevance included: a) large differences between results from a model fitted to the entire sample and a model fitted to each individual dyad, and b) very large variability in both affect structure and dynamics across dyads, without support for a model that represents all couples – "the average couple". In another study, Castro-Schilo and Ferrer (2013), employed DFA to extract information about daily affective dynamics in couples and compared the predictive validity of such information against standard measures, such as mean and standard deviation, of the time series. The DFA parameters representing interrelations between the two individuals in the dyad over time were predictive of relationship quality – but not breakup – one and two years later after the daily data.

Figure 5 depicts a path diagram of a DFA (top panel) and the manifest and latent scores of one couples over 95 days (bottom panel). In this figure, the latent variables y_t and x_t represent negative affect over time for a female and a male in the couple. Suppose we want to address the question: Is the negative affect of each dyad member equally important for predicting the negative affect of the other member? In other words, are the time-lagged partner effects symmetrical? The latent factors representing negative affect are measured by three manifest variables (Y_1–Y_3 and X_1–X_3, for the female and male, respectively). Different specifications are possible for such a multivariate dyadic system. Here, we describe a *process* DFA model in which time dependencies are modeled through relations among the factors (Browne & Nesselroade, 2005; Browne & Zhang, 2007; Ferrer & Zhang, 2009).

INSERT FIGURE 5 HERE.

In a standard specification of a process DFA, at any given occasion, there is a measurement structure representing how the various observed variables relate to the latent factor. Such a measurement structure is typically held invariant across occasions, so relations among the factors over time can be examined. For example, according to Figure 5, the female's and male's negative affect factors are being measured by three variables. Each of these variables relates to its latent factor and also has its unique variance. Thus, at each measurement occasion, the model describes the measurement structure of negative affect for each person. The associations among the latent factors are specified to examine time-dependencies. In the path diagram of Figure 5, the latent negative affect factor for each person is influenced by his or her own affect, and the partner's affect at the previous occasion (lag-1 effects), as well as their own affect at the occasion before the previous (lag-2 effects). These auto- and cross-lagged influences are analogous to those described for the AR model, but relate latent factors that take into consideration their measurement structure. Two random shock variables z_y and z_x represent the variance in each factor that is not accounted for by the system.

In a standard specification, stationarity of the system is assumed, and these parameters are constrained to be invariant over time, indicating that the effects are the same throughout the entire time series. This constraint, however, can be relaxed to test hypotheses of temporal sequences (Ferrer & Nesselroade, 2003), examine possible time-varying effects in the parameters (Chow, Zu, Shifren, & Zhang, 2011), or investigate trends in the data (Molenaar, Gooijer, & Schmitz, 1992; Molenaar & Nesselroade, 2001). Similarly, the processes can be specified to be influenced not only by the adjacent occasion but also by other occasions before, by including additional regression coefficients from t-2, t-3 … up to t-k, leading to a process of k^{th} *order*. If the members of the dyad are influenced by each other in a symmetrical manner, the two cross-lagged influences will have similar values. If the influence is asymmetrical, one of them will have a lower value.

Differential equations models for dyads

Differential equation models (DEMs) are a class of models to examine the dynamics of a process in continuous time. DEMs are particularly useful for examining dyadic interactions, as these models explicitly consider the two members of a dyad as an interdependent system.

DEMs have been primarily used as a theoretical framework to investigate the predictive behaviour of a dyadic system under formal mathematical assumptions (Felmlee, 2006; Felmlee & Greenberg, 1999). In psychology, they have been used to examine a wide array of topics, including, intimacy and disclosure in marriage (Boker & Laurenceau, 2006), attachment and affect corregulation (Butner, Diamond, & Hicks, 2007), dynamics in families (Chow, Mattson, & Messinger, 2014; Ram, Shiyko, Lunkenheimer, Doerksen, & Conroy, 2014), daily emotional ups and downs in couples (Chow, Ferrer, & Nesselroade, 2007; Steele & Ferrer, 2011), self-organization and nonstationarity in dyadic interactions (Chow, Ou, Cohn, & Messinger, 2017), temporal evolution of emotions in romantic partners (Butler, 2017; Reed, Barnard, & Butler, 2015), and the dynamics of physiological signals between partners in romantic couples (Ferrer & Helm, 2013; Helm, Sbarra, & Ferrer, 2014, 2012).

In general terms, DEMs directly model the changes in the system – and each of its units – as a continuous process. As such, they are a general framework to study dynamics. A desirable feature of these models is that such generality allows researchers to specify a particular model that best represents the potential mechanisms underlying such dynamics. For dyads, the model would involve two differential equations, one for each person in the dyad. One such model developed in the context of dyadic interactions was developed by Felmlee and colleagues (Felmlee, 2006; Felmlee & Greenberg, 1999) to study individual goals and dyadic influences.

In the context of, say, daily emotions of two individuals in a married couple, this model would specify the rate of change in the daily emotions for each individual as a function of two parameters: one representing the extent to which each person changes as a function of the partner's current emotion. Therefore, the first component can be understood as representing self-regulation, whereas the second term would represent co-regulation, or the degree of emotional interrelation between both individuals. Different values and restrictions for these four parameters lead to different behaviors of the system over time (Felmlee, 2006; Ferrer & Steele, 2013, 2012; Steele, Gonzales, & Ferrer, in press). The top panel in Figure 6 depicts four combinations of parameters, leading to different regulatory patterns. The bottom panel in Figure 6 depicts two examples of predicted and observed trajectories.

INSERT FIGURE 6 HERE.

If the parameters representing self-regulation are positive for both individuals, they are expected to change towards their own emotional equilibrium. If they are negative, their affect tends to drift away from their corresponding equilibrium points –i.e., the within-partner influence does not regulate the system, because the farther they are from the equilibrium, the faster they will move away. If the parameters representing co-regulation are positive for both individuals, they partners engage in a cooperative process in which they tend to converge over time. If they are negative, both individuals tend to drift away from the partner's emotional state.

Exploratory and computational methods for studying dyadic data

In addition to the models described thus far, several newer exploratory methods are now available for capturing relevant features of the dyad without relying on statistical assumptions such as normality, homoscedasticity or stationarity (Chow, Ferrer, & Hsieh, 2011). The application of some of these methods to dyadic interactions is still in its nascent form but they will become increasingly common in the near future. Some examples of this methodology includes computational algorithm to identify periods of similarity in couples' daily emotional fluctuations (Ferrer, Chen, Chow, & Hsieh, 2010, p. 20; Ferrer, Steele, & Hsieh, 2012; Hsieh, Ferrer, Chen, & Chow, 2010), or network analysis for investigating the structure and dynamics of affect in couples (Bringmann et al., 2013, 2016; Ferrer et al., 2010). Ferrer (2016) provides a brief overview of these innovative approaches.

A note on computer programs for dyadic data analysis

All the models described in this chapter can be specified in within different modeling frameworks. The APIM, LGC, LCS and AR models are often specified through structural equation modeling (SEM). Some of the most popular computer software for estimating SEMs are standalone programs such as Mplus (Muthén & Muthén, 1998), and the packages lavaan (Rosseel, 2012) and OpenMx (Boker et al., 2011; Neale et al., 2016) for the R programming language (R Core Team, 2017). Kline (2016) provides a comprehensive review of computer tools for SEM. Most of these models can also be specified in the multilevel framework (hierarchical linear models, mixed-effects models), using standard multilevel modeling software such as SAS, HLM, or, within the R environment, the packages lme4 (Bates, Mächler, Bolker, & Walker, 2015) and MCMCglmm (Hadfield, 2010).

Regarding the dynamic models described here (i.e., AR, DFA, DEM), multiple software options are available for fitting them. Some recently developed packages are flexible enough for specifying and fitting any of these dynamic systems models: OpenMx (Boker et al., 2011; Neale et al., 2016), dynr (Ou, Hunter, & Chow, 2017) and ctsem (Driver, Oud, & Voelkle, 2017) are powerful tools for fitting any of these dynamic models to dyadic data. Other programs are also available that were developed specifically for time series (DyFA; Browne & Zhang, 2003; Zhang & Browne, 2008).

Conclusion

Research on dyads in clinical research – as in any other social and behavioral science – fundamentally involves studying systems over time. This premise relies on the interdependence between the two people in a dyad, which leads to many interesting questions about processes and dynamics. Understanding the emotional underpinnings of romantic couples, for example, requires knowledge about how each person's emotions, thoughts, and behaviors influence those of the other person. Knowing how the working alliance between a therapist and a client develops over time depends on insights about the interactions between both individuals, as they exchange information and emotion. Finally, fully understanding child psychopathology requires knowledge about their parents' psychological well-being as well. To answer these questions, analytic techniques are needed that can capture key aspects of the interdependence between the members of a dyad.

Many authors emphasize that research in clinical psychology must focus on the process of change and the factors that moderate and mediate this change (Granic & Patterson, 2006; Hayes & Strauss, 1998; Hollon et al., 2002; Laurenceau et al., 2007). This implies transitioning from asking questions about the outcomes (i.e., Did the therapy work?) to questions about the processes and mechanisms (i.e., How did it work?). Accordingly, clinical researchers need models that can describe the temporal dynamics of these processes. Recent advances in quantitative methodology have yielded multiple techniques that allow researchers to examine such questions about processes and dynamics. In this chapter we reviewed a number of models developed to capture different aspects of dyadic interactions. We emphasized models that focus on change and dynamics because they are the best suited to answer questions related to processes in dyads. We hope the information provided here is useful as psychological scientists deepen their focus on the study of dyadic processes.

References

Anker, M. G., Owen, J., Duncan, B. L., & Sparks, J. A. (2010). The alliance in couple therapy: Partner influence, early change, and alliance patterns in a naturalistic sample. *Journal of Consulting and Clinical Psychology*, *78*(5), 635–645. https://doi.org/10.1037/a0020051

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, *67*(1). https://doi.org/10.18637/jss.v067.i01

Baucom, B. R., Dickenson, J. A., Atkins, D. C., Baucom, D. H., Fischer, M. S., Weusthoff, S., … Zimmermann, T. (2015). The interpersonal process model of demand/withdraw behavior. *Journal of Family Psychology*, *29*(1), 80–90. http://dx.doi.org/10.1037/fam0000044

Baucom, B. R., Sheng, E., Christensen, A., Georgiou, P. G., Narayanan, S. S., & Atkins, D. C. (2015). Behaviorally-based couple therapies reduce emotional arousal during couple conflict. *Behaviour Research and Therapy*, *72*, 49–55. https://doi.org/10.1016/j.brat.2015.06.015

Berghuis, J. P., & Stanton, A. L. (2002). Adjustment to a dyadic stressor: A longitudinal study of coping and depressive symptoms in infertile couples over an insemination attempt. *Journal of Consulting and Clinical Psychology*, *70*(2), 433–438. https://doi.org/10.1037/0022-006X.70.2.433

Bisgaard, S., & Kulahci, M. (2011). *Time series analysis and forecasting by example*. Hoboken, NJ: Wiley.

Bodenmann, G., Hilpert, P., Nussbeck, F. W., & Bradbury, T. N. (2014). Enhancement of couples' communication and dyadic coping by a self-directed approach: A randomized controlled trial. *Journal of Consulting and Clinical Psychology*, *82*(4), 580–591. https://doi.org/10.1037/a0036356

Boker, S. M., & Laurenceau, J.-P. (2006). Dynamical systems modeling: An application to the regulation of intimacy and disclosure in marriage. In T. A. Walls & J. L. Schafer (Eds.), *Models for Intensive Longitudinal Data* (pp. 195–218). New York, NY: Oxford University Press.

Boker, S. M., Neale, M., Maes, H., Wilde, M., Spiegel, M., Brick, T., … Bates, T. (2011). OpenMx: an open source extended structural equation modeling framework. *Psychometrika*, *76*(2), 306–317.

Bolger, N., & Laurenceau, J.-P. (2013). Design and Analysis of Intensive Longitudinal Studies of Distinguishable Dyads. In *Intensive longitudinal methods: an introduction to diary and experience sampling research* (pp. 143–175). New York, NY: Guilford Press.

Bollen, K. A., & Curran, P. J. (2006). *Latent curve models: a structural equation perspective*. Hoboken, N.J: Wiley-Interscience.

Bringmann, L. F., Hamaker, E. L., Vigo, D. E., Aubert, A., Borsboom, D., & Tuerlinckx, F. (2017). Changing dynamics: Time-varying autoregressive models using generalized additive modeling. *Psychological Methods*, *22*(3), 409–425. https://doi.org/10.1037/met0000085

Bringmann, L. F., Pe, M. L., Vissers, N., Ceulemans, E., Borsboom, D., Vanpaemel, W., … Kuppens, P. (2016). Assessing Temporal Emotion Dynamics Using Networks. *Assessment*, *23*(4), 425–435. https://doi.org/10.1177/1073191116645909

Bringmann, L. F., Vissers, N., Wichers, M., Geschwind, N., Kuppens, P., Peeters, F., … Tuerlinckx, F. (2013). A Network Approach to Psychopathology: New Insights into Clinical Longitudinal Data. *PLOS ONE*, *8*(4), e60188. https://doi.org/10.1371/journal.pone.0060188

Browne, M. W., & Nesselroade, J. R. (2005). Representing psychological processes with dynamic factor models: some promising uses and extensions of arma time series models. In A. Maydeu-Olivares & J. J. McArdle (Eds.), *Advances in Psychometrics: A Festschrift for Roderick P. McDonald* (pp. 415–452). Mahwah, N.J: Lawrence Erlbaum Associates.

Browne, M. W., & Zhang, G. (2003). DyFA 2.03 User Guide. Retrieved from http://quantrm2.psy.ohiostate.edu/browne/software.htm

Browne, M. W., & Zhang, G. (2007). Developments in the factor analysis of individual time series. In R. Cudeck & R. C. MacCallum (Eds.), *Factor Analysis at 100: Time Series in Psychology. Historical Developments and Future Directions* (pp. 265–291). Mahwah, N.J: Lawrence Erlbaum Associates.

Butler, E. A. (2017). Emotions are temporal interpersonal systems. *Current Opinion in Psychology*, *17*(Supplement C), 129–134. https://doi.org/10.1016/j.copsyc.2017.07.005

Butner, J., Diamond, L. M., & Hicks, A. M. (2007). Attachment style and two forms of affect coregulation between romantic partners. *Personal Relationships*, *14*(3), 431–455.

Butterfield, R. M., & Lewis, M. A. (2002). Health-Related Social Influence: A Social Ecological Perspective on Tactic Use. *Journal of Social and Personal Relationships*, *19*(4), 505–526. https://doi.org/10.1177/0265407502019004050

Cabrieto, J., Tuerlinckx, F., Kuppens, P., Grassmann, M., & Ceulemans, E. (2017). Detecting correlation changes in multivariate time series: A comparison of four non-parametric change point detection methods. *Behavior Research Methods*, *49*(3), 988–1005. https://doi.org/10.3758/s13428-016-0754-9

Campbell, L., Simpson, J. A., Kashy, D. A., & Rholes, W. S. (2001). Attachment Orientations, Dependence, and Behavior in a Stressful Situation: An Application of the Actor-Partner

Interdependence Model. *Journal of Social and Personal Relationships*, *18*(6), 821–843. https://doi.org/10.1177/0265407501186005

Castro-Schilo, L., & Ferrer, E. (2013). Comparison of Nomothetic Versus Idiographic-Oriented Methods for Making Predictions About Distal Outcomes From Time Series Data. *Multivariate Behavioral Research*, *48*(2), 175–207. https://doi.org/10.1080/00273171.2012.736042

Chow, S.-M., Ferrer, E., & Hsieh, F. (2011). *Statistical methods for modeling human dynamics: An interdisciplinary dialogue*. New York, NY: Taylor & Francis.

Chow, S.-M., Ferrer, E., & Nesselroade, J. R. (2007). An unscented Kalman filter approach to the estimation of nonlinear dynamical systems models. *Multivariate Behavioral Research*, *42*(2), 283–321.

Chow, S.-M., Mattson, W. I., & Messinger, D. S. (2014). Representing Trends and Moment-to-Moment Variability in Dyadic and Family Processes Using State-Space Modeling Techniques. In *Emerging Methods in Family Research* (pp. 39–55). Springer, Cham. https://doi.org/10.1007/978-3-319-01562-0_3

Chow, S.-M., Nesselroade, J. R., Shifren, K., & McArdle, J. J. (2004). Dynamic Structure of Emotions Among Individuals with Parkinson's Disease. *Structural Equation Modeling: A Multidisciplinary Journal*, *11*(4), 560–582. https://doi.org/10.1207/s15328007sem1104_4

Chow, S.-M., Ou, O., Cohn, J. F., & Messinger, D. S. (2017). Representing Self- Organization and Non-Stationarities in Dyadic Interaction Processes Using Dynamic Systems Modeling Techniques. In A. Von Davier, P. C. Kyllonen, & M. Zhu (Eds.), *Innovative Assessment of Collaboration*. New York, NY: Springer.

Chow, S.-M., Zu, J., Shifren, K., & Zhang, G. (2011). Dynamic Factor Analysis Models With Time-Varying Parameters. *Multivariate Behavioral Research*, *46*(2), 303–339. https://doi.org/10.1080/00273171.2011.563697

Cook, W. L., & Snyder, D. K. (2005). Analyzing Nonindependent Outcomes in Couple Therapy Using the Actor-Partner Interdependence Model. *Journal of Family Psychology*, *19*(1), 133–141. https://doi.org/10.1037/0893-3200.19.1.133

Crowell, S. E., Baucom, B. R., Yaptangco, M., Bride, D., Hsiao, R., McCauley, E., & Beauchaine, T. P. (2014). Emotion dysregulation and dyadic conflict in depressed and typical adolescents: Evaluating concordance across psychophysiological and observational measures. *Biological Psychology*, *98*(Supplement C), 50–58. https://doi.org/10.1016/j.biopsycho.2014.02.009

Curran, P. J., & Bollen, K. A. (2001). The best of both worlds: Combining autoregressive and latent curve models. In L. M. [Ed Collins & A. G. [Ed Sayer (Eds.), *New methods for the analysis of change* (p. 107–135, Chapter xxiv, 442 Pages). American Psychological Association (Washington, DC, US). Retrieved from https://search.proquest.com/docview/619570047/abstract/C78BA068C0774423PQ/1

Driscoll, K. A., Schatschneider, C., McGinnity, K., & Modi, A. C. (2012). Application of Dyadic Data Analysis in Pediatric Psychology: Cystic Fibrosis Health-Related Quality of Life and Anxiety in Child–Caregiver Dyads. *Journal of Pediatric Psychology*, *37*(6), 605–611. https://doi.org/10.1093/jpepsy/jss063

Driver, C. C., Oud, J. H. L., & Voelkle, M. C. (2017). Continuous Time Structural Equation Modeling with R Package ctsem. *Journal of Statistical Software*, *77*(5). https://doi.org/10.18637/jss.v077.i05

Engle, R., & Watson, M. (1981). A One-Factor Multivariate Time Series Model of Metropolitan Wage Rates. *Journal of the American Statistical Association*, *76*(376), 774–781. https://doi.org/10.1080/01621459.1981.10477720

Felmlee, D. H. (2006). Application of dynamic systems analysis to dyadic interactions. In D. Ong & M. van Dulmen (Eds.), *Oxford handbook of methods in positive psychology* (pp. 409–422).

Felmlee, D. H., & Greenberg, D. F. (1999). A dynamic systems model of dyadic interaction. *The Journal of Mathematical Sociology*, *23*(3), 155–180. https://doi.org/10.1080/0022250X.1999.9990218

Ferrer, E. (2016). Exploratory Approaches for Studying Social Interactions, Dynamics, and Multivariate Processes in Psychological Science. *Multivariate Behavioral Research*, *51*(2–3), 240–256. https://doi.org/10.1080/00273171.2016.1140629

Ferrer, E., Balluerka, N., & Widaman, K. F. (2008). Factorial invariance and the specification of second-order latent growth models. *Methodology: European Journal of Research Methods for the Behavioral and Social Sciences*, *4*(1), 22–36. http://dx.doi.org/10.1027/1614-2241.4.1.22

Ferrer, E., Chen, S., Chow, S.-M., & Hsieh, F. (2010). Exploring intra-individual, inter-individual and inter-variable dynamics in dyadic interactions. In S.-M. Chow, E. Ferrer, & F. Hsieh (Eds.), *Statistical methods for modeling human dynamics: An interdisciplinary dialogue* (pp. 381–411). New York, NY: Taylor and Francis.

Ferrer, E., & Helm, J. L. (2013). Dynamical systems modeling of physiological coregulation in dyadic interactions. *International Journal of Psychophysiology*, *88*(3), 296–308. https://doi.org/10.1016/j.ijpsycho.2012.10.013

Ferrer, E., & McArdle, J. J. (2003). Alternative structural models for multivariate longitudinal data analysis. *Structural Equation Modeling-a Multidisciplinary Journal*, *10*(4), 493–524. https://doi.org/10.1207/S15328007SEM1004_1

Ferrer, E., & McArdle, J. J. (2004). An experimental analysis of dynamic hypotheses about cognitive abilities and achievement from childhood to early adulthood. *Developmental Psychology*, *40*(6), 935–952. https://doi.org/10.1037/0012-1649.40.6.935

Ferrer, E., & McArdle, J. J. (2010). Longitudinal Modeling of Developmental Changes in Psychological Research. *Current Directions in Psychological Science*, *19*(3), 149–154. https://doi.org/10.1177/0963721410370300

Ferrer, E., McArdle, J. J., Shaywitz, B. A., Holahan, J. M., Marchione, K., & Shaywitz, S. E. (2007). Longitudinal models of developmental dynamics between reading and cognition from childhood to adolescence. *Developmental Psychology*, *43*(6), 1460–1473. https://doi.org/10.1037/0012-1649.43.6.1460

Ferrer, E., & Nesselroade, J. R. (2003). Modeling Affective Processes in Dyadic Relations via Dynamic Factor Analysis. *Emotion*, *3*(4), 344–360. https://doi.org/10.1037/1528-3542.3.4.344

Ferrer, E., & Rast, P. (2017). Partitioning the variability of daily emotion dynamics in dyadic interactions with a mixed-effects location scale model. *Current Opinion in Behavioral Sciences*, *15*(Supplement C), 10–15. https://doi.org/10.1016/j.cobeha.2017.05.005

Ferrer, E., & Steele, J. (2013). Differential equations for evaluating theoretical models of dyadic interactions. In P. C. M. Molenaar, R. M. Lerner, & K. M. Newell (Eds.), *Handbook of developmental systems theory and methodology*. New York: Guilford.

Ferrer, E., & Steele, J. (2014). Differential equations for evaluating theoretical models of dyadic interactions. *Handbook of Developmental Systems Theory and Methodology. New York: Guilford*.

Ferrer, E., & Steele, J. S. (2012). Dynamic systems analysis of affective processes in dyadic interactions using differential equations. In G. . Hancock & J. . Harrings (Eds.), *Advances in longitudinal methods in the social and behavioral sciences* (pp. 111–134). Charlotte, NC.: Information Age Publishing.

Ferrer, E., Steele, J. S., & Hsieh, F. (2012). Analyzing the Dynamics of Affective Dyadic Interactions Using Patterns of Intra- and Interindividual Variability. *Multivariate Behavioral Research*, *47*(1), 136–171. https://doi.org/10.1080/00273171.2012.640605

Ferrer, E., & Widaman, K. F. (2008). Dynamic factor analysis of dyadic affective processes with inter-group differences. *Modeling Dyadic and Interdependent Data in the Developmental and Behavioral Sciences*, 107–137.

Ferrer, E., & Zhang, G. (2009). Time series models for examining psychological processes: Applications and new developments. In R. E. Millsap & A. Maydeu-Olivares (Eds.), *Modeling dyadic and interdependent data in the developmental and behavioral sciences* (pp. 107–137). London: Sage Publications.

Fisher, A. J., Newman, M. G., & Molenaar, P. C. M. (2011). A quantitative method for the analysis of nomothetic relationships between idiographic structures: Dynamic patterns create attractor states for sustained posttreatment change. *Journal of Consulting and Clinical Psychology*, *79*(4), 552–563. http://dx.doi.org/10.1037/a0024069

Franks, M. M., Wendorf, C. A., Gonzalez, R., & Ketterer, M. (2004). Aid and Influence: Health-Promoting Exchanges of Older Married Partners. *Journal of Social and Personal Relationships, 21*(4), 431–445. https://doi.org/10.1177/0265407504044839

Garcia-Lopez, L. J., Díaz-Castela, M. del M., Muela-Martinez, J. A., & Espinosa-Fernandez, L. (2014). Can parent training for parents with high levels of expressed emotion have a positive effect on their child's social anxiety improvement? *Journal of Anxiety Disorders, 28*(8), 812–822. https://doi.org/10.1016/j.janxdis.2014.09.001

Girard, J., Wright, A., Beeney, J., Lazarus, S., Scott, L., Stepp, S., & Pilkonis, P. (2017). *Interpersonal Problems Across Levels of the Psychopathology Hierarchy*. Open Science Framework. https://doi.org/10.17605/OSF.IO/6W23E

Goldfried, M. R., Greenberg, L. S., & Marmar, C. (1990). Individual psychotherapy: Process and outcome. *Annual Review of Psychology*, *41*(1), 659–688.

Gonzalez, R., & Griffin, D. (1997). On the statistics of interdependence: Treating dyadic data with respect. In S. Duck (Ed.), *Handbook of personal relationships: Theory, research and interventions* (pp. 271–302). Hoboken, NJ: John Wiley.

Gottman, J. M., Murray, J. D., Swanson, C. C., Tyson, R., & Swanson, K. R. (2002). *The mathematics of marriage: Dynamic nonlinear models*. MIT Press.

Gottman, J. M., & Notarius, C. I. (2000). Decade Review: Observing Marital Interaction. *Journal of Marriage and Family, 62*(4), 927–947. https://doi.org/10.1111/j.1741-3737.2000.00927.x

Gottman, J. M., Swanson, C., & Murray, J. (1999). The mathematics of marital conflict: Dynamic mathematical nonlinear modeling of newlywed marital interaction. *Journal of Family Psychology*, *13*(1), 3.

Granic, I., & Patterson, G. R. (2006). Toward a comprehensive model of antisocial development: A dynamic systems approach. *Psychological Review*, *113*(1), 101–131. http://dx.doi.org/10.1037/0033-295X.113.1.101

Hadfield, J. D. (2010). MCMC Methods for Multi-Response Generalized Linear Mixed Models: The MCMCglmm R Package. *Journal of Statistical Software*, *33*(2). https://doi.org/10.18637/jss.v033.i02

Hagedoorn, M., Kuijer, R. G., Buunk, B. P., DeJong, G. M., Wobbes, T., & Sanderman, R. (2000). Marital satisfaction in patients with cancer: Does support from intimate partners benefit those who need it most? *Health Psychology*, *19*(3), 274–282. https://doi.org/10.1037/0278-6133.19.3.274

Hamaker, E. L., Zhang, Z., & Maas, H. L. J. van der. (2009). Using Threshold Autoregressive Models to Study Dyadic Interactions. *Psychometrika*, *74*(4), 727. https://doi.org/10.1007/s11336-009-9113-4

Hawrilenko, M., Gray, T. D., & Córdova, J. V. (2016). The heart of change: Acceptance and intimacy mediate treatment response in a brief couples intervention. *Journal of Family Psychology*, *30*(1), 93–103. https://doi.org/10.1037/fam0000160

Hayes, A. M., & Strauss, J. L. (1998). Dynamic systems theory as a paradigm for the study of change in psychotherapy: An application to cognitive therapy for depression. *Journal of Consulting and Clinical Psychology*, *66*(6), 939–947. https://doi.org/10.1037/0022-006X.66.6.939

Hedeker, D., Mermelstein, R. J., & Demirtas, H. (2008). An Application of a Mixed-Effects Location Scale Model for Analysis of Ecological Momentary Assessment (EMA) Data. *Biometrics*, *64*(2), 627–634. https://doi.org/10.1111/j.1541-0420.2007.00924.x

Helm, J. L., Sbarra, D. A., & Ferrer, E. (2014). Coregulation of respiratory sinus arrhythmia in adult romantic partners. *Emotion*, *14*(3), 522–531. http://dx.doi.org/10.1037/a0035960

Helm, J. L., Sbarra, D., & Ferrer, E. (2012). Assessing Cross-Partner Associations in Physiological Responses via Coupled Oscillator Models. *Emotion*, *12*(4), 748–762. https://doi.org/10.1037/a0025036

Hollon, S. D., Muñoz, R. F., Barlow, D. H., Beardslee, W. R., Bell, C. C., Bernal, G., … Sommers, D. (2002). Psychosocial intervention development for the prevention and treatment of depression: promoting innovation and increasing access. *Biological Psychiatry*, *52*(6), 610–630. https://doi.org/10.1016/S0006-3223(02)01384-7

Hsieh, F., Ferrer, E., Chen, S.-C., & Chow, S.-M. (2010). Exploring the Dynamics of Dyadic Interactions via Hierarchical Segmentation. *Psychometrika*, *75*(2), 351–372. https://doi.org/10.1007/s11336-009-9146-8

Kenny, D. A. (1996). Models of Non-Independence in Dyadic Research. *Journal of Social and Personal Relationships*, *13*(2), 279–294. https://doi.org/10.1177/0265407596132007

Kenny, D. A., & Judd, C. M. (1986). Consequences of violating the independence assumption in analysis of variance. *Psychological Bulletin*, *99*(3), 422–431. https://doi.org/10.1037/0033-2909.99.3.422

Kenny, D. A., Kashy, D. A., & Bolger, N. (1998). Data analysis in social psychology. In D. Gilbert, S. Fiske, & G. Lindzey (Eds.), *Handbook of Social Psychology* (4th ed., Vol. 1, pp. 233–265). Boston: McGraw-Hill.

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

Kivlighan, D. M., Clements, L., Blake, C., Arnzen, A., & Brady, L. (1993). Counselor Sex Role Orientation, Flexibility, and Working Alliance Formation. *Journal of Counseling & Development*, *72*(1), 95–100. https://doi.org/10.1002/j.1556-6676.1993.tb02284.x

Kivlighan, D. M., Marmarosh, C. L., & Hilsenroth, M. J. (2014). Client and therapist therapeutic alliance, session evaluation, and client reliable change: A moderated actor–partner interdependence model. *Journal of Counseling Psychology*, *61*(1), 15–23. https://doi.org/10.1037/a0034939

Kline, R. B. (2016). Computer Tools. In *Principles and Practice of Structural Equation Modeling* (4th ed., pp. 97–113). New York, NY: The Guilford Press.

Kopta, S. M., Lueger, R. J., Saunders, S. M., & Howard, K. I. (1999). Individual Psychotherapy Outcome and Process Research: Challenges Leading to Greater Turmoil or a Positive Transition? *Annual Review of Psychology*, *50*(1), 441–469. https://doi.org/10.1146/annurev.psych.50.1.441

Kouros, C. D., & Cummings, E. M. (2010). Longitudinal Associations Between Husbands' and Wives' Depressive Symptoms. *Journal of Marriage and Family*, *72*(1), 135–147. https://doi.org/10.1111/j.1741-3737.2009.00688.x

Laurenceau, J.-P., & Bolger, N. (2005). Using Diary Methods to Study Marital and Family Processes. *Journal of Family Psychology*, *19*(1), 86–97. http://dx.doi.org/10.1037/0893-3200.19.1.86

Laurenceau, J.-P., Hayes, A. M., & Feldman, G. C. (2007). Some methodological and statistical issues in the study of change processes in psychotherapy. *Clinical Psychology Review*, *27*(6), 682–695. https://doi.org/10.1016/j.cpr.2007.01.007

Lawrence, E., Yoon, J., Langer, A., & Ro, E. (2009). Is Psychological Aggression as Detrimental as Physical Aggression? The Independent Effects of Psychological Aggression on Depression and Anxiety Symptoms. *Violence and Victims*, *24*(1), 20–35. https://doi.org/10.1891/0886-6708.24.1.20

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

Ledermann, T., & Macho, S. (2014). Analyzing change at the dyadic level: The common fate growth model. *Journal of Family Psychology*, *28*(2), 204–213. https://doi.org/10.1037/a0036051

Ledermann, T., Macho, S., & Kenny, D. A. (2011). Assessing Mediation in Dyadic Data Using the Actor-Partner Interdependence Model. *Structural Equation Modeling: A Multidisciplinary Journal*, *18*(4), 595–612. https://doi.org/10.1080/10705511.2011.607099

Levenson, R. W., & Gottman, J. M. (1983). Marital interaction: Physiological linkage and affective exchange. *Journal of Personality and Social Psychology*, *45*(3), 587–597. http://dx.doi.org/10.1037/0022-3514.45.3.587

Madhyastha, T. M., Hamaker, E. L., & Gottman, J. M. (2011). Investigating spousal influence using moment-to-moment affect data from marital conflict. *Journal of Family Psychology*, *25*(2), 292–300. https://doi.org/10.1037/a0023028

Marmarosh, C. L., Kivlighan, D. M., Bieri, K., LaFauci Schutt, J. M., Barone, C., & Choi, J. (2014). The insecure psychotherapy base: Using client and therapist attachment styles to understand the early alliance. *Psychotherapy, 51*(3), 404–412. https://doi.org/10.1037/a0031989

McArdle, J. J. (1982). Structural equation modeling of an individual system: Preliminary results from “A case study in episodic alcoholism.” *Unpublished Manuscript, Department of Psychology, University of Denver*.

McArdle, J. J. (1988). Dynamic but Structural Equation Modeling of Repeated Measures Data. In J. R. Nesselroade & R. B. Cattell (Eds.), *Handbook of Multivariate Experimental Psychology* (pp. 561–614). Springer US.

McArdle, J. J. (2001). A latent difference score approach to longitudinal dynamic structural analysis. In R. Cudeck, S. du Toit, & D. Sörbom (Eds.), *Structural equation modeling, present and future: a festschrift in honor of Karl Jöreskog*. Lincolnwood, IL: Scientific Software International.

McArdle, J. J. (2009). Latent Variable Modeling of Differences and Changes with Longitudinal Data. *Annual Review of Psychology*, *60*(1), 577–605. https://doi.org/10.1146/annurev.psych.60.110707.163612

McArdle, J. J., & Epstein, D. (1987). Latent Growth Curves within Developmental Structural Equation Models. *Child Development*, *58*(1), 110. https://doi.org/10.2307/1130295

McArdle, J. J., & Hamagami, F. (2001). Latent difference score structural models for linear dynamic analyses with incomplete longitudinal data. In L. M. Collins & A. G. Sayer (Eds.), *New methods for the analysis of change.* (pp. 139–175). Washington: American Psychological Association. https://doi.org/10.1037/10409-005

McArdle, J. J., Hamagami, F., Meredith, W., & Bradway, K. P. (2000). Modeling the dynamic hypotheses of Gf–Gc theory using longitudinal life-span data. *Learning and Individual Differences*, *12*(1), 53–79. https://doi.org/10.1016/S1041-6080(00)00036-4

Medina-Pradas, C., Navarro, J. B., López, S. R., Grau, A., & Obiols, J. E. (2011). Dyadic view of expressed emotion, stress, and eating disorder psychopathology. *Appetite*, *57*(3), 743–748. https://doi.org/10.1016/j.appet.2011.08.016

Meredith, W. (1993). Measurement invariance, factor analysis and factorial invariance. *Psychometrika*, *58*(4), 525–543. https://doi.org/10.1007/BF02294825

Meredith, W., & Tisak, J. (1990). Latent curve analysis. *Psychometrika*, *55*(1), 107–122. https://doi.org/10.1007/BF02294746

Molenaar, P. C. M. (1985). A dynamic factor model for the analysis of multivariate time series. *Psychometrika*, *50*(2), 181–202.

Molenaar, P. C. M., Gooijer, J. G. D., & Schmitz, B. (1992). Dynamic factor analysis of nonstationary multivariate time series. *Psychometrika*, *57*(3), 333–349. https://doi.org/10.1007/BF02295422

Molenaar, P. C. M., & Nesselroade, J. R. (2001). Rotation in the dynamic factor modeling of multivariate stationary time series. *Psychometrika*, *66*(1), 99–107. https://doi.org/10.1007/BF02295735

Muthén, L. K., & Muthén, B. O. (1998). *Mplus User's Guide* (Sixth Edition). Los Angeles, CA: Muthén & Muthén.

Neale, M. C., Hunter, M. D., Pritikin, J. N., Zahery, M., Brick, T. R., Kirkpatrick, R. M., … Boker, S. M. (2016). OpenMx 2.0: Extended structural equation and statistical modeling. *Psychometrika*, *81*(2), 535–549.

Nesselroade, J. R., & Boker, S. M. (1994). Assessing constancy and change. In T. Heatherton & J. Weinberg (Eds.), *Can personality change?* (pp. 121–147). Washington, DC: American Psychological Association.

Nestler, S., Grimm, K. J., & Schönbrodt, F. D. (2015). The Social Consequences and Mechanisms of Personality: How to Analyse Longitudinal Data from Individual, Dyadic, Round-Robin and Network Designs. *European Journal of Personality*, *29*(2), 272–295. https://doi.org/10.1002/per.1997

Ou, L., Hunter, M. D., & Chow, S.-M. (2017). *What´s for dynr. A package for linear and nonlinear DYNamic modeling in R*. Retrieved from https://quantdev.ssri.psu.edu/sites/qdev/files/OuHunterChow_Dynr.pdf

Perry, N. S., Baucom, K. J. W., Bourne, S., Butner, J., Crenshaw, A. O., Hogan, J. N., … Baucom, B. R. W. (2017). Graphic methods for interpreting longitudinal dyadic patterns from repeated-measures actor–partner interdependence models. *Journal of Family Psychology*, *31*(5), 592–603. https://doi.org/10.1037/fam0000293

Proulx, C. M., & Snyder-Rivas, L. A. (2013). The longitudinal associations between marital happiness, problems, and self-rated health. *Journal of Family Psychology*, *27*(2), 194–202. https://doi.org/10.1037/a0031877

Przeworski, A., Zoellner, L. A., Franklin, M. E., Garcia, A., Freeman, J., March, J. S., & Foa, E. B. (2012). Maternal and Child Expressed Emotion as Predictors of Treatment Response in Pediatric Obsessive–Compulsive Disorder. *Child Psychiatry & Human Development*, *43*(3), 337–353. https://doi.org/10.1007/s10578-011-0268-8

R Core Team. (2017). R: A language and environment for statistical computing. Vienna, Austria.

Ram, N., Shiyko, M., Lunkenheimer, E. S., Doerksen, S., & Conroy, D. (2014). Families as Coordinated Symbiotic Systems: Making use of Nonlinear Dynamic Models. In *Emerging Methods in Family Research* (pp. 19–37). Springer, Cham. https://doi.org/10.1007/978-3-319-01562-0_2

Rao, C. R. (1958). Some Statistical Methods for Comparison of Growth Curves. *Biometrics*, *14*(1), 1. https://doi.org/10.2307/2527726

Rast, P., Hofer, S. M., & Sparks, C. (2012). Modeling Individual Differences in Within-Person Variation of Negative and Positive Affect in a Mixed Effects Location Scale Model Using BUGS/JAGS. *Multivariate Behavioral Research*, *47*(2), 177–200. https://doi.org/10.1080/00273171.2012.658328

Reed, R. G., Barnard, K., & Butler, E. A. (2015). Distinguishing emotional coregulation from codysregulation: An investigation of emotional dynamics and body weight in romantic couples. *Emotion, 15*(1), 45–60. http://dx.doi.org/10.1037/a0038561

Rosseel, Y. (2012). lavaan: An R Package for Structural Equation Modeling. *Journal of Statistical Software*, *48*(2). https://doi.org/10.18637/jss.v048.i02

Sbarra, D. A., & Ferrer, E. (2006). The structure and process of emotional experience following nonmarital relationship dissolution: Dynamic factor analyses of love, anger, and sadness. *Emotion*, *6*(2), 224–238. https://doi.org/10.1037/1528-3542.6.2.224

Sbarra, D. A., & Wishman, M. A. (2013). Marital and relational discord. In L. . Castonguay & T. C. Oltmans (Eds.), *Psychopathology: Bridging the gap between basic empirical findings and clinical practice* (pp. 393–418). New York: Guilford Press.

Shifren, K., Hooker, K., Wood, P., & Nesselroade, J. R. (1997). Structure and variation of mood in individuals with Parkinson's disease: A dynamic factor analysis. *Psychology and Aging*, *12*(2), 328–339. https://doi.org/10.1037/0882-7974.12.2.328

Shumway, R. H., & Stoffer, D. S. (2011). *Time series analysis and its applications: with R examples* (3. ed). New York, NY: Springer.

Steele, J. S., & Ferrer, E. (2011). Latent Differential Equation Modeling of Self-Regulatory and Coregulatory Affective Processes. *Multivariate Behavioral Research*, *46*(6), 956–984. https://doi.org/10.1080/00273171.2011.625305

Steele, J. S., Gonzales, J. E., & Ferrer, E. (in press). Uses and limitations of continuous time models to examine dyadic interactions. In K. van Montfort, J. Oud, & M. C. Voelkle (Eds.), *Continuous time modeling in the behavioral and related sciences*. New York, NY: Springer.

Thorson, K., West, T., & Mendes, W. (2017). *Measuring physiological influence in dyads: A guide to designing, implementing, and analyzing dyadic physiological studies*. PsyArXiv. https://doi.org/10.17605/OSF.IO/9NDKF

Zhang, G., & Browne, M. W. (2008). DyFA Bootstrap: Dynamic Factor Analysis of Lagged Correlation Matrices with Bootstrap Standard Errors and Goodness of Fit Test. Version: Beta 1. Retrieved from http://faculty.psy.ohiostate.edu/browne/

Table and Figures

Table 1. Overview of dyadic models

Model	Type of data	Example of clinical research question
Focus on outcomes		
Actor-Partner Interdependence Model (APIM)	Cross-sectional. At least two variables measured on each dyad member	Couples with one partner affected by cancer, “Perception of active engagement of the non-affected partner” and “marital satisfaction” are measured on both partners. Does engagement explain satisfaction? Are the interpersonal and intrapersonal effects equally important? Are the influences reciprocal or is one partner more influential than the other?
	Pre-post. At least one variable measured at pre- and post- for each dyad member (same or different variables measured at each occasion)	“Attachment style” of therapists and clients are measured at the beginning of therapy sessions, and “working alliance” is reported by both individuals after 3 weeks. Does attachment predict alliance? Are the interpersonal and intrapersonal effects equally important? Are the influences reciprocal or is one partner more influential than the other?
Focus on processes		
Large sample size, few measurement occasions per case (↑N, ↓T)	*At least one variable measured on each dyad member; >2 occasions*	*Standard goal: To characterize dyadic change and interrelations at the group level*
Latent Growth Curve Model (LGC)		Couples anticipating an upcoming stressful event for one member. “Anxiety” is being measured on the target member and “relational dissatisfaction” is measured on the partner. What are the trajectories for anxiety and dissatisfaction, as the event approaches? What is the relation between the trajectories in both partners?
Latent Change Score Model (LCS)		“Depressive symptoms” are measured in a sample of mothers, while “anxiety” is measured on their daughters. What is the trajectory of both variables over time? What is the relation between both trajectories? Does mother’s depression predict subsequent increases in the daughter’s anxiety. What about the other way around?
Many measurement occasions per case (↑T)	*Stationarity is typically assumed*	*Standard goal: To characterize change for each dyad member and interrelations among them.*
Auto-Regressive Model (AR) (Equivalent to a Repeated Measures [RM-] APIM)	At least one variable measured on each dyad member; multiple occasions	Daily measures of “anxiety” in couples for four months. Are both partners equally influenced by their own previous anxiety? Are partner effects equally important? How many previous measures are needed to explain the state of the system at any given time (i.e., what is the time-dependency of the system)?

Dynamic Factor Analysis (DFA)	Multiple variables measured on each dyad member; multiple occasions. These variables measure one or more common latent factors on each partner. Measurement invariance is assumed	Daily reports of negative mood reported by both dyad members. A latent factor representing "negative affect" is extracted from the observed variables. What is the structure of negative affect? What is the time dependency of negative affect? Are there differences between both partners? Regarding the latent processes of each partner, are they influenced by their own previous states or by those of the partner? How long until such influences dissipate?
Differential Equations Model (DEM)	One of multiple variables measured on each dyad member; multiple occasions. Time is treated as continuous	Daily measures of negative affect in couples for two months. What are the dynamics of affect for each person in the dyad? What are the dynamics between both individuals? Does each partner self-regulate affect autonomously? Do they co-regulate each other's affect? Is the system stable and progress towards an equilibrium point?

Figure 1. Path diagram of an Actor Partner Independence Model (APIM).

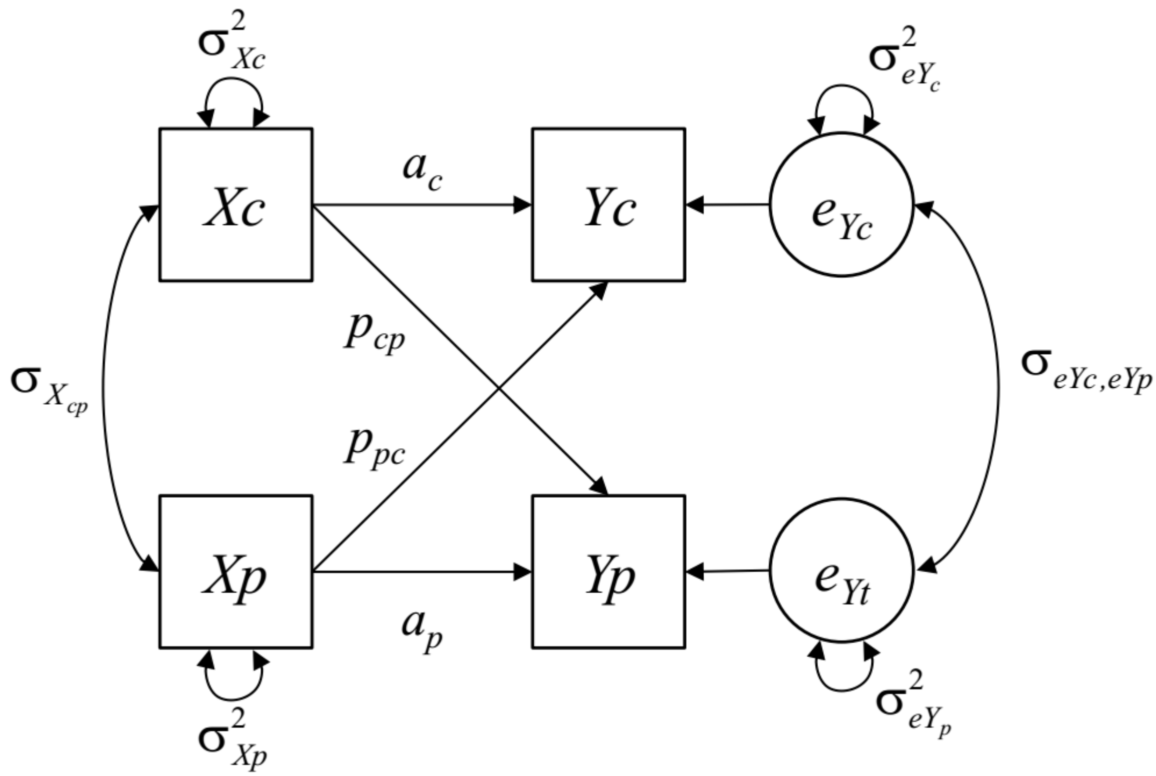

Figure 2. Bivariate (dyadic) Latent Growth Curve (LGC) Model. Path diagram (top panel) and trajectories of a sample of *n*=100 (bottom panel).

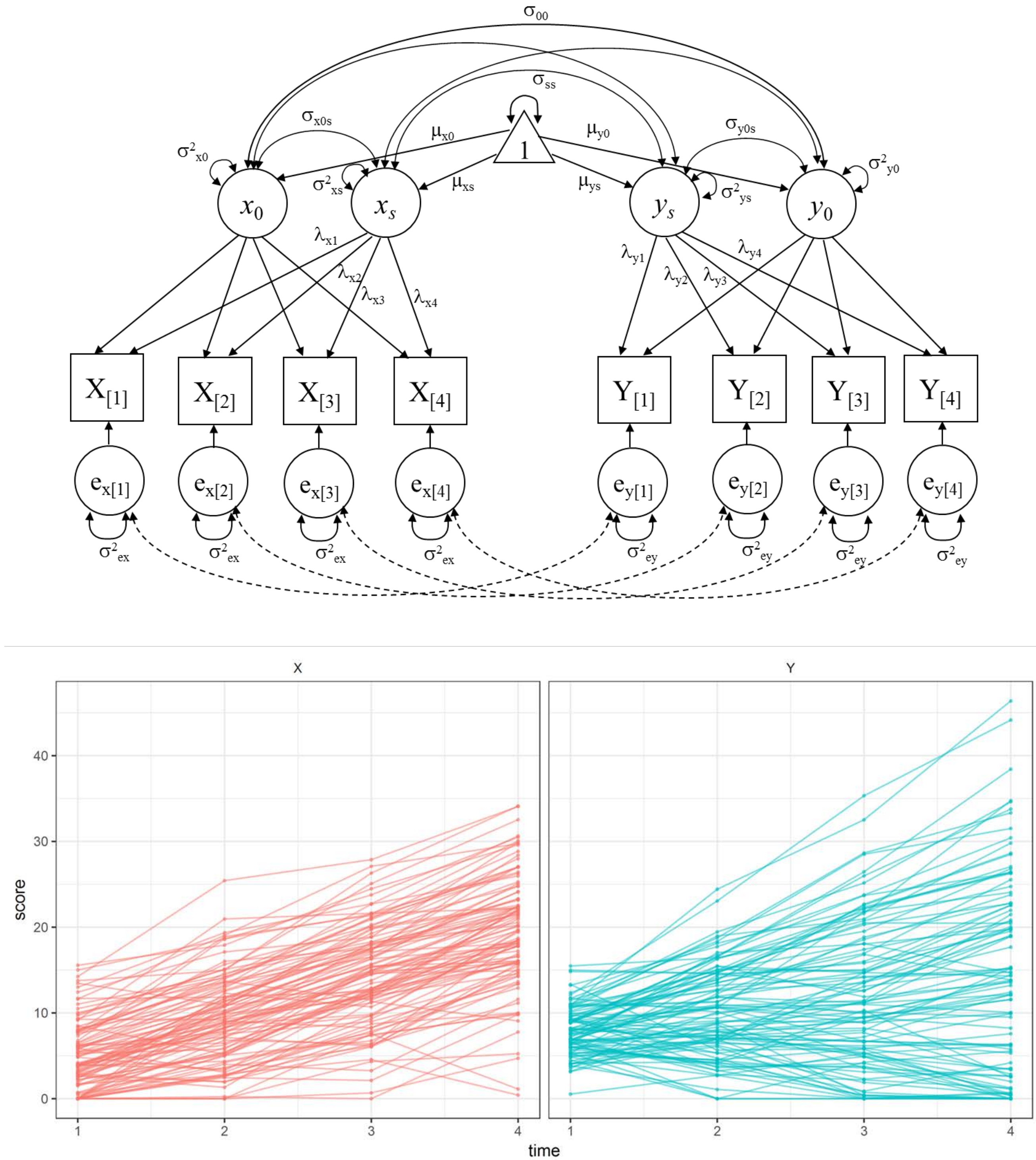

Figure 3. Bivariate (dyadic) Latent Change Score (LCS) Model. Path diagram (top panel) and trajectories of a sample of n=100 (bottom panel).

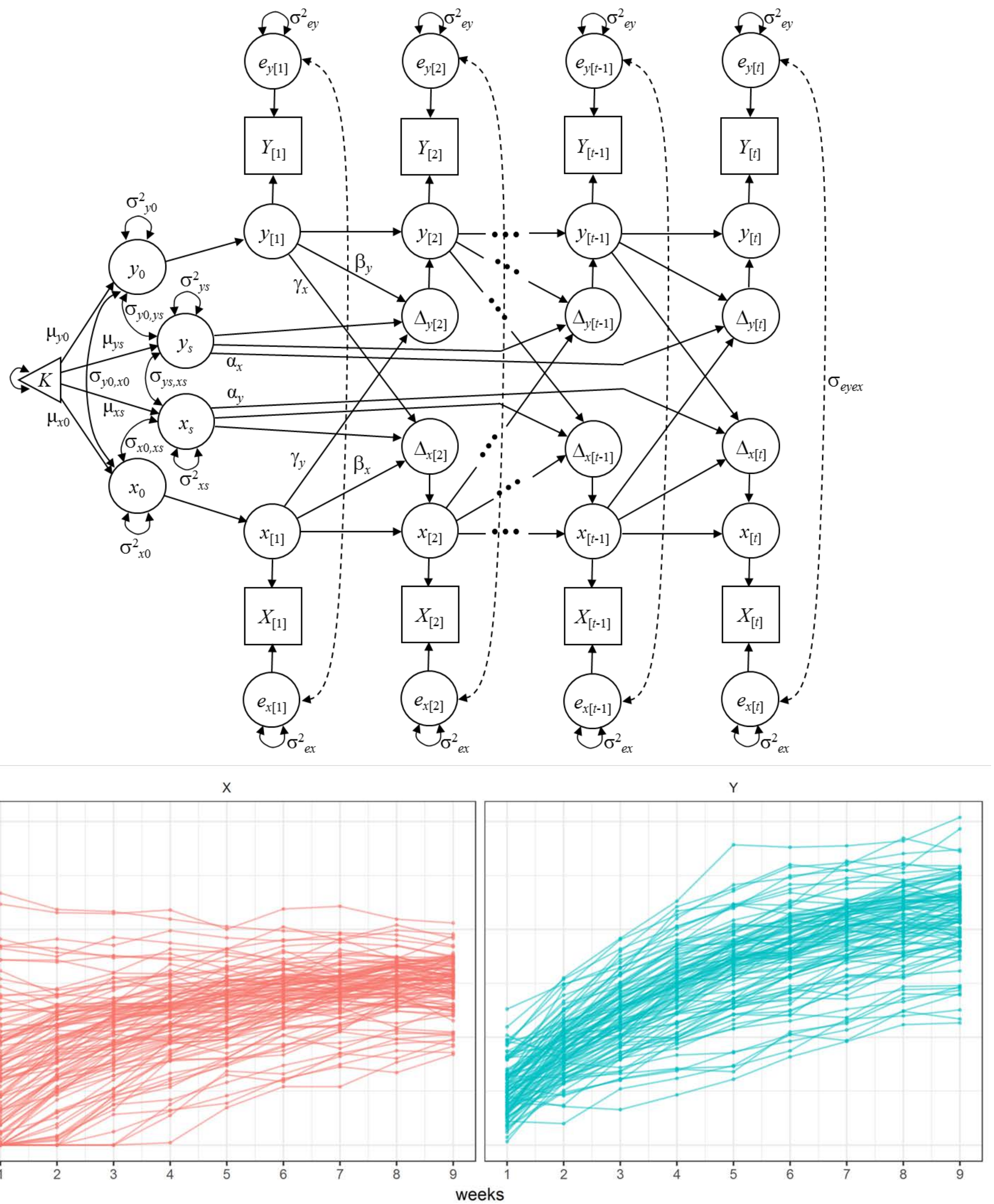

Figure 4. Bivariate (dyadic) Auto-regressive Cross-lagged Model. Path diagram (top panel) and trajectories of three different couples (bottom panel).

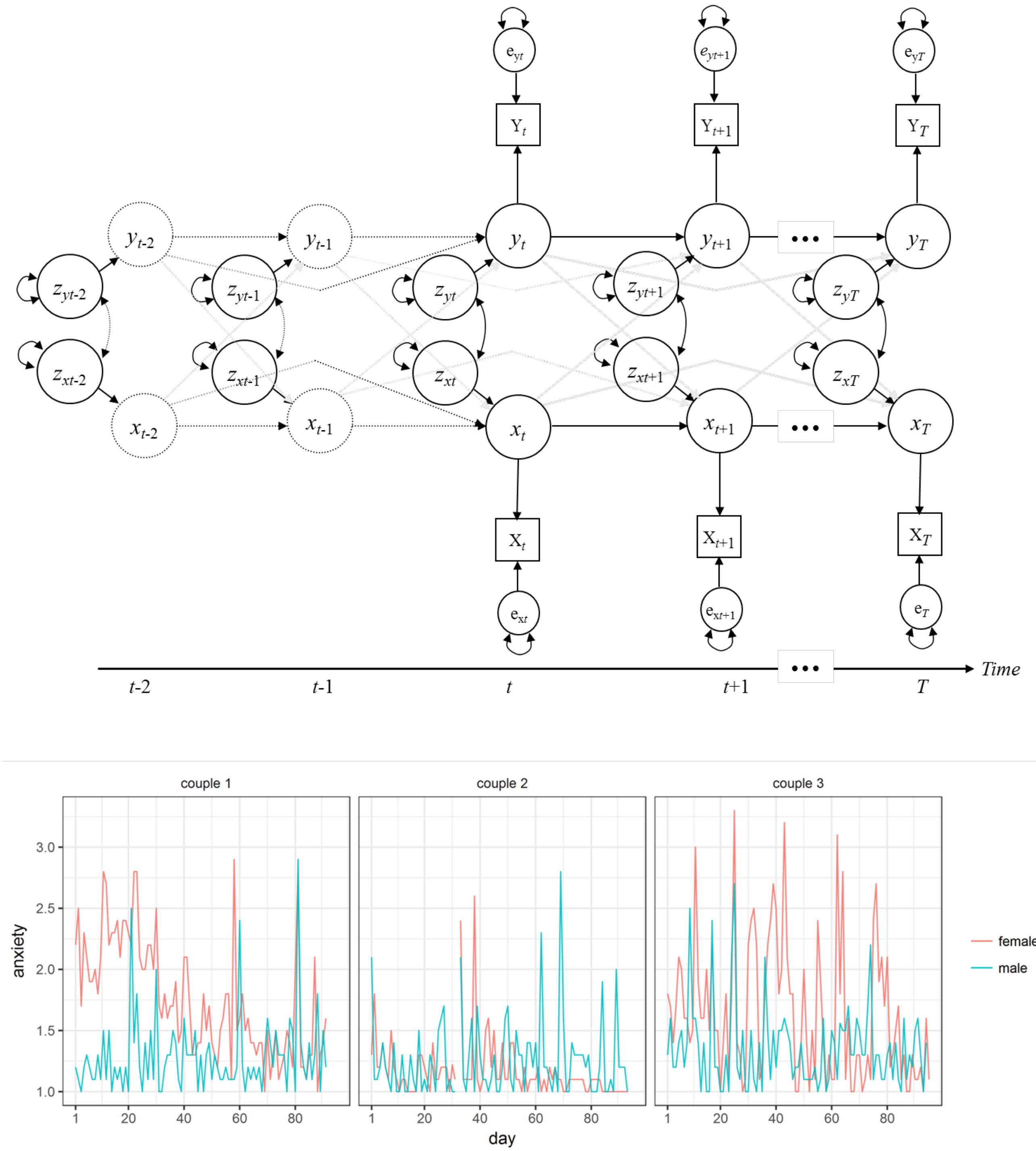

Figure 5. Bivariate (dyadic) Dynamic Factor Analysis (DFA) Model. Path diagram (top panel) and trajectories of one couple in the manifest and latent variables (bottom panel).

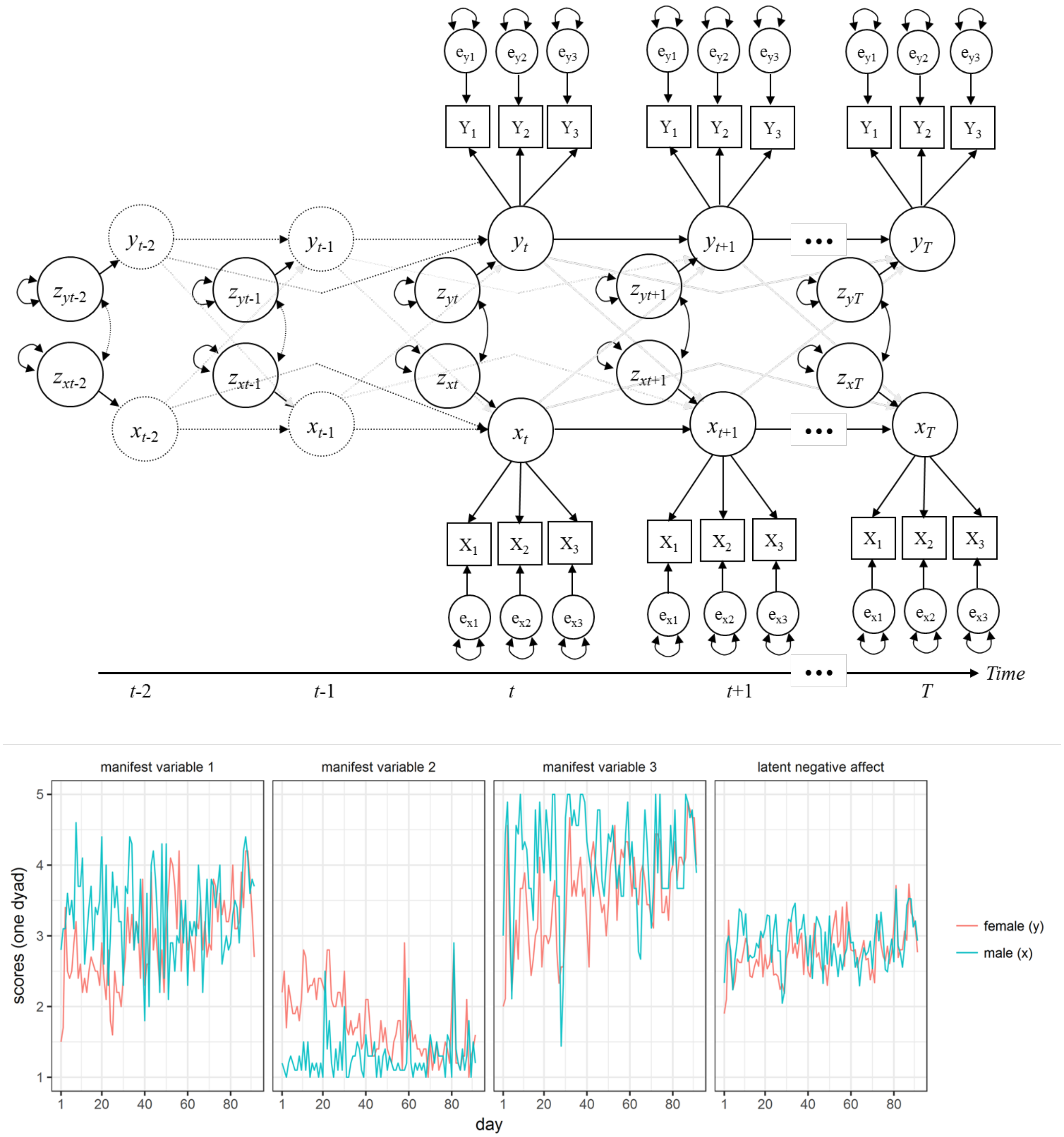

Figure 6. Bivariate (dyadic) Differential Equation Model (DEM). Examples of different trajectories expressed by model parameters (top panel) and observed and predicted trajectories of two couples (bottom panel).