

**Dyadic Models Emerging
From the Longitudinal
Structural Equation Modeling Tradition:
Parallels With Ecological Models of
Interspecific Interactions**

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“Developmental psychology . . . deals with changes within and among bio-cultural ecologies and with the relationships of these changes to changes within and among individuals” (Baltes, Reese, & Nesselroade, 1977, p. 1). Both biological and developmental systems theory has long suggested that there is a “dynamic interaction” or “transaction” between an individual and his or her context or environment (including other individuals) that occurs over time (Bronfenbrenner, 1979; Ford & Lerner, 1992; Lerner, 1991; Sameroff & Chandler, 1975). As illustrated in the three following quotes, the theory underlying the study of development in an ecological context is that individuals and contexts are changing while interacting with one another:

“ . . . the individual is changing in a changing world” (Baltes et al., 1977, p. 1);

"Individuals are dynamically interactive with a complex and changing context" (Ford & Lerner, 1992, p. 80);

"The properties of the person and of the environment, ... and the processes taking place within and between them must be viewed as interdependent and analyzed in systems terms" (Bronfenbrenner, 1979, p. 15).

In order for models to reflect the theory of developmental contextualism, multiple change processes or interactions should be considered: including individual changes, context/environmental changes, and the reciprocal relationships among individuals and/or their environments (see Ram & Nesselrode, 2007, for further elaboration). Or, as put by Wohlwill (1991), "... what [reciprocal relationships] would call for are methodologies that allow one to model the inter patterning between two sets of processes each of which is undergoing change, in part as a function of the other" (p. 128). In sum, the predominant theoretical perspective underlying the study of human development highlights the need for models that articulate how, when, and why dynamic entities interact.

Wohlwill (1991) also suggested that, in particular, models used in the study of organisms (e.g., animals) and their environments may provide a base for inquiry. "The closest approach to this kind of modeling that is indicated for this purpose are probably some of the models from the field of ecology, and similar systems-analytical work" (p. 128). Following this suggestion, we have attempted here to examine how perspectives from the field of ecology might relate to, benefit, and expand some of the modeling procedures and methodology currently being used in lifespan developmental psychology—and in particular the study of dyads.

Almost in parallel to developmental perspectives, the theoretical core in biology and ecology underscores dynamic interactions—how one or more species grow and decline within the context of other species and the environment. Ecologists, for instance, aim to understand the distribution and abundance of species, with a particular focus on how a species' long-term dynamics are affected by interactions with the surrounding environment or other organisms. From the early 20th century, ecologists have been using a combination of theory, observational data, and experimental manipulations to understand how both intraspecific (within a species) and interspecific (between species) interactions affect a species' distribution and abundance (Begon, Harper, & Townsend, 1996). Given the underlying similarity in theoretical perspectives and modeling needs, it appears that much can be gained by exploring how each field has approached and attempted to articulate, test, and understand the mechanisms driving "reciprocal relationships" and "dyadic interactions."

Ecological Models of Interspecific Interactions

For over a century ecologists have been developing and using dynamic models to understand and articulate how species interact with one another (Morin, 1999; Townsend, Begon, & Harper, 2002). These between-species (interspecific) interactions can vary dramatically based on the direction (+/0/-) and strength of the interactions, the size of the interacting species and whether the interactions are reciprocal. These interactions can range from mutualisms or commensalisms, wherein each species is either positively affected or unchanged (e.g., +/+, +/0) by the presence of another species, through neutralism, wherein two species do not compete or interact (e.g., 0/0); to parasitism or competition, wherein one or both species is negatively affected or even killed by the other species (e.g., +/−, 0/−, −/−). Examples include interactions where both species benefit from one another's presence, as in the case of bees and flowers, to those where both species harm each other, as in mixed forest stands of oaks and maples where individual trees compete for water, light, and nutrients (Begon et al., 1996).

Building on the work of two mathematical biologists, A. J. Lotka and V. Volterra (see Wangersky, 1978), ecologists have built a mathematical/theoretical framework for modeling and exploring the mechanisms that underlie interspecific interactions. This framework, presented originally as a pair of first order, nonlinear differential equations, has been used and expanded to describe interspecific interaction processes based on symbiosis, competition, neutralism, mutualism, amensalism, commensalism, predation, parasitism, parasitoidism, etc. (Begon et al., 1996; Gotelli & Ellison, 2004; Murray, 2002; Townsend et al., 2002). In general, the Lotka-Volterra model (for competing species) can be expressed by:

$$\text{Species X: } \frac{dN_x}{dt} = r_x N_x \left[\left(1 - \frac{N_x}{K_x} \right) \pm \left(\alpha_{xy} \frac{N_y}{K_x} \right) \right] \quad (1a)$$

$$\text{Species Y: } \frac{dN_y}{dt} = r_y N_y \left[\left(1 - \frac{N_y}{K_y} \right) \pm \left(\alpha_{yx} \frac{N_x}{K_y} \right) \right] \quad (1b)$$

where the subscripts denote the species (x or y), N represents the population abundance of each species, r is the per capita growth rate, K is the population carrying capacity (e.g., maximum population abundance given intraspecific constraints), and α is the "interaction coefficient" indicating the effect that the abundance of one species has on the growth or decline (i.e., change, dN/dt) of the other species (Murray, 2002). These basic equations have provided a useful framework for the study of interspecific interactions in ecology. Coupled with graphical (isocline analysis) and simulation analysis,

the modeling framework has provided key predictions and knowledge about the competition, co-existence, and extinction of competing species (Begon et al., 1996; Gotelli & Ellison, 2004).

Without going into the particulars of the competition model given above, we would like to highlight three aspects of how ecologists have used the model to link theories of interspecies interactions with empirical data. Generally, we believe that the focus on change, methodological approaches, and data constraints found in the study of natural systems are similar to those faced by psychologists. We examine how the paradigms and models used to study interspecies interactions might also be applied in the study of dyadic interactions (see also Gottman et al., 2002).

A focus on change. First, we highlight an underlying perspective—that entities are dynamic and can change. The mathematics of the model above are based on nonlinear dynamical systems, wherein a system of (one or more) differential equations is used to articulate how the prior (in time) state of the system leads to the present state of the system (i.e., how entities change over time). Note that the outcome variable (dN/dt) is the first derivative of population size with respect to time—or when written in discrete terms ($\Delta N/\Delta t$) is how much the population changed between $t - 1$ and t . Thus, explicitly, change is the dependent variable or outcome of interest. The pair of differential equations, together, provide a mathematical representation of the theoretical within-species changes occurring over time (e.g., growth rates) and between-species interactions (e.g., one species out-competing the other for shared resources). This representation is made explicit in Figure 5.1 wherein the within-entity or “intraspecific” dynamics of the model are represented by two rectangles and the between-entity or “interspecific” interactions are depicted as the connecting arrows. The model articulates the “coupling” of two sets of processes, each of which is undergoing change, in part as a function of the other (just as Wohlwill, 1991, argued).

In sum, the “theory” articulated by such models is that entities (species or individuals) change over time and are influenced by environmental forces. In other words, species or individuals are viewed as dynamic entities rather than static or “trait-like” entities that are affected by (and affect) their surroundings. The parallelism to the contextualist and lifespan theoretical approaches taken in developmental psychology is very apparent (see e.g., Baltes, Lindenberger, & Staudinger, 2006).

Methodological approaches. Second, there are multiple perspectives on how theory and empirical data are linked in order to attain insight into the how and why of intra-entity change and inter-entity interactions. Theory and data must be connected. Usually, if not always, this connection happens through a mathematical model. But, there are a number of different perspec-

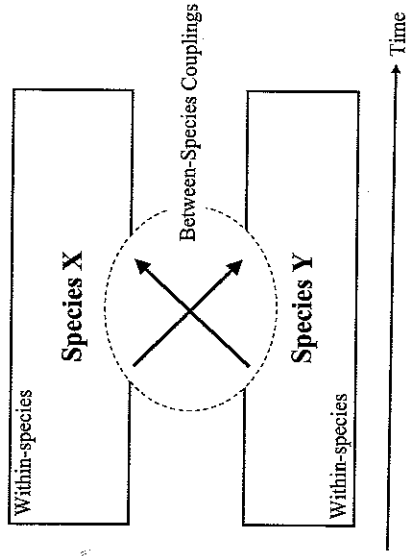


Figure 5.1. A general description of how coupled models include within-entity or “intraspecific” dynamics, the two rectangles, and between-entity or “interspecific” interactions, the connecting arrows. All three components are used to capture the change processes as they occur across time.

tives on how and in what manner the “appropriate” methodology should be selected or built in order to test theory and/or represent data (Bjørnstad & Grenfell, 2001; Hilborn & Mangel, 1997). We highlight two perspectives that are unfolding in ecology (and other fields), a mechanism-oriented approach and a data-driven approach (see also Kendall et al., 1999).

Ecologists and psychologists are interested in processes and mechanisms through which entities (e.g., species or individuals) interact with one another. Generally, the objective of the “mechanism-oriented approach” is to write out the theory of change and interaction as a set of mathematical equations, explicitly including parameters or variables that represent the specific mechanisms thought to be involved in the interaction (e.g., conversion rates, reproduction rates, etc.). Supplemented with “priors” obtained from experiments or observations (e.g., how many hares does a lynx eat in a week?) the mathematical model then is used to generate “synthetic” data (e.g., Markov Chain Monte Carlo procedures), which in turn are evaluated with respect to plausibility (e.g., is the simulated outcome possible?). In sum, the focus of the mechanistic-oriented approach is on building a theoretically sound and biologically plausible mathematical representation of the theory. Data observations are sometimes used to parameterize and evaluate the model but often play a secondary role. Thus, the mathematical model may be built “naive,” so to speak, to empirical data.

An alternative perspective is to focus on the empirical observations directly, with the intent of modeling or representing the data as accurately as possible. In the extreme case a "data-driven" approach is focused on selecting or finding the (mathematical/statistical) model that "fits" the data best. It is of secondary concern whether or not the parameters or variables in the model represent or can be directly translated to theoretical mechanisms. In other words, the model may be "naïve" to theory, yet provide a very accurate description of the current data and some ability to forecast future occurrences.

Our intent is not to make a value judgment regarding either approach, as each has strengths and weaknesses. As presented these are two rather extreme approaches, one naïve to data and the other naïve to theory. Most researchers, however, use elements of both. Within a single analysis even, theory may at certain times be used to build and judge one's models while at other times indicators of fit to the data are used. We issue a caution, though, that one should be aware of when, why, and along what criteria one's models are judged. By doing so, and as is the case in interdisciplinary research generally, the systematic "blending" of approaches should be highly productive and informative (Hilborn & Mangel, 1997).

Data constraints. Third, the data generated by or fitted to such a coupled system of differential (or discrete) equations are longitudinal time-series data—multiple observations of the same entities obtained over multiple, ordered (and usually equivalently spaced) occasions. In the study of interspecies population dynamics, accurate yearly (or monthly, etc.) estimates of population size are often difficult and laborious to obtain. Data sets are often short time-series, consisting of only 10 to 25+ repeated observations of two species (Bjørnstad & Grenfell, 2001). Comparable data in the psychological domain are often based on what is available or obtainable. For instance, in many diary studies daily observations are collected over the course of just a few weeks from a relatively small sample of couples (Bolger, Davis, & Rafaeli, 2003; Laurenceau & Bolger, 2005). Thus, it seems ecologists and psychologists are often limited to short time series. Constrained by the amount of data available to them, ecologists have often turned to modeling approaches that exploit the power of simulations in order to inform model building and theory testing. Using such techniques, even with short time-series and necessarily small N (e.g., one dyad or pair of species) ecologists have been able to obtain a rich and rather detailed picture of the different types of interspecies interactions existent in nature. Psychologists might also consider how such techniques could be used more widely in the study and examination of interpersonal processes.

Generally, ecologists have, for the greater part of a century now, maintained a theoretical focus on change and have used methodological approaches

(often mechanism-oriented approaches) that are, even with relatively small amounts of empirical data, still informative to the theoretical processes underlying interspecies interactions across a wide spectrum of ecological systems (Begon et al., 1996; Bjørnstad & Grenfell, 2001; Gotelli & Ellison, 2004; Morin, 1999). We have attempted to understand and present some of the similarities between developmental contextual and ecological perspectives, modeling approaches, and data. It seems, as Wohlwill (1991) rightly pointed out, ecologists have developed a wide variety of models that may also be useful for characterizing dyadic interactions between persons and we should further explore how the paradigms and models used to study interspecies interactions might also be applied in the study of dyadic interactions (see also Gottman et al., 2002). In the following sections we examine three models developed within the longitudinal structural equation modeling tradition in psychology to see how they relate to those being used in ecology.

Developmental Methods: Recent "Dynamic" Innovations

Recently, a number of multivariate "dynamic" longitudinal models, similar to those being applied in ecology, have emerged and can be adapted and used to more clearly understand dyadic interactions and contextualist theory (Collins & Sayer, 2001). As in ecology, the aim of these models is to articulate and test specific hypotheses regarding the reciprocal influences of two or more entities over time. In particular, models based on latent difference scores (McArdle & Hamagami, 2001), coupled differential structural equation models (Boker, 2001), and dynamic factor models (Molenaar, 1985), now provide for explicit interactions of multiple dynamic entities. These reciprocal relationships or "interspecific interactions" allow us to test a variety of hypotheses about how multiple entities (species, individuals, or even domains within an individual) interact and influence each other over time (see also Ram & Nesselroade, 2007).

Latent Difference Score Models of Change. Latent growth curve modeling has become one of the main frameworks used to analyze developmental data within the longitudinal structural equation modeling tradition, allowing researchers to articulate, describe, and test hypotheses about interindividual differences in within-person change (see McArdle & Nesselroade, 2003 for an overview). Recently, the framework has been extended such that explicit renderings of the discrete changes individuals exhibit from one occasion to the next are incorporated explicitly. In particular, McArdle and Hamagami (2001) have presented a formulation of the standard latent growth curve model that is based on successive latent differences. In general form this (univariate) latent difference score model can be written as

$$X_{nt} = x_{n0} + \left(\sum_{t=2}^t \Delta x_{nt} \right) + e_{xnt} \quad (2)$$

where individual n 's score at time t , X_{nt} , is the sum of an initial score, x_{n0} , and all of the subsequent changes that have occurred up to that time (sum of Δx_{nt} from $t = 2$ to t). The changes, then, can be written as a function of the other variables,

$$\Delta x_{nt} = f[x, y, z]_{nt} \quad (3)$$

In the standard growth curve modeling version of the model the function of change is given by a random slope variable (e.g., $\Delta x_{nt} = \alpha_x S_{xn}$, where α_x is a constant and S_{xn} is an individual n 's overall rate of change across all t , on variable x ; see Ferrer, Hamagami, & McArdle, 2004 for further elaboration of the equivalence between standard growth curve models and latent difference score renditions). More generally, however, the key innovation of this model is that the discrete changes, which accumulate over time to produce an individual's long-term trajectory, become the focal point of inquiry. Within this framework, then, the occasion-to-occasion changes, Δx_{nt} , or the "outcome" variable can be related to any "internal" and/or "external" factors or processes (e.g., x, y, z). Thus, the model opens up a number of new possibilities for examining how processes are linked together or interact over time.

Note that this framework is, in essence, the same as that outlined by the ecological model given above (Eqs. 1a and 1b). Change, Δx (or dx/dt in continuous form) is the outcome variable. Similarly, the factors driving the change can be expressed as a set of variables and parameters that model the internal (within-person or "intraspecific") or external (between-person or "interspecific) factors affecting change. Thus, in parallel to the coupled differential equations of the ecological model, we can also couple together two univariate latent difference score models (e.g., one for each member, x and y of a dyad). A model for these two "coupled" sets of changes might take this form:

$$\text{Person X: } \Delta x_{nt} = \alpha_x S_{xn} + \beta_x(x_{n(t-1)}) + \gamma_x(y_{n(t-1)}) \quad (4a)$$

$$\text{Person Y: } \Delta y_{nt} = \alpha_y S_{yn} + \beta_y(y_{n(t-1)}) + \gamma_y(x_{n(t-1)}) \quad (4b)$$

where n subscripts identify a particular dyad and x and y subscripts denote particular members of each dyad (e.g., mothers and children). A graphical representation is given in Figure 5.2. The changes in each variable (or person), Δx_{nt} and Δy_{nt} , are written as a function of overall within-person rates of change (given by $\alpha_x S_{xn}$ or $\alpha_y S_{yn}$), each member's prior state (given

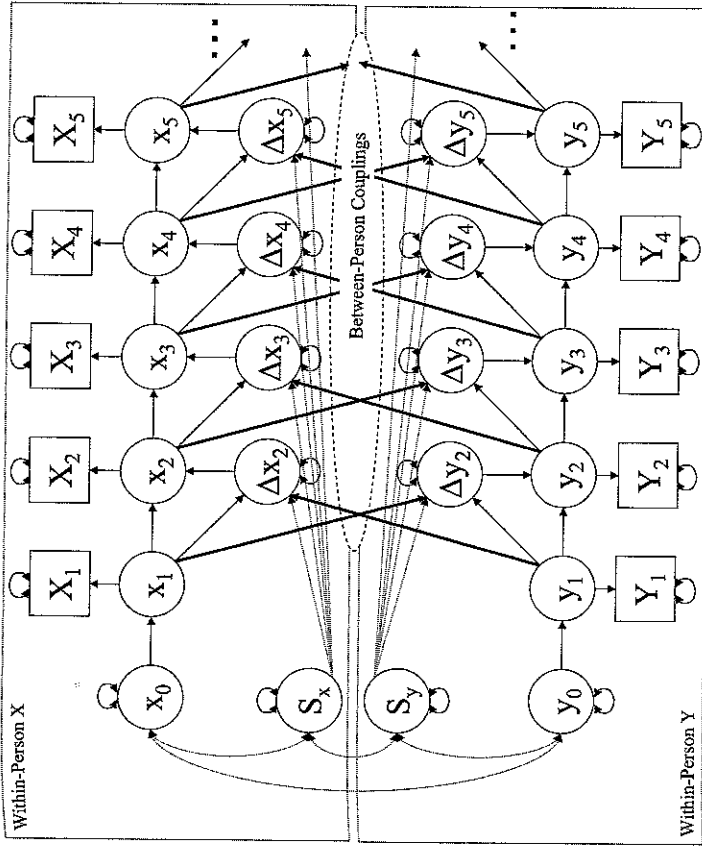


Figure 5.2. A coupled latent difference score model wherein the upper portion of the model is used to represent the within-person changes for Person X and the lower portion to represent within-person changes for Person Y. "Dynamic interactions" or between-person couplings are represented by the arrows spanning between the upper and lower portions.

by $\beta_x(x_{n(t-1)})$ or $\beta_y(y_{n(t-1)})$, and the other member's prior state (given by $\gamma_x(y_{n(t-1)})$ or $\gamma_y(x_{n(t-1)})$). The γ_x and γ_y terms serve as "interaction coefficients," indicating how one member of the dyad "influences" the subsequent changes of the other member. These interaction coefficients parallel the competition coefficients that are used to express the competitive effects of one species on another species in the Lotka-Volterra competition model (Eqs. 1a and 1b). For completeness, and as was the case for the changes in x , the changes in y are also embedded within a "measurement model" and connected to the observed scores,

$$Y_{nt} = y_{n0} + \left(\sum_{t=2}^t \Delta y_{nt} \right) + e_{ynt} \quad (5)$$

The coupled latent difference score model (McArdle & Hamagami, 2001) has proven applicable for modeling co-occurring within-person developmental changes in multiple domains and obtaining information about how one domain may lead or lag the other (see McArdle & Nesselroade, 2003). Initial application in the study of dyads has also begun. For example, McArdle and colleagues (McArdle, Hamagami, Kaldec, & Fisher, 2007, in preparation) have used the model to examine how, within a large sample of married couples, one member's level of depression affected subsequent changes in the others' (e.g., husband's depression affecting wife's change). Given the usefulness of this model in examining within-person couplings, and its similarity to the models used to study interspecific interactions in ecology, we see the coupled latent difference score model (or adaptations of it) as having strong potential for use in the study of dyadic and between-person interactions. We would encourage researchers to further explore the possibilities for application.¹

Coupled Latent Differential Equations. In addition to allowing discrete changes to be explicit through latent differences, longitudinal structural equation models have also begun articulating continuous change (and acceleration) through latent differential equation models (Boker, 2001; Boker & Graham, 1998; Boker & Bisconti, 2006). In addition to the conceptual advances obtained by rendering change explicit and modeling it as continuous in time, the innovation of such models also has practical advantages, namely that a set of differential equations can be fitted to data within the manifest and latent variable framework of "off-the-shelf" SEM programs (e.g., LISREL, Mplus, Mx, etc.). A coupled linear oscillator model, one of many models in the family of coupled differential equation models, can be written as

$$\text{Person X: } \left(\frac{d^2x}{dt^2} \right) = \eta_x(x)_t + \zeta_x \left(\frac{dx}{dt} \right)_t + \left[\eta_{yx}(y)_t + \zeta_{yx} \left(\frac{dy}{dt} \right)_t \right] + e_{xt} \quad (6a)$$

$$\text{Person Y: } \left(\frac{d^2y}{dt^2} \right) = \eta_y(y)_t + \zeta_y \left(\frac{dy}{dt} \right)_t + \left[\eta_{xy}(x)_t + \zeta_{xy} \left(\frac{dx}{dt} \right)_t \right] + e_{yt} \quad (6b)$$

¹We note that the latent difference score model has thus far been applied to long-term within-person changes that exhibit "strong shapes" and has usually been fit to panel data from multiple individuals under the assumption that individuals are in many ways replicates of one another (as is typical in growth curve modeling and other interindividual differences approaches). However, there is flexibility in how the model can be parameterized and applied. Thus, we see further extensions for the modeling of short-term interactive processes and single-dyad time-series type data (of the type that ecologists use) as within reach.

where x and y subscripts denote particular members of a dyad (e.g., wives and husbands). The general set-up of the model is similar to those described earlier in this chapter. Here, though, the rate at which a variable (or person) x is accelerating at a given point in time t (i.e., the second-derivative with respect to time), d^2x/dt^2 , is articulated as a function of location (or level) of the variable, the rate at which the variable is changing (i.e., the first-derivative with respect to time), dx/dt , the location and rate of change of the other variable (i.e., the portion of equation 6a that is in square brackets), and residual, e_{xt} . A parallel function denotes the accelerations of the y variable. Without delving too far into the specifics of the model, we hope that the similarities in structure between this model and the general ecological interspecies interaction model presented earlier are clear (i.e., with Equations 1a and 1b). Both models are written in a differential equation form, and express changes (or accelerations) in couplings between variables (persons). A graphical SEM representation of the coupled latent differential model is given in Figure 5.3. We again highlight that the model includes formal representations of the intrinsic or within-person dynamics for each member of the dyad and the "dynamic couplings" between the two persons.

Boker and Laurenceau (2007, see also 2006) used a coupled linear oscillator model (Figure 5.3) to capture the systematic dynamics of spousal disclosure (of facts, information, thoughts, and feelings)—as obtained via daily diaries over 42 days (6 weeks). Given that married couples exhibit interdependent behaviors, model parameters suggested, on average (across 96 dyads), a significant coupling between dyad members. More specifically, in the prototypical couple, wives were more affected by how far away their husband was from his equilibrium level of disclosure than by how rapidly he was changing. In contrast, husbands were more affected by how quickly their wife's level of disclosure was changing than by how far away she was from equilibrium. This complex pattern of results illustrates how such models can be used to extract and test specific hypotheses about the nature of mutual influence between members of a dyad—thus parameterizing dyadic intimacy and disclosure as a process reflecting variability, change, and fluctuation over time (Boker & Laurenceau, 2006).

Dynamic Factor Analysis. Dynamic factor models (Molenaar, 1985) emerged as a combination of P-technique factor analysis (Cattell & Scheier, 1961) and time-series methods (e.g., Shumway & Stoffer, 2006) and are used to represent multivariate, multi-occasion data obtained from a single individual (more in depth treatment is given in Ferrer & Widaman, chapter 6). In brief, the underlying notion of the basic model is that the state of the individual at any given time point, as observed via a multivariate vector of variables, X_t , is a function of the state of the organism (observed or unobserved) at both

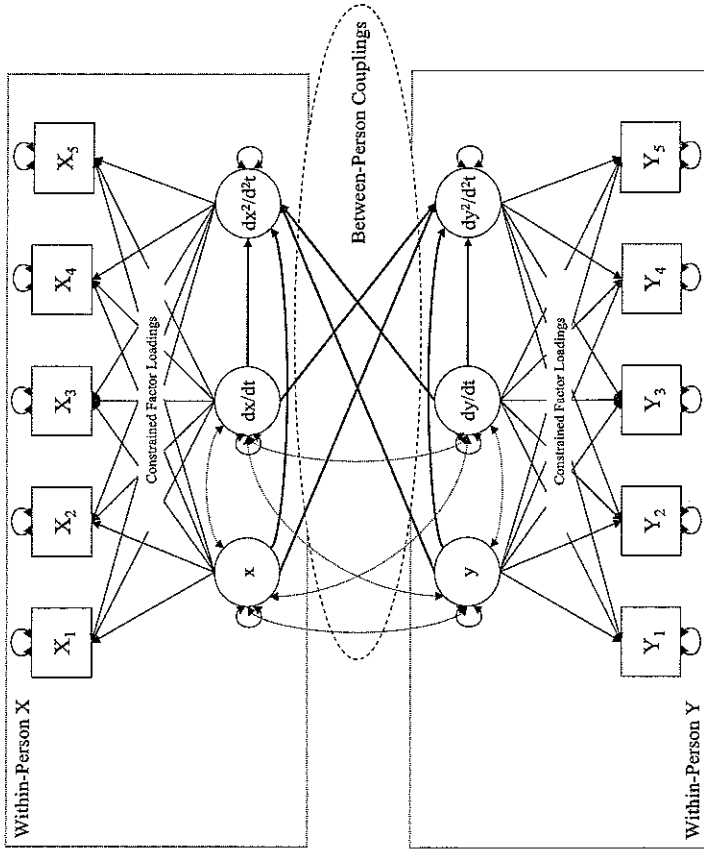


Figure 5.3. Model of two coupled oscillators, one modeling within-person changes for Person X, the other within-person changes for Person Y. Dynamic interactions between the two are represented by the between person couplings.

the current time and previous times (e.g., X_{t-1}, X_{t-2}). One general form of the model (see Browne & Nesselroade, 2005 and Ferrer & Widaman, chapter 6, for more complete descriptions and other general forms) is

$$\xi_t = [A_1\xi_{t-1} + A_2\xi_{t-2} + \dots + A_S\xi_{t-s}] + \delta_t \tag{7}$$

where ξ_t , the multivariate latent state of the individual at time t , is a weighted combination of his or her prior latent states, $\xi_{t-1} \dots \xi_{t-s}$, and some residual, δ_t . Weights (autoregressive) are given by the A matrices. As can be seen, Equation 7 takes the form of a standard autoregression type model. The latent states, however, are unobserved and thus must themselves be connected to the observed variables via a “measurement” model, in this case the standard P-technique factor model

$$X_t = \Lambda_X \xi_t + u_t \tag{8}$$

where X_t , the multivariate observed state of the individual at time t , is a weighted (by Λ_X) combination of his or her concurrent latent states, ξ_t , and a residual, u_t . Together Equations 7 and 8 can be used to represent how an individual, as a complex multivariate entity, progresses through time and are easily implemented within a structural equation modeling framework (see e.g., Nesselroade, McArdle, Aggen, & Meyers, 2002).

In the context of this chapter, our interest is in how such a model might be applied to dyadic or multi-person data. Suppose we have two individuals. We can create a “parallel” dynamic factor model for the second individual

$$\eta_t = [B_1\eta_{t-1} + B_2\eta_{t-2} + \dots + B_S\eta_{t-s}] + \zeta_t \tag{9}$$

$$Y_t = \Lambda_Y \eta_t + v_t \tag{10}$$

where η_t and Y_t represent the multivariate latent and observed states of the second individual, the B matrices his or her autoregressive weights, and ζ_t and v_t his or her residual scores. Thus, we have a system of equations for each individual. Expanding to the dyad, we can conceptualize “dynamic interactions,” where, as the two individuals interact, each person’s state is affected by the other’s previous states. Within the general framework, such “reciprocal relations” are incorporated in a straightforward manner by including the appropriately weighted cross-regressions. Equations 7 and 9 become

$$\text{Person A: } \xi_t = [A_1\xi_{t-1} + A_2\xi_{t-2} + \dots + A_S\xi_{t-s}] \tag{11a}$$

$$+ [C_1\eta_{t-1} + C_2\eta_{t-2} + \dots + C_S\eta_{t-s}] + \delta_t$$

$$\text{Person B: } \eta_t = [B_1\eta_{t-1} + B_2\eta_{t-2} + \dots + B_S\eta_{t-s}] \tag{11b}$$

$$+ [D_1\xi_{t-1} + D_2\xi_{t-2} + \dots + D_S\xi_{t-s}] + \zeta_t$$

where the C and D matrices represent how the (past) latent states of one individual affect the latent states of the other individual, and vice versa—within dyad cross-regressions. More specifically, each individual’s latent states are a function (linear combination) of his or her own previous states as well the previous states of his or her partner in the dyad. A minimalist version of the model is presented in graphical form in Figure 5.4. As with the previous models, and as is indicated in the figure, the model can be visualized as consisting of three overlapping parts: the within-person model for one member of the dyad, the within-person model for the other member of the dyad, and the “dynamic interactions” between the two. Further, although written in a

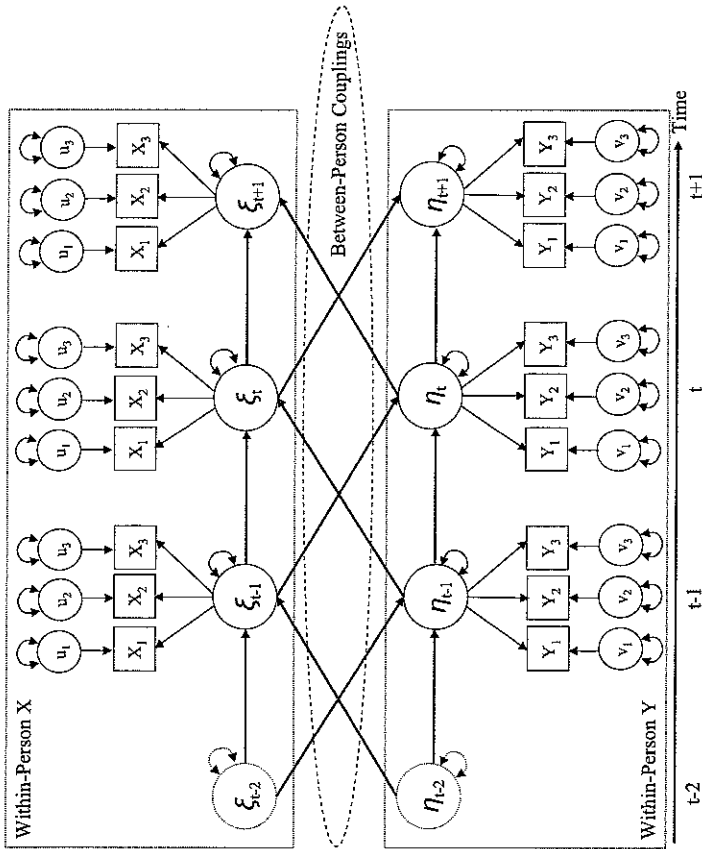


Figure 5.4. Coupled dynamic factor model depicting within-person changes for Person X, Person Y, and the bidirectional influences between X and Y as they occur over time.

different notation, the model also has strong parallels to the ecological model in Equations 1a and 1b.²

Ferrer and Nesselrode (2003; see also Ferrer & Widaman, chapter 6) used a dynamic factor model to capture the systematic dynamic interactions occurring between a married couple, husband and wife, over 180 days. The model was applied as indicated above, with portions of the full model representing the wife's within-person changes in mood over time, the husband's within-

²Both the ecological model given above and the dynamic factor model can be conceptualized or rewritten in the form of a state-space model (see e.g., Browne & Nesselrode, 2005; Murray, 2002). For instance, a discrete-time representation of the Lotka-Volterra competition model for Species X (Equations 1a) highlighting the within-species and between-species portions of the model is given by $N_{x(t+1)} = \left(1 + r_x - \frac{N_{x(t)}}{K_x}\right) N_{x(t)} - \left(\frac{\alpha_{xy} r_x N_{x(t)}}{K_y}\right) N_{y(t)}$. While the parameters are nonlinear, similar to the dynamic factor model, abundance of Species X at the next time point, $N_{x(t+1)}$, is "determined" by a weighted combination of Species X's abundance at the previous time point, $N_{x(t)}$, and Species Y's abundance at the previous time point, $N_{y(t)}$ (Murray, 2002).

person changes in mood, and the "dyadic interactions" occurring between the two. The model articulated how the mood of each individual "led to" or "influenced" his or her own subsequent mood and the subsequent mood of their partner. In the within-person portions of the model it was found that the wife's current mood was determined, in part, by her own mood on the previous day and that the husband's current mood was determined, in part, by his own moods from the previous two days. Additionally, in the between-person couplings portion of the model, the husband's current negative mood affected the wife's negative mood on the following day, but not vice versa. The wife's current mood did not affect the husband's future mood. In full, the model captures each partner's within-person mood process and the between-person interactive process by which the members of the dyad influence one another.

In sum, there is a growing set of tools for modeling dyadic "dynamic interactions" emerging from the longitudinal structural equation modeling tradition. We have reviewed three such innovations here, latent difference score equations of change (McArdle & Hamagami, 2001), latent differential structural equation models (Boker, 2001), and dynamic factor models (Browne & Nesselrode, 2005; Molenaar, 1985). In line with theories of ecological interspecific interactions, these models (and others like them) provide for the articulation and testing of theory regarding how dyads, as an interactive system of components (e.g., equations), function over time. We are confident that such models can and will be useful in our quest to understand how, when, and why individuals affect one another.

CONCLUSION

When colleagues from different perspectives, departments, fields of study, etc. come together to explore a topic, they are often struck by differences in terminology, approach, and outlook. However, when pressed to find them, many similarities become apparent. In this chapter we have attempted to highlight how ecological theory and methods may be useful in psychology, and how some of the recently developed longitudinal structural equation models are similar to the interspecies interaction models being used in ecology. With regard to the study of dyads we highlighted a common approach that focuses on change (as an outcome or consequent) and the need for complementary use of mechanism-oriented and data-driven modeling approaches, especially when faced with data constraints.

Using a general dynamic systems framework, based in coupled differential equations, ecologists have articulated and modeled a diverse set of "transactions" or types of dyadic interaction including symbiosis, competition, neutralism, mutualism, amensalism, commensalism, predation, parasitism – all

of which can and are often articulated in a manner consistent with the theoretical language of dyadic and group interactions within developmental contextualist theory (e.g., types of proximal, distal, and bidirectional influences). The methodological and computational innovations of the past decade have made it increasingly easy to incorporate dynamical systems modeling approaches, simulation studies, and the fitting of complex nonlinear models (see e.g., Gottman et al., 2002; Newell & Molenaar, 1998; Thelen & Smith, 1994; Vallacher & Nowak, 1994). As these advancements continue we encourage further consideration of how the mathematical models developed over the last century in the field of ecology might be drawn upon and extended in the study of human dyadic interaction.

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