

Chapter 2

Families as Coordinated Symbiotic Systems: Making use of Nonlinear Dynamic Models

Nilam Ram, Mariya Shiyko, Erika S. Lunkenheimer, Shawna Doerksen
and David Conroy

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Families are often conceptualized as continually evolving, relational systems (Cox and Paley 1997; Minuchin 1985). Individual members influence and are influenced by all other members. These reciprocal relations coalesce into family-level symbiotic processes and are the core of study in family systems research and therapy (see Lunkenheimer et al. 2012). Wohlwill (1991) noted that, “. . . what [reciprocal relationships] would call for are methodologies that allow one to model the interpat-
tern between two [or more] sets of processes each of which is undergoing change, in part as a function of the other . . . The closest approach to this kind of modeling that is indicated for this purpose are probably some of the models from the field of

N. Ram (✉)

Department of Human Development and Family Studies, The Pennsylvania
State University, University Park, PA, USA
e-mail: nur5@psu.edu

M. Shiyko

Department of Applied Counseling and Educational Psychology,
Northeastern University, Boston, MA, USA
e-mail: M.Shiyko@neu.edu

E. S. Lunkenheimer

Department of Human Development & Family Studies,
Colorado State University, Fort Collins, CO, USA
e-mail: erika.lunkenheimer@colostate.edu

S. Doerksen

Department of Recreation, Park and Tourism Management,
The Pennsylvania State University, University Park, PA, USA
e-mail: sxd49@psu.edu

D. Conroy

Department of Kinesiology, The Pennsylvania State University,
University Park, PA, USA
e-mail: dec9@psu.edu

ecology and similar systems-analytical work” (p. 128). Following this suggestion we began exploring how the theoretical and analytical approaches used in ecology relate to study of person-context transactions and longitudinal structural equation models (Ram and Nesselroade 2007; Ram and Pedersen 2008). Here we extend our thinking to the modeling of family systems.

Theory: Families as Dynamic Systems

Over the last half-century, developmental scientists have often argued for and sometimes formulated dynamic systems and process-based accounts of development (Ford and Lerner 1992; Gottlieb 1997; Sameroff 1983; Schneirla 1957; Werner 1957). Likewise, family therapists and researchers often promote a systems view, stressing that the family is a whole, has interdependent subsystems, and that interactions among these subsystems are governed by homeostatic and circular processes that emerge and adapt to internal and external demands (e.g., Minuchin 1974, 1985). Families are dynamic systems capable of both (a) adaptive self-stabilization, wherein coordinated action of subsystems compensate for changing conditions in the environment and maintain homeostasis, and (b) adaptive self-organization, wherein the system as a whole transforms to accommodate change in or challenge to the existing configuration (see Cox and Paley 1997, Thelen and Ulrich 1991).

These principles provide a framework for examining change within family systems at multiple time scales (Granic 2005; van Geert 1998). Shorter-term, micro-level changes indicate how a family system self-stabilizes and functions as a unit to achieve homeostasis. For instance, consider a couple who tells jokes every evening as a way to lift each others’ mood and decompress from the day’s stress. When a major change occurs, the system may self-organize into a qualitatively different pattern of self-stabilization. When a new child joins the family, the sharing of jokes is replaced by a new homeostasis—diaper changing and fatigue. If we explicitly consider the dynamic and reciprocal interactions among family members as the actions of a dynamic system that self-stabilizes and self-organizes, we can begin to model the structure, organization, and patterning of these relationships within and across time and context (Fogel 1993; Lunkenheimer and Dishion 2009).

Methods: Nonlinear Dynamic Models

Applications to Biological Systems

As does family systems theory, biological theory underscores the importance of dynamic interactions. However, rather than elaborating how an individual functions within the family context (e.g., parent-child or marital relations), biologists are concerned with how one species grows and declines within the context of other species and the environment (e.g., foxes and rabbits). Ecologists, for instance, aim

to understand the distribution and abundance of animals and plants, with particular focus on how a species' short- and long-term population dynamics are affected through interaction with the surrounding environment and presence and/or absence of other organisms (e.g., predators, prey). Since early in the 20th century, ecologists have been using a combination of theory, observational data, and mathematical modeling to understand how both intra-specific (within a species) and inter-specific (between-species) interactions contribute to population change.

Two mathematical biologists, Lotka (1925) and Volterra (1926) introduced a robust framework for translating theories about interspecies associations into a mathematical form. This framework has been very useful for modeling, exploring, and theorizing about the distribution and abundance of multiple species living in the same space—symbiosis (see Paracer and Ahmadjian 2000). Formally, a two-species model can be written using a set of nonlinear differential equations. Using x to represent a characteristic of one species (e.g., the size of the population), and y to represent a characteristic of the other species (e.g., also, the size of the population), the dynamics (i.e., the rates of change) of these characteristics can be modeled as

$$\begin{aligned}\frac{dx}{dt} &= a_1 + b_1x \pm f_1(y, x) \\ \frac{dy}{dt} &= a_2 + b_2y \pm f_2(x, y)\end{aligned}\tag{2.1}$$

where $\frac{dx}{dt}$ and $\frac{dy}{dt}$ are the *rates of change* in x and y , respectively, over time. The parameters a_1 and a_2 represent each species' "uninfluenced" trajectory when isolated from self-influence and influence of other aspects of the environment, and can be interpreted as an indicator of the species' *homeostatic* or *dynamic equilibrium*. Non-zero values indicate the natural trajectory of change (moving vs. resting). The parameters b_1 and b_2 indicate the extent to which each species (x and y) changes as a function of their own characteristics (e.g., the size of the population at a given moment). Positive parameters indicate a *self-exciting* mechanism wherein higher population levels foster more growth. In contrast, negative b_1 and b_2 parameters indicate a *self-inhibiting* mechanism wherein higher population levels invoke declines. For example, animal populations (humans excluded) tend to keep themselves in check when living in a resource limited environment. The functions f_1 and f_2 articulate how each party changes as a function of the interactions between the two species, and are interpreted as indicators of the *co-regulatory* mechanisms operating within the system (e.g., cooperation/competition). One set of straightforward influence functions can be operationalized as the interactions between the two species (literally the product),

$$\begin{aligned}f_1(y, x) &= \pm c_1yx, \text{ and} \\ f_2(x, y) &= \pm c_2xy,\end{aligned}\tag{2.2}$$

where the signs of the parameters c_1 and c_2 indicate how the cross-species interactions affect the growth or decline of each species. For example, when foxes (x) have

the opportunity to meet with rabbits (y), species x tends to eat species y , and the interactions invoke positive progression for the foxes ($c_1 > 0$), but negative progression for rabbits ($c_2 < 0$). The influence functions characterize the *predator-prey* nature of the relationship. The species co-regulate, in that the abundance or scarcity of rabbits influences foxes ability to reproduce, and the abundance or scarcity of foxes influences the ability of rabbits to reproduce. Co-regulation may also manifest in ways that are positive for both species. For example, when humming-birds (x) have the opportunity to meet with flowers (y), species x pollinates species y and species y feeds species x . The exchange invokes positive progression for the humming-birds ($c_1 > 0$) and the flowers ($c_2 > 0$). Here, the influence functions characterize the *mutualistic* nature of the co-regulation. Generally, the overall pattern of parameters (e.g., $+/+$, $+/0$, $+/-$, $-/-$) provides a system-level description of the mutualistic, commensal, parasitic, or competitive nature of the association. Using variants of the Lotka-Volterra equations, biologists have spawned a vast knowledge of how ecological systems change over the short-term and evolve over the long-term (Murray 2002). From a modeling perspective, the elegance of the framework holds great value for articulating and describing aspects of the human ecology.

Applications to Family (and Work-Family) Systems

In combing through the existing literature on family systems we found relatively few papers that explicitly used the biological systems terminology to describe family (or work-family) systems. Noting that the conceptual underpinnings of family systems theory were developed from frameworks used to describe natural systems (e.g., Bowen 1978), Noone (1988) elaborates in detail how the concepts of symbiosis are used in the mental health field and the life sciences, and how they might apply to human families. Werbel and Walter (2002) use the biological analogies of mutualism and parasitism to elaborate on work and family role dynamics. They note how, in a dysfunctional system, an individual's work role may have a negative impact on his or her family role ($+/-$ parasitism), while in a more functional system, feelings of productivity at work may contribute to a better family life and, vice versa, a better family life may contribute to greater productivity at work ($+/+$ mutualism). Less flattering usage of the biological vernacular is the labeling of young people (up to about age 30) who, after finishing formal schooling and obtaining employment, continue living with their parents as "parasite singles" (Yieh et al. 2004).

Although the biological terminology surrounding symbiosis appears to have been used in a very limited manner in studies of family systems, the accompanying mathematical framework (Eqs. 1 and 2) has proved quite useful in the study of marital relations. Gottman et al. have a long line of work using the theoretico-mathematical framework outlined above to study marital behavior (e.g., Gottman et al. 1999; 2002a, 2002b). Drawing directly from mathematical biology (e.g., Murray 2002), they formulated a version of the Lotka-Volterra models that matched their theoretical models of how spouses (husband = x , wife = y) influence each other's behavior within

marital interactions. This model was then used to identify specific features within the dynamics of conversation that are indicative of relationship quality and contribute to marriage dissolution. The partners' relative positivity during alternating speaking turns within a 15-min conversation/argument (e.g., # of positive comments—# of negative comments) was modeled as a combination of “uninfluenced” tendencies (analogous to the system dynamics described by the parameters a_1 , a_2 and b_1 , b_2 from above) related to the past history of the relationship and personality (or what we called self-exciting and self-inhibiting mechanisms) and “influence” tendencies (co-regulatory mechanisms) related to how the spouses affected one another. At the basic level, the influence functions are straightforward,

$$\begin{aligned} f_1(y, x) &= \pm c_1 y, \text{ and} \\ f_2(y, x) &= \pm c_2 x, \end{aligned}$$

where person x 's trajectory is influenced either positively or negatively by the level of positivity person y expressed in her speaking turn, and person y 's subsequent trajectory is influenced either positively or negatively by the level of positivity person x expressed in his speaking turn, and so on, back and forth.

A further level of complexity was introduced to accommodate the finding that negative comments are more detrimental than positive comments are supportive. This is accommodated by a bilinear influence function which includes a threshold k , whereby content with positivity below k (e.g., all negative statements) has a specific amount of influence, c_{1a} , while content with positivity above k (e.g., all positive statements) has a different amount of influence, c_{2a} . Formally,

$$\begin{aligned} f_1(y, x) &= c_{1a}y \text{ when } y \leq k_1 \text{ and } f_1(y, x) = c_{1b}y \text{ when } y > k_1 \text{ and} \\ f_2(x, y) &= c_{2a}x \text{ when } x \leq k_2 \text{ and } f_2(x, y) = c_{2b}x \text{ when } x > k_2. \end{aligned}$$

In practice, both bilinear (2-part spline functions) and ogive (step functions), and combined bilinear-ogive functions are used to articulate a wide variety of theoretically interesting influence functions (see Madhyastha et al. 2011). The mathematical models based on these functions have been used very successfully to obtain qualitative and quantitative descriptions of the dynamics of couples' marital interactions that are both associated with relationship satisfaction and predictive of dissolution (Gottman et al., 2002a).

Two quick notes about how Gottman and colleagues' model is constructed. (1) The model translates a very straightforward theory about how the two members of a dyad influence one another into a mathematical form. In this case, the influence functions operationalize pure *other-focused regulation* and not co-regulation (as we described earlier). That is, dx is only influenced by the other person's behavior (y), rather than by the product of both partners' behavior ($y \cdot x$) as in the biological models above. Given the micro-time scale being examined, this makes sense. (2) The threshold parameter, k , is an important aspect of the system that may differ across individuals and across family members. Each individual has his or her own threshold, and these differences in tolerance for or perception of negativity contribute to how the dynamics

of the conversation unfold (Gottman et al. 1999). In sum, the influence function is the key aspect of the model that can be used to operationalize specific theories about how family members influence one another. Expanding the vocabulary of mutual influences beyond the simple forms of commensalism, mutualism, parasitism, and competition noted above (Murray 2002; Stadler and Dixon 2008), many theories can be articulated precisely within the mathematical model.

For example, Felmlee and Greenberg (Felmlee 2007; Felmlee and Greenberg 1999), wrote out a set of influence functions that emphasize the importance the degree of congruence between family members' states plays in system-level functioning. The influence functions were articulated as

$$f_1(y, x) = \pm c_1(y - x), \text{ and} \\ f_2(x, y) = \pm c_2(x - y),$$

with c_1 and c_2 indicating the extent to which differences between partner's states drive each person's behavioral change. In contrast to the Gottman models articulating a pure other-focused regulation based solely on the other person's state (e.g., y), these dyad-focused influence functions explicitly incorporate dyad-level variables (e.g., $y - x$) that quantify the distance between individuals' states. Holding the other parts of the model fixed (e.g., when the a s and b s = 0), a positive c_1 parameter indicates person x tends to act in ways that decrease the distance between him and his partner's states (e.g., emotions). When the c_2 parameter is also positive both partners' trajectories tend to move toward each other. In contrast, negative parameters indicate divergence of partners over time. And, a parameter of zero indicates a tendency for independent and uninfluenced change.

Note that the specific influence functions used here, which are based on dyad-level differences ($x - y$) rather than dyad-level products (xy), were conceptualized for specific kinds of behavior, such as the balance between partner's physical (exercise) and social (# of phone calls) activities. Thus, they are not equivalent to the biological models, and likely do not map directly to the taxonomy of interspecies interactions and population dynamics. Instead, Felmlee (2007) purposively used the modeling framework (a , b and c parameters) to describe a rich typology of dyads' potential dynamics; independents, dependents, cooperatives, reactionaries, etc. Fitting these models to data obtained in a micro-longitudinal study of relationship partners' daily emotional states (similar to the data used in our forthcoming example), Ferrer and Steele (2012) confirmed that the hypothesized typology of couples articulated by the model was indeed related to relationship satisfaction and dissolution.

More generally, all the models above translate precise theory about how partner's behavior or congruence between family members' behavior drives the on-going dynamics of the system into a mathematical form that then allows that theory to be tested against empirical data (for alternative frameworks see Boker and Laurenceau 2006; Butner et al. 2005; Butner et al. 2007; Chow et al. 2010; Ferrer and Nesselroade 2003; Sbarra and Ferrer 2006; Steele and Ferrer 2011). Many more influence functions can be formulated and the work easily extended to reflect the many nuances of family interaction (e.g., Liebovitch et al. 2010).

Data: Empirical Example

To illustrate how the nonlinear dynamic modeling framework outlined above can be used to describe both the ongoing dynamics of a family system *and* changes in those dynamics, we collected a set of EMA data from a White, heterosexual, married couple around the time of the birth of their first child. Using nonlinear dynamic models we describe (a) the dynamic processes (e.g., homeostasis, self-focused regulation and dyad-focused regulation) within a dyadic family system, and (b) changes in those dynamics that occurred in conjunction with passage through a developmental transition.

The study of both *family dynamics* and *change in family dynamics* was facilitated by a multiple-time-scale study design (see Nesselroade 1991; Ram and Gerstorf 2009) wherein multiple reports or assessments were obtained over a relatively short span of time (e.g., 3 weeks of EMA) during multiple “bursts” of measurement obtained at more widely spaced intervals (e.g., years of longitudinal panel) or in different stages of development (e.g., before and after the transition to parenthood). Repeated measures obtained within-burst provide for observation of dynamic process (self-stabilization). Comparison across bursts provides for observation of family-level adaptations to the transition (self-organization).

Data Collection. For 23 consecutive days, the two members of the couple reported on their interpersonal interactions as they went about their daily lives. Specifically, immediately after face-to-face interactions (of longer than 5 min) the husband and wife used separate smartphone-based survey applications to provide independent ratings of the interaction (location, duration, quality) and their emotional states (e.g., happy, sad). Then, this family system went through a major developmental transition—and a “natural experiment” was born (a daughter). Ten days after the birth of the child, the couple resumed reporting about their interpersonal interactions for 42 more days. In total the couple provided reports about 103 interactions, 47 during the pre-baby burst (between 1 and 4 reports per day; Median = 2, SD = 0.69), and 56 during the post-baby burst (0 to 2 per day; Median = 2, SD = 0.54). Here, we make use of responses to the items “How HAPPY do you feel?” and “How SAD do you feel?” each rated using a “touch point continuum” slider-type interface that was digitally coded on a 0–100 scale.

Data Preparation. By design, the couple’s reports were provided at unequally spaced intervals reflecting the natural occurrence and time spacing of interactions. To facilitate analyses, the data were pre-processed using usual time-series techniques (see Ramsey et al. 2009; Shumway and Stoffer 2006). First, data for the small amount of days on which no reports were provided were interpolated using third-order local splines (1 point per day). Then, the time series of repeated measures from each burst were smoothed using third-order local splines, with knots placed at 1.0 and 1.2 day intervals for the pre-baby and post-baby bursts, respectively, and resampled at 100 equidistant points. The main objective of the pre-processing was to reduce some of the noise in the data while still maintaining a relatively precise picture of the nonlinear progression of each individual’s feelings across time. A few general

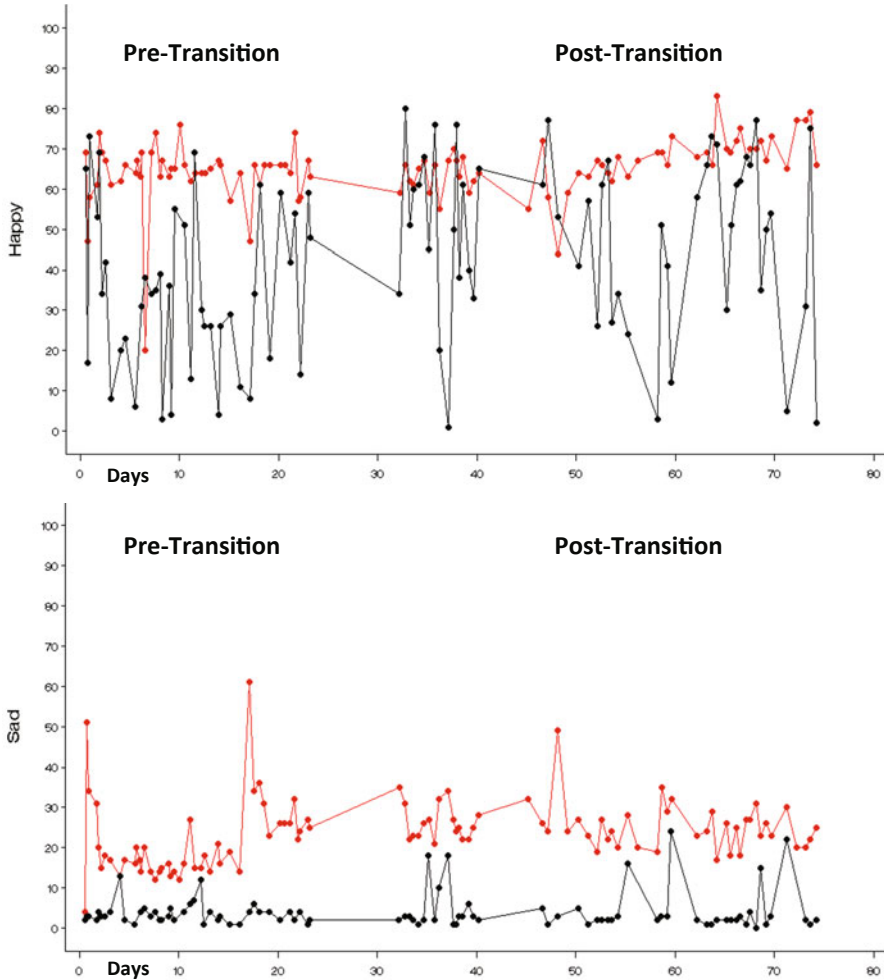


Fig. 2.1 Raw data from husband's (black) and wife's (red) reports of happy (*top panel*) and sad (*bottom panel*) during two bursts of data collection (pre-baby and post-baby)

features can be noted in Fig. 2.1. Overall, the husband's time series (black lines) was characterized by lower mean level and higher variance in *happy* than the wife's time series (red lines). As well, for both the husband and the wife, there were differences in mean levels and variance between the pre-baby and post-baby periods. While the differences in these dynamic characteristics are interesting in their own right (see Ram and Gerstorff 2009), our main interest here was in describing the dynamics of the family system. Thus, we set these differences aside by standardizing each time-series to a Mean = 0 and SD = 1. This removes the "distraction" of needing to interpret the usual "static" features of the time-series, keeps us focused on the dynamics, and allows for easy comparison of those dynamics across bursts and persons.

Model formulation. Our interest was to use the nonlinear dynamic modeling framework outlined above to describe the dynamics of the dyad's emotions during each burst (pre- and post-baby) and to identify any qualitative differences in those dynamics between the two bursts. Following the Ferrer and Steele (2012) work, we formulated a model based on the Felmlee (2007) influence functions. Specifically, the following model was fit separately to the dyad's *happy* and *sad* time-series for each burst:

$$\begin{aligned}\frac{dx}{dt} &= a_1 + b_1x \pm c_1(y - x) \\ \frac{dy}{dt} &= a_2 + b_2y \pm c_2(x - y)\end{aligned}$$

The a_1 (and a_2) parameter indicates the husband's (and wife's) trajectory at equilibrium, when personal and partner's influences are assumed absent. Positive scores on a_1 and a_2 indicate a tendency to remain on an increasing trajectory; negative scores indicate a tendency to remain on a decreasing trajectory; and zero scores indicate a tendency to remain at rest. The b_1 (and b_2) parameter indicates the extent to which the husband's (and wife's) trajectory is prone to change from endogenous influences. Positive scores indicate a tendency for escalation or movement away from equilibrium; negative scores indicate a tendency for inhibition or movement towards the equilibrium. The c_1 (and c_2) parameter indicates the extent to which husband's (wife's) trajectory is influenced exogenously by the imbalance between partners' emotional states (e.g., levels of happy). A positive parameter indicates a tendency to regulate or be regulated toward the partner's score, and a negative parameter indicates a tendency to push or be pushed further away from the partner's score. Note that because the influence function is based on the difference score between the two people, it is not possible to infer whether one or the other member of the dyad is doing the "pulling" or "pushing". Rather, these parameters should be interpreted as family-level parameters that describe the dyadic system as a whole rather than a sum of the parts (Minuchin 1985).

Model fitting. Four models [2 bursts (pre-baby, post-baby) x 2 emotions (happy, sad)] were fitted to time-series data using SAS PROC MODEL, a flexible and general purpose procedure for fitting systems of non-linear differential equations to time-series data and/or simulating data from those equations (e.g., Erdman and Morelock 1996). In brief, the procedure numerically integrates the system of equations using a variable order, variable step-size, backwards difference scheme, and then fits the integral to the data using full information maximum likelihood (or another chosen estimation method) to account for dependence in the error structure due to the simultaneous equation modeling (see SAS documentation and Steele et al. (in press), for further details). Of note, given the didactic nature of our example we have not evaluated the statistical tests of whether each parameter is significantly different than zero, made comparisons among competing models (using model fit indices), nor evaluated the specific influences our arbitrary choice of 100-occasion (vs. 50-occasion) resampling within burst has on the results. Rather, we use the example to demonstrate how the general framework of nonlinear dynamic models might be used to articulate family systems theory.

Results and Interpretation. Estimated parameters from the four models are reported in Table 2.1. Here we provide a detailed interpretation of the dynamics of the dyad's happiness during the pre- and post-baby periods (top section of Table 2.1). The parameters describing the husband's dynamics were $a_1 = -0.006$, $b_1 = -1.474$, and $c_1 = -0.971$. The near zero a_1 parameter indicates that the husband tended toward a non-changing, near zero, resting-state equilibrium. The large negative b_1 parameter indicates a strong self-focused regulatory tendency, such that deviations above or below equilibrium induced a change towards his set-point. The negative c_1 parameter indicates the tendency for dyad-focused regulation; specifically, a tendency to move away from his wife's mood. Following occasions when the wife is happier, $(y - x) > 0$, the husband's happiness would decrease. In complement, on the occasions when the wife is less happy, $(y - x) < 0$, the husband's happiness would tend to increase, perhaps, in the attempt to cheer her up. In comparison, parameters describing the wife's dynamics were estimated to be $a_2 = -0.011$, $b_2 = -0.539$, and $c_2 = +0.509$. As before, the near zero a_2 parameter indicated that the wife tended toward a non-changing, near zero, resting state equilibrium. The negative b_2 parameter indicates a self-regulatory tendency, such that deviations above or below equilibrium induced change towards her set-point. The positive c_2 parameter indicates a tendency to move toward the husband's mood. If the husband was happier than the wife, $(x - y) > 0$, the wife's happiness would tend to increase *and vice versa*. If the husband was less happy than the wife, $(x - y) < 0$, the wife's happiness would tend to decrease.

After the developmental transition, the dynamics were different. The parameter describing the husband's equilibrium state stayed near zero, $a_1 = -0.006$. The self-regulatory parameter substantially decreased, $b_1 = -0.260$, indicating a weaker self-focused regulatory mechanism following childbirth. The influence parameter changed sign to positive and decreased in magnitude, $c_1 = +0.232$, indicating a switch in the husband's dyad-focused regulation—a tendency to move toward (rather than away from) his wife's mood. The parameters describing the wife's dynamics are also somewhat different. The near-zero equilibrium is similar, $a_2 = +0.011$, but there is a stronger self-focused regulatory tendency, $b_2 = -0.905$, and, perhaps in coordination with the husband, a complementary change in sign for $c_2 = -0.500$. In the post-baby period, the wife has the tendency to move away from the husband's mood, perhaps either to retain happiness of equilibrium or try to cheer him up.

The estimated model parameters governing the dynamics of happiness during the pre- and post-baby bursts were used to simulate scenarios of dyadic reactions under a variety of hypothetical perturbations (e.g., emotions perturbed far away from equilibrium, close to equilibrium). One of these many scenarios is visually depicted in the upper panel of Fig. 2.2. In the left, pre-baby panel, we see the dyad progressing along at equilibrium until time = 0, when an event (external or internal) perturbs the system driving the partners into different states (husband lower than equilibrium, wife higher than equilibrium). After the perturbation we see how the coordinated pulling and pushing of self-focused and dyad-focused influences bring the dyad back to homeostasis in about 4 time steps (arbitrary scaling). As can be seen in the right panel, the same perturbation in the post-baby period emphasizes the change in the dynamics. In the post-baby period, the dyad does not reach mutual equilibrium until about the seventh time step.

Table 2.1 Parameter estimates from nonlinear dynamic model articulating (a) homeostasis, (b) self-focused regulation, and (c) dyad-focused regulation

	Husband		Wife		Husband		Wife	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
R^2	Pre-baby: SAD				Post-baby: SAD			
	a_1	-0.006	0.333		a_1	0.309	a_2	0.196
	b_1	-1.474	0.312		b_1	0.401	b_2	0.380
	c_1	-0.971	0.261		c_1	0.512	c_2	0.269
	0.73				0.61		0.80	
Log-likelihood	-152.9				-156.1			
R^2	Pre-baby: SAD				Post-baby: SAD			
	a_1	0.379	0.374		a_1	0.341	a_2	0.183
	b_1	-0.497	0.541		b_1	0.56	b_2	0.187
	c_1	-0.039	0.411		c_1	0.637	c_2	0.141
	0.81				0.79		0.69	
Log-likelihood	-135.2				-145.8			

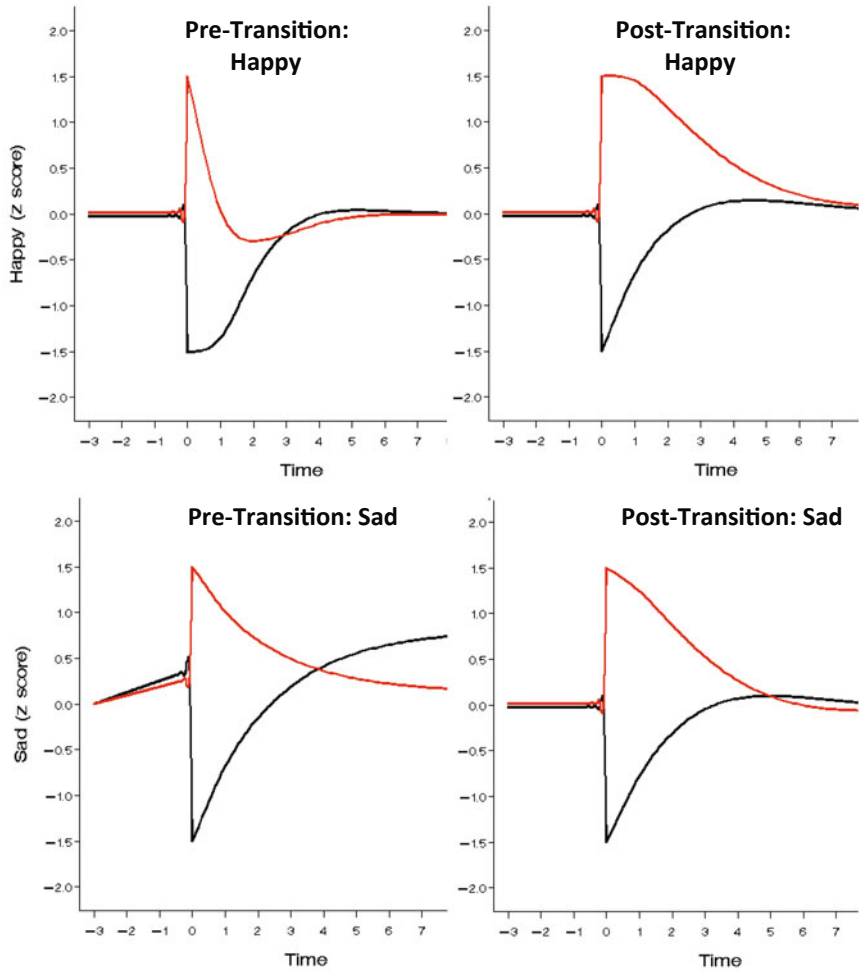


Fig. 2.2 Response simulations of husband’s (black) and wife’s (red) changes in happy (top panel) and sad (bottom panel) during the pre-baby and post-baby periods

Estimated parameters from the pre- and post-baby models of the dynamics of sadness are reported in the lower section of Table 2.1. Briefly, the pre-baby period was characterized by a tendency for increases in sadness for both the husband ($a_1 = 0.379$) and the wife ($a_2 = 0.282$) and seen as upward sloping lines prior to the perturbation in the lower panel of Fig. 2.2. However, there was also a good amount of self-regulatory pressure in the system. When sadness was higher, both partners down-regulated towards the personal equilibrium ($b_1 = -0.479$ and $b_2 = -1.04$). Influence of the impact of differences in levels of sadness between partners on the rate of change was evident for the wife ($c_2 = -0.224$) but not for the husband

($c_1 = -0.039$). The dynamics were somewhat different in the post-baby period. The dyad's homeostasis no longer included any evidence of upward trajectories of sadness. The uninfluenced trajectories had shifted towards zero for both partners ($a_1 = -0.007$ and $a_2 = -0.029$). As well, the husband's self-regulation was weaker ($b_1 = 0.091$) than in the pre-baby period, whereas the wife's self-regulation remained strong and negative ($b_2 = -1.077$), indicating a tendency to return to her homeostasis. Finally, the effect of mood differences on the husband's tendency to change became positive ($c_1 = 0.33$), while the wife's continued to be negative and doubled in magnitude ($b_1 = -0.505$). We briefly note that individuals' emotion regulation is often described as a process that depends on individual set points and homeostatic strategies (roughly corresponding to a_1, a_2) (Forgas and Ciarrochi 2002) regulatory skill and/or endogenous influences (b_1, b_2) (Larsen and Prizmic 2005), and sensitivity to environmental cues (such as empathy based on others' emotions) and/or exogenous influences (c_1, c_2) (Gross and Thompson 2005). Thus, the mathematical models may provide a robust framework for integrating knowledge about the specific phenomena with family systems theory.

Discussion

Systems theory is a useful epistemological approach to study small and large systems, such as family units, that naturally arise in biological and social environments. In biology, systems theory has been used successfully as both a theoretical foundation and to formulate methods for modeling a wide variety of individual-, population-, and community-level phenomena (Begon et al. 1996; Murray 2002). In social sciences, many theorists have noted the parallels between biological units and social units and elaborated how individuals function within context and have direct and indirect impacts on each other's actions and feelings (e.g., Ford and Lerner 1992; Gottlieb 1997; Sameroff 1994; Schneirla 1957; Werner 1957). As technological advances in mobile computing provide for easy collection of intensive longitudinal data (e.g., via smartphones) and advances in computing speed provide capacity for numerical estimation of highly complex models, there are many new opportunities to study family dynamics. The goal of this chapter was to review the basic framework of nonlinear dynamic models that is being used in the ecology (following Wohlwill's 1991, recommendation) and illustrate how it can be used to articulate and model intra-family dynamics.

Theory, Method, and Data

For many decades, systems theory was far ahead of the available methodology. We simply did not have the data or statistical procedures needed to render the theory operational. In recent decades, both barriers have been successfully overcome. Technological innovations allow for frequent (and often unobtrusive) assessment of

humans behavior, physiology, and psychological states in natural settings (Bolger et al. 2003; Stone et al. 2007). As illustrated here, the many-occasion, multivariate time-series data suitable for studying the dynamics of change can be obtained. Many of the analytical tools needed to estimate nonlinear dynamic models are now available, even within typically used statistical software (e.g., PROC MODEL in SAS, CollocInfer package in R) (Ramsay et al. 2007).

In fact, these tools, and the rates at which social network and other on-line data are obtained suggest that the data collection methods and analytical methods are now ahead of theory. In the last decade, a few groups have demonstrated the viability of using the precision of the mathematical framework underlying nonlinear dynamic systems for both theorizing and studying family systems (e.g., work by Boker, Gottman, Felmlee, Ferrer, Laurenceau). The results from these efforts are exciting, especially in that their utility for making long-term predictions about tangible and important outcomes (e.g. family dissolution) has been convincingly demonstrated.

Research Questions

Our exploration of theory and empirical modeling highlight how integration of dynamic systems principles and dynamic modeling leads into new directions for basic and applied family research. As seen in our empirical example, the framework reveals a detailed landscape of family change and captures several levels of transition. Using data collected in a multiple-time-scale study design, we were able to model both family dynamics during a specific micro-time frame (within the pre-baby period) and change in family dynamics across a developmental transition (pre- vs. post-baby). More generally, the dynamic systems framework is extremely useful in that it allows for modeling change over many time scales, from change across the course of a single conversation (à la Gottman) to change across the course of a relationship or the entire life span of a family system. As well, the framework can be used to model many different types of family systems and behaviors. We used two coupled equations to model the dynamics of specific emotions within a dyad (à la Felmlee and Ferrer), but the model is easily extended to include more individuals (by adding more equations) or adapted for use with other behaviors (by incorporating different influence functions). That the framework is used by ecologists to model system-level changes in animal populations suggests that it may also have utility for demographers modeling demographic changes in family structure. In sum, we see that the dynamic systems framework reviewed here might be used to investigate a wide variety of family-oriented research questions.

Research Methods

Our exploration of theory and empirical modeling also highlighted some of the ways that the basic modeling framework might be extended. For example, an interesting and important extension would be to use the model to predict relational transitions.

Repeated sampling bursts over longer time periods may reveal shifts in the dynamics (attractor patterns) that may have important implications for tangible outcomes, including relationship formation and dissolution, risk of maltreatment and, more generally family health and well-being. Identifying shifts may be particularly informative in marital or family therapy in terms of identifying the specific events that are strong triggers for positive or negative changes in a couple or in family dynamics. From a modeling perspective, this requires modeling how the parameters describing the dynamics (attractors) change over time. In our empirical example, we modeled the pre- and post-baby periods separately to examine a qualitative change in the parameters. Other forms of dynamic modeling (e.g., state-space grids) have also been used to model qualitative shifts in individual and dyadic development over time (Granic et al. 2003; Lewis et al. 2004; van Dijk and van Geert 2007). With some work, all of these methods might be extended to include time-varying parameters, so as to continuously track how the parameters describing the family dynamic evolve over time, and or shift in relation to specific events (Chow et al. 2011; Molenaar and Ram 2010; Tan et al. 2011). Such extensions might then be used prospectively to identify periods of transition and/or risk in romantic relationships, parental functioning, friendships, and other systems. Not yet known, though, are the number and spacing of assessments needed for such evaluations (for discussion, see Collins 2006; Ram and Gerstorff 2009; Shiyko and Ram 2011).

Our empirical example highlighted how nonlinear dynamic models can be applied to time-series data to describe the dynamics of a dyadic system. Data from multiple systems would offer additional opportunities for describing inter-system (e.g., between-couple) similarities and differences that might also be examined in relation to other inter-system differences (e.g., demographics, relationship history). Placing the models within a multilevel modeling framework that allows for simultaneous examination of within-system change and between-system differences is relatively straightforward (Boker and Laurenceau 2006; Chow et al. 2010). Given that a primary area of interest for family researchers and practitioners is understanding why maladaptive relationships are resistant to change, such an approach may shine additional light on patterns of resistance and potential for intervention.

Conclusion

The success of the modeling approach is rooted in the explicit articulation of families as dynamic entities that interact in complex ways—as systems. Nonlinear dynamic models, such as those used here, focus on *change*, rather than focusing on where a person or family happens to be located at a particular or arbitrary moment in time. The “outcomes” in the models are derivatives, rates of change and acceleration, and thus focus inquiry on the dynamics of change. Individuals in the same family are modeled simultaneously, recognizing both their organismic continuity and reciprocal relations. These ideas have been discussed in family systems theory for decades. Now we have the tools and opportunity to write them down in a precise mathematical form that allows them to be tested against empirical data. We look forward to what emerges!

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References

- Begon, M., Harper, J. L., & Townsend, C. R. (1996). *Ecology: Individuals, populations and communities, Third edition*. Cambridge: Blackwell Science.
- Boker, S. M., & Laurenceau, J. P. (2006). Dynamical systems modeling: An application to the regulation of intimacy and disclosure in marriage. In T. A. Wall, & J. L. Schafer (Eds.), *Models for intensive longitudinal data* (pp. 195–218). New York: Oxford University Press.
- Bolger, N., Davis, A., & Rafaeli, E. (2003). Diary methods: Capturing life as it is lived. *Annual Review of Psychology*, 54, 579–616. doi:10.1146/annurev.psych.54.101601.145030.
- Bowen, M. (1978). *Family therapy in clinical practice*. New York: Jason Aronson.
- Butner, J., Amazeen, P. G., & Mulvey, G. M. (2005). Multilevel modeling of two cyclical processes: Extending differential structural equation modeling to nonlinear coupled systems. *Psychological Methods*, 10, 159–177. doi:10.1037/1082-989X.10.2.159.
- 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. doi:10.1111/j.1475-6811.2007.00164.x.
- Chow, S.-M., Haltigan, J. D., & Messinger, D. S. (2010). Dynamic infant-parent affect coupling during face-to-face/still-face. *Emotion*, 10, 101–114.
- 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.
- Collins, L. M. (2006). Analysis of longitudinal data: The integration of theoretical model, temporal design, and statistical model. *Annual Review of Psychology*, 57, 505–528.
- Cox, M. J., & Paley, B. (1997). Families as systems. *Annual Review of Psychology*, 48, 243–267.
- Erdman, D., & Morelock, M. M. (1996). A study of kinetics: The estimation and simulation of systems of first-order differential equations. Proceedings of the 21st Annual SAS Users Group International Conference, 1407–1414. <http://support.sas.com/rnd/app/papers/kinetics.pdf>.
- Felmlee, D. H. (2007). Application of dynamic systems analysis to dyadic interactions. In A. D. Ong & M. van Dulmen (Eds.), *Handbook of methods in positive psychology* (pp. 409–422). New York: Oxford University Press.
- Felmlee, D. H., & Greenberg, D. F. (1999). A dynamic systems model of dyadic interaction. *Journal of Mathematical Sociology*, 23, 155–180.
- Ferrer, E., & Nesselroade, J. R. (2003). Modeling affective processes in dyadic relations using dynamic factor analysis. *Emotion*, 3, 344–360.
- Ferrer, E., & Steele, J. (2012). Dynamic systems analysis of affective processes in dyadic interactions using differential equations. In G. R. Hancock & J. R. Harring (Eds.), *Advances in longitudinal methods in the social and behavioral sciences* (pp. 111–134). Charlotte: Information Age Publishing.
- Fogel, A. (1993). Two principles of communication: Co-regulation and framing. In J. Nadel & L. Camaioni (Eds.), *New perspectives in early communicative development* (pp. 9–22). London: Routledge.
- Ford, D., & Lerner, R. (1992). *Developmental systems theory: An integrative approach*. Newbury Park: Sage.
- Forgas, J. P., & Ciarrochi, J. V. (2002). On managing moods: Evidence for the role of homeostatic cognitive strategies in affect regulation. *Personality and Social Psychology Bulletin*, 28(3), 336–345.

- Gottlieb, G. (1997). Commentary: A systems view of psychobiological development. In D. Magnusson (Ed.), *The lifespan development of individuals: Behavioral, neurobiological, and psychosocial perspectives: A synthesis* (pp. 76–103). New York: Cambridge University Press.
- Gottman, J., Swanson, C., & Murray, J. (1999). The mathematics of marital conflict: Dynamic mathematical nonlinear modeling of newlywed marital interaction. *Journal of Family Psychology*, 13, 3–19.
- Gottman, J. M., Murray, J. D., Swanson, C. C., Tyson, R., & Swanson, K. R. (2002a). *The mathematics of marriage: Dynamic nonlinear models*. Cambridge: MIT Press.
- Gottman, J., Swanson, C., & Swanson, K. (2002b). A general systems theory of marriage: Nonlinear difference equation modeling of marital interaction. *Personality and Social Psychology Review*, 6, 326–340.
- Granic, I. (2005). Timing is everything: Developmental psychopathology from a dynamic systems perspective. *Developmental Review*, 25, 386–407. doi:10.1016/j.dr.2005.10.005.
- Granic, I., Hollenstein, T., Dishion, T. J., & Patterson, G. R. (2003). Longitudinal analysis of flexibility and reorganization in early adolescence: A dynamic systems study of family interactions. *Developmental Psychology*, 39, 606–617.
- Gross, J. J., & Thompson, R. A. (2005). Emotion regulation: Conceptual foundations. In J. J. Gross (Ed.), *Handbook of emotion regulation* (pp. 3–24). New York: Guilford Press.
- Larsen, R. J., & Prizmic, Z. (2005). Affect regulation. In L. F. Barrett, P. M. Niedenthal, & P. Winkielman (Eds.), *Emotion and consciousness* (pp. 40–61). New York: Guilford Press.
- Lewis, M. D., Zimmerman, S., Hollenstein, T., & Lamey, A. V. (2004). Reorganization in coping behavior at 1½ years: Dynamic systems and normative change. *Developmental Science*, 7, 56–73.
- Liebovitch, L. S., Vallacher, R. R., & Michaels, J. (2010). Dynamics of cooperation-competition interaction models. *Peace and Conflict*, 16, 175–188.
- Lotka, A. J. (1925). *Elements of physical biology*. Baltimore: Williams & Wilkins Co.
- Lunkenheimer, E. S., & Dishion, T. J. (2009). Developmental psychopathology: Maladaptive and adaptive attractors in children's close relationships. In S. Guastello, M. Koopmans, & D. Pincus (Eds.), *Chaos and complexity: Recent advances and future directions in the theory of nonlinear dynamical systems psychology* (pp. 282–306). New York: Cambridge University Press.
- Lunkenheimer, E. S., Hollenstein, T., Wang, J., & Shields, A. M. (2012). Flexibility and attractors in context: Family emotion socialization patterns and children's emotion regulation in late childhood. *Nonlinear Dynamics, Psychology, and Life Sciences*, 16, 269–291.
- 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, 292–300.
- Minuchin, S. (1974). *Families and family therapy*. Cambridge: Harvard University Press.
- Minuchin, P. (1985). Families and individual development: Provocations from the field of family therapy. *Child Development*, 56, 289–302.
- Molenaar, P. C. M., & Ram, N. (2010). Dynamic modeling and optimal control of intra-individual variation: A computational paradigm for non-ergodic psychological processes. In S. M. Chow, E. Ferrer, & F. Hsieh (Eds.), *Statistical methods for modeling human dynamics: An interdisciplinary dialogue* (pp. 13–35). New York: Routledge.
- Murray, J. D. (2002). *Mathematical biology: I. An introduction*, (3rd ed.). New York: Springer.
- Nesselroade, J. R. (1991). The warp and woof of the developmental fabric. In R. Downs, L. Liben, & D. Palermo (Eds.), *Visions of development, the environment, and aesthetics: The legacy of Joachim F. Wohlwill* (pp. 213–240). Hillsdale: Erlbaum.
- Noone, R. J. (1988). Symbiosis, the family, and natural systems. *Family Process*, 27, 285–292.
- Paracer, S., & Ahmadian, V. (2000). *Symbiosis: An introduction to biological association* (2nd ed.). New York: Oxford University Press.
- Ram, N., & Gerstorff, D. (2009). Time structured and net intraindividual variability: Tools for examining the development of dynamic characteristics and processes. *Psychology and Aging*, 24, 778–791.

- Ram, N., & Nesselroade, J. R. (2007). Modeling intraindividual and intracontextual change: Operationalizing developmental contextualism. In T. D. Little, J. A. Bovaird, & N. A. Card (Eds.), *Modeling contextual effects in longitudinal studies* (pp. 325–342). Mahwah: Lawrence Erlbaum.
- Ram, N., & Pedersen, A. B. (2008). Dyadic models emerging from the longitudinal structural equation modeling tradition: Parallels with ecological models of interspecific interactions. In N. A. Card, J. P. Selig, & T. D. Little (Eds.), *Modeling dyadic and interdependent data in the developmental and behavioral sciences* (pp. 87–105). New York: Routledge.
- Ramsay, J. O., Hooker, G., Cao, J., & Campbell, D. (2007). Parameter estimation in ordinary differential equations: A generalized smoothing approach. *Journal of the Royal Statistical Society*, 69, 741–796.
- Ramsey, J. O., Hooker, G., & Graves, S. (2009). *Functional data analysis with R and Matlab*. New York: Springer.
- Sameroff, A. (1983). Developmental systems: Contexts and evolution. In W. Kessen (Ed.), *Handbook of child psychology Vol. 1: History, theory and methods* (4th ed., pp. 237–294). New York: Wiley.
- Sameroff, A. (1994). Developmental systems and family functioning. In R. D. Parke & S. G. Kellman (Eds.), *Exploring family relationships with other social contexts*. (pp. 199–214). Hillsdale: Erlbaum.
- Sbarra, D. A., & Ferrer, E. (2006). The structure and process of emotional experience following non-marital relationship dissolution: Dynamic factor analyses of love, anger, and sadness. *Emotion*, 6, 224–238.
- Schneirla, T. C. (1957). The concept of development in comparative psychology. In D. B. Harris (Ed.), *The concept of development: An issue in the study of human behavior* (pp. 78–108). Minneapolis: University of Minnesota Press.
- Shiyko, M. P., & Ram, N. (2011). Conceptualizing and estimating process speed in studies employing ecological momentary assessment designs: A multilevel variance decomposition approach. *Multivariate Behavioral Research*, 46, 875–899.
- Shumway, R. H., & Stoffer, D. S. (2006). *Time series analysis and its applications: With R examples* (2nd ed.). New York: Springer.
- Stadler, B., & Dixon, T. (2008). *Mutualism: Ants and their insect partners*. New York: Cambridge University Press.
- Steele, J. S., & Ferrer, E. (2011). Latent differential equation modeling of self-regulatory and coregulatory affective process. *Multivariate Behavioral Research*, 46, 956–984.
- Steele, J. S., Ferrer, E. & Nesselroade, J. R. (in press) An idiographic approach to estimating models of dyadic interactions with differential equations. *Psychometrika*.
- Stone, A., Shiffman, S., Atienza, A. A., & Nebeling, L. (2007). *The Science of real-time data capture: Self-reports in health research*. New York: Oxford University Press.
- Tan, X., Shiyko, M. P., Li, R., Li, Y., & Dierker, L. (2011). Intensive longitudinal data and the time-varying effects model. *Psychological Methods*, 17(1), 61–77.
- Thelen, E., & Smith, L. B. (1998). Dynamic systems theories. In W. Damon (Ed.), *Handbook of child psychology: Vol. 1. Theoretical models of human development* (5th ed., pp. 563–633). New York: Wiley.
- Thelen, E., & Ulrich, B. D. (1991). Hidden skills: A dynamic systems analysis of treadmill stepping during the first year. *Monographs of the Society for Research in Child Development*, 56(1), 1–103.
- van Dijk, M., & van Geert, P. (2007). Wobbles, humps and sudden jumps: A case study of continuity, discontinuity and variability in early language development. *Infant and Child Development*, 16, 7–33.
- van Geert, P. (1998). A dynamic systems model of basic developmental mechanisms: Piaget, Vygotsky, and beyond. *Psychological Review*, 105(4), 634–677. doi:10.1037/0033-295X.105.4.634-677.
- von Bertalanffy, L. V. (1968). *General systems theory*. New York: George Braziller.

- Volterra, V. (1926). Fluctuations in the abundance of a species considered mathematically. *Nature*, 118, 558–560.
- Werbel, J., & Walter, M. H. (2002). Changing views of work and family roles: A symbiotic perspective. *Human Resource Management Review*, 12, 293–298.
- Werner, H. (1957). The concept of development from a comparative and organismic view. In D. B. Harris (Ed.), *The concept of development: An issue in the study of human behavior* (pp. 125–148). Minneapolis: University of Minnesota Press.
- Wohlwill, J. F. (1991). Relations between method and theory in developmental research: A partial-isomorphism view. In P. Van Geert & L. P. Mos (Eds.), *Annals of theoretical psychology* (Vol. 7, pp. 91–138). New York: Plenum Press.
- Yieh, K., Tsai, Y.-F., & Kuo, C.-Y. (2004). An exploratory study of “parasites” in Taiwan. *Journal of Family and Economic Issues*, 25, 527–539.

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