Integrating the Dynamics of Personality and Close Relationship Processes: Methodological and Data Analytic Implications

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ABSTRACT A common theme that has emerged from classic and contemporary theoretical work in both the fields of personality and relationship science is a focus on process. Current process-focused theories bearing on personality invoke a view of the individual in ongoing action and interaction with the environment, reflecting a flow of experience rather than a static depiction. To understand the processes by which personality interacts with the social environment (particularly dyads), investigations must capture individuals interacting in multiple interpersonal situations, which likely necessitates complex study designs and corresponding data analytic strategies. Using an illustrative simulated data set, we focus on diary methods and corresponding individual and dyadic multilevel models to capture person-situation interaction within the context of processes in daily close relationship life. Finally, we consider future directions that conceptualize personality and close relationship processes from a dynamical systems theoretical and methodological perspective.

Despite some diversity in their historical roots, the fields of personality psychology and relationship science have a shared goal: to infer and uncover processes that give rise to both stability and change that are observed in a system’s behavior. The term system here refers to a set of variables or components that are linked and interact to
create a whole. Personality psychology focuses on a system that consists of the individual, his or her situational context, and the ongoing interaction between the two (see Shoda, Cervone, & Downey, 2007). Relationship science focuses on the dyad, the dyad’s context, and the ongoing interaction between the two (Kelley et al. 1983). The components of a system interact through some sorts of processes to produce an outcome. A dictionary definition of process typically refers to “a series of actions, changes, or functions bringing about a result.” As this definition implies, an important research goal for the fields of personality and relationship science is to understand the factors, mechanisms, and conditions (processes) that bring about behavioral stability and variability (outcomes) that are observed in individuals and dyads (systems) in context.

The fields of personality and relationship science have both had a history of focusing on outcomes. For example, personality researchers have attempted to use dispositional factors to predict individual behavior as an outcome (Mischel, 1968), whereas relationship researchers have focused on the prediction of satisfaction and divorce as outcomes (Karney & Bradbury, 1995). There is also a well-documented and long-standing line of work linking measures of personality and relationship outcomes (Asendorpf, 2002; Cooper & Sheldon, 2002). Increasingly, a call has been made for the elaboration and investigation of the processes underlying personality phenomena, processes underlying close relationship phenomena, and processes by which personality has an influence on close relationships (e.g., Reis, Capobianco, & Tsai, 2002; Zayas, Shoda, & Ayduk, 2002). The dual focus on process across both these domains presents a daunting challenge for researchers attempting to tackle these questions. One theoretical challenge will no doubt be how to conceptualize the fact that the same behavior can be the outcome of different underlying processes, whereas seemingly different behaviors can result from the same underlying process. There are also other theoretical challenges. Equally daunting, however, will be the challenge of identifying methodological designs and data analytic approaches that best facilitate the examination of process related to system behavior.

This article has three goals. Our first goal is to highlight the significance of addressing process in the study of personality, close relationships, and any attempt to examine their interface. Our second goal is to detail one methodological framework for modeling personality processes and close relationship processes. Our final goal
consists of looking to the future and arguing for the utility of dynamic systems concepts, and corresponding designs and methods, for studying personality processes, close relationship processes, and their interface in the coming era of research.

**Studying Process in Personality and Relationship Science**

A common theme that has emerged from classic and contemporary theoretical work in the fields of both personality and close relationships is a focus on process. While demonstrating utility in many respects, purely trait-based conceptions of personality have at times proven limited on several grounds—particularly that a descriptive or lexical taxonomy of between-person individual differences does not address why the same person will behave differently across different situations (Cervone, Shoda, & Downey, 2007). Moreover, knowing that people differ on extraversion does not explain what makes them differ from each other, nor does it explain why a highly extraverted person will behave differently over time. An important feature that distinguishes process from trait-based conceptions is a within-person conception of how an individual’s feelings, cognitions, and behavior interact in such a way to produce consistency and variability in patterns. Current process-focused theories bearing on personality invoke a view of the individual in ongoing action and interaction with the environment, reflecting a flow of experience rather than a more static depiction (Carver & Scheier, 1998; Mischel & Shoda, 1995). As a starting point, we focus on the CAPS model of personality.

**CAPS Model of Personality**

The Cognitive-Affective Processing System model (CAPS; Mischel & Shoda, 1995), which is deeply based in the process view of personality, provides a framework for examining the way in which the individual as a system operates in response to environmental contingencies. According to the CAPS model, individuals have if-then contingencies, which may differ between persons and also differ within person across situations (e.g., across interactions with other persons). By examining determinants of consistency within an individual’s if-then contingency patterns, “behavioral signatures” emerge in which an individual shows stability in his or her respond-
ing to particular situations. This idea has helped reconcile the “stable” perception of personality and the variability observed in behavior (Shoda & Mischel, 1998). Although the behaviors per se may not appear stable, the if-then contingencies point to stable responding. They themselves represent a within-person dynamic system of responding to the environment.

Examining these behavioral signatures requires a form of intensive intraindividual sampling across diverse situations that will allow for the observation of different behavioral responses to differing environments. Compelling evidence for the utility of the CAPS model comes from, for example, Mischel and Shoda’s (1995) Wediko study of boys in a summer camp. Situation-behavior profiles were operationalized via observation of children’s social behavior (e.g., withdrawn, prosocial behavior) in a variety of psychological situations throughout the camp day (e.g., teased, provoked, or threatened by peer; praised by adult). If-then contingencies were identified for individual campers by observing stable patterns of particular behaviors in particular situations (e.g., high verbal aggression when warned by an adult). Interestingly, the situations were largely interpersonal in nature. These behavioral signatures were both stable and distinct for individual campers.

This approach to the study of personality and the social world has led to other, similar approaches, such as that of Fleeson and Noflle (2009). Fleeson and Noflle (2009) argued for a synthetic resolution of the personality-situation debate that emphasizes both consistency and inconsistency (i.e., consistent responding across similar situations and inconsistent responding across different situations), which can be mapped onto the if-then contingencies described in the CAPS model. Although there has been important theoretical work extending the CAPS framework to the domain of relationships (Zayas et al., 2002), empirical support for this direction has been limited.

**Personality and Close Relationship Processes**

Consistent with a process-based view of personality, close relationship processes are conceptualized as reflecting the ongoing interaction of the mutually influencing properties of two individuals and the social, cultural, and physical environments in which relationship interactions occur (Kelley et al., 1983). The heart of the study of relationships lies in the interactions between partners and how par-
ticular dyadic patterns of interaction lead to particular relationship outcomes. To echo Harry Stack Sullivan (1953), our close relationships are a primary, if not the primary, venue in which to observe personality operate (Cooper, 2002). Close relationship research has tended to focus primarily on relationship stability and global relationship satisfaction as key outcomes (for an alternative view, see Fowers & Owenz, in press). These outcomes are typically assessed at a macro level (i.e., a global relationship evaluation obtained at a single point in time). This can hinder the examination of processes at the level of daily relationship life that influence ongoing thoughts, feelings, and behavior, which eventually give rise to more global relationship evaluations (e.g., satisfaction) or decisions (e.g., divorce). For example, in a review of the empirical literature on personality and close relationships since 1932, Cooper and Sheldon (2002) observed that over three fourths of this work involved cross-sectional designs and most made use of broadband trait measures of personality.

Decontextualized, broadband traits such as neuroticism and extraversion (Cooper & Sheldon, 2002; Karney & Bradbury, 1995) are often used to establish links between personality and close relationship phenomena. Nevertheless, Reis et al. (2002) made a compelling poignant recommendation in this regard:

We propose that research intended to identify the distal person factors that influence relationship behavior may profit by moving away from reliance on general, decontextualized traits, and instead examining predispositions more closely connected to the type of relationship under scrutiny and to the person’s history with that particular partner. . . . Predispositions may still matter, then, but primarily those predispositions that pertain to that relationship, not to the general social world. (p. 830)

Consistent with this recommendation, Laurenceau, Kleinman, Kaczynski, and Carver (2010) developed relationship-specific incentive and threat sensitivity scales and used them to predict marital quality and situational affect following negative and positive laboratory interaction tasks. Interestingly, the relationship-specific sensitivity measures emerged as significant predictors even after controlling for global incentive and threat sensitivities using the behavioral inhibition system (BIS) and behavioral activation system (BAS) scales. Although useful, this work was limited to examining the link
between personality-based motivational sensitivities and marital quality, without delving further into how personality influences ongoing, everyday relationship processes in specific ways that result in these outcomes.

Recent theoretical work has pointed to a confluence of views reflecting a comprehensive framework for examining how personality interacts with the social world: through the lens of a systems approach (Reis et al., 2002; Zayas et al., 2002). Using the CAPS model as a point of departure, Zayas et al. (2002) considered a relationship partner as representing an important part of the situation or environment that an individual is confronting and with which his or her own stable set of characteristics is interacting. Therefore, a person may act differently when interacting with different others, such as one’s spouse or one’s mother, because the “environment” has changed. Different environments are also reflected in the different situations in which partners from the same relationship find themselves. Zayas et al. (2002) provided a systems-based framework for conceptualizing how personality is found in the individual situated in context as well as in a couple where partner behaviors represent salient contexts for an individual.

To understand the processes by which personality interacts with the unfolding social environment of a close relationship, investigations must capture persons interacting in multiple interpersonal situations. This likely necessitates complex study designs and corresponding data analytic strategies. Although the data can be collected in different ways, this approach will likely involve collecting large amounts of data from each participant, and from both partners within a couple. However, the data could be self-report measures, observational ratings, or physiological indexes. The methods must go beyond cross-sectional studies, as such data fail to capture the dynamic nature of any unfolding process.

A Multilevel Modeling Framework for Investigating Personality and Relationship Processes

Taken as a whole, these views suggest that those interested in the interface of personality and relationship science refocus their methods of study to capture processes by which personality influences close relationships in the social world. In what follows, we outline a set of methods and analytic techniques to study and model personality and close relationship processes and their interaction. An
important implication of this focus is the use of intensive, within-person/within-dyad assessments across a variety of situations and relationship contexts.

In this section of the article, we will use an illustrative simulated data set to examine these processes and corresponding data analytic strategies and understand the joint contributions of personality and the social environment. To obtain proper sampling of individuals in dyads and the situations or environments they encounter, intensive, longitudinal data collection will be necessary. We first describe the simulated diary data set and identify particular parameters from a multilevel model for an individual that represent central aspects of the CAPS framework. We then move to extending the model to the dyadic context.

For the present purpose, we focus on diary methods and corresponding individual and dyadic multilevel models (Bolger, Davis, & Rafaeli, 2003; Laurenceau & Bolger, 2005). Multilevel modeling has become a staple tool of the personality and relationship scientist because of its flexibility for simultaneously analyzing within-person time-based processes and between-person individual differences in those processes (Fleeson, 2007) or within-couple time-based processes and between-couple individual differences in those processes (Kenny, Kashy, & Cook, 2006). Data obtained via diary methods have been readily analyzed using multilevel modeling. Moreover, diary methods can provide the type of data needed to be able to identify the unique if-then links between relationship-related situational factors and reports of relationship behavior. Such methods can include collecting data over the course of a long period of time (e.g., weekly for 1 year) or collecting data more intensively for a shorter period of time (e.g., events-based diary where a person completes a questionnaire following every interaction with another person greater than 10 min. in length). In studying close relationships, it is of particular importance to get data from both relationship partners. Otherwise it is impossible to assess the potential influence of one partner on the other, and the ways in which personality and social aspects of environmental contingencies play a role.

Description of the Example Data Set

As an example of how a systems-based personality process model, such as the CAPS model, can be examined in a multilevel modeling...
framework, we simulated a data set that permitted us to model a person-situation interaction within the context of daily relationship life (Zayas et al., 2002). Consider a 21-day diary data set that contains daily measures of relationship threat and negative relationship behavior from both partners in a sample of married couples. Following Zayas et al. (2002), one partner’s threatening behavior can be conceptualized as the salient daily situational feature to which the other partner is responding. In addition to the diary data, both partners also have provided cross-sectional global marital satisfaction ratings prior to the daily diary recording period. Global satisfaction can be conceptualized as a contextual feature reflecting global positive versus negative evaluations of the relationship or partner that can influence the unfolding of daily relationship processes (Weiss, 1980). Positive global evaluations may attenuate the influence of perceived threat on negative behavior.

The example data set consisted of 100 heterosexual couples and was simulated and analyzed using Mplus 5.21. We selected Mplus as the statistical software for the present analyses because of its Monte Carlo simulation capabilities and convenience in data structuring for dyadic multilevel modeling (i.e., Mplus does not require users to stack the data with male and female variables on top of one another; see Laurenceau & Bolger, 2005). However, the analyses reported in this article can be conducted in other statistical programs, such as HLM and SAS PROC Mixed with equivalent results (or within rounding). The corresponding HLM setups can be found in Appendix 3 and the necessary data structure is detailed in Laurenceau and Bolger (2005). The sample contains data for both partners, with daily measures of relationship conflict and negative relationship behaviors across 21 days (Level 1 data) and a one-time measure of relationship satisfaction (Level 2 data). Each of these three variables is discussed below in terms of how they can be measured and their correspondence to the CAPS model.

Daily relationship threat. Daily relationship threat can be measured in multiple formats. It can be measured as a dichotomous indicator or as a continuous variable, with a single-item measure asking about conflict that may have occurred during the course of the day that was perceived as transgressive or threatening. This item represents the “situation” component that couples experience, which can vary from day to day (i.e., a conflict day or a no-conflict day). Because this is a
daily measure, some participants will vary in their responses from day to day. Therefore, this measure can be thought of as comprising two components: a within-person average across the 21 days and the day-to-day variance from that mean. To evaluate the effects of the variance on the outcome variable, we partialed out the within-person average from each partner’s data (i.e., person-centered the data). This is discussed in more detail below.

**Daily negative behaviors toward partner.** For our outcome variable, we used a daily count variable that represents the number of negative behaviors expressed toward one’s partner in the course of the day. Because Monte Carlo simulation in Mplus does not as yet permit the simulation of a count variable, the daily behavior outcomes created were generated as continuous in nature. However, these same analyses could be conducted with a count outcome, and the analyses will be described taking a count distribution into consideration.

**Global relationship satisfaction.** We used a continuous measure to represent relationship satisfaction for each partner. Unlike relationship threat, which was measured daily, satisfaction was measured at a single time point, represents a “person” variable in the CAPS model, and will be a Level 2 predictor in the present analyses.

**Conceptualizing the Multilevel Model for Individuals**

Although the diary design is one whose aim was to collect dyadic data, we will first focus on the data from one individual (in this case, the female partner). Consider the following simple linear regression model for a single individual’s diary data where $t$ indexes day:

$$\text{NegBeh}_t = b_0 + b_1 \times \text{Threat}_t + e,$$

(Eq. 1)

We begin by identifying how parameters starting with this model represent important personality components. Drawing from Zayas et al. (2002), the important personality phenomena that can be identified in the CAPS framework are (a) overall levels of behaviors as outcomes (i.e., what is the typical level of a behavioral outcome for a sample of individuals, and how much do people differ from each other in terms of these typical levels?), (b) encountered or construed situations (i.e., to what extent does the typical person vary being in a
situation on a day-to-day basis from his or her own overall tendency of being in that situation, and how much do people differ from each other in these overall tendencies?), and (c) if-then contingencies (i.e., to what extent is the amount of a behavioral outcome linked to being in a situation for the typical person, and how much do people differ from each other in the strength of this link?).

*Overall levels of behavior.* The most easily observable aspect of a person’s personality is the overall level of an individual’s behavior. This is typically represented as the consistent level, amount, or intensity of a behavior as compared to another individual. Across a sample of individuals, some individuals are typical in that one can observe average levels of the behavior compared to others, whereas there will be individuals who display high levels and low levels of the behavior compared to the average.

A conceptualization of personality that seeks to explain how an individual behaves differently at different times and in different situations must also focus on within-person variability in observed behavior. In Equation 1, NegBeh, represents the distribution of reported negative relationship behaviors across 21 days for a single individual, which is regressed on Threat, representing the distribution of perceived relationship threat across the same 21 days for that individual. Applying a general principle of regression analysis, if Threat is centered about its mean, then \( b_0 \) represents the individual’s average level of NegBeh. Without knowing anything about the daily events and situations that this individual encounters, or averaging across all daily events and situations, \( b_0 \) represents an individual’s overall level of a behavioral outcome. Extending the model to represent many individuals who each have 21 days of diary data allows for the likely scenario that each individual has a different \( b_0 \) and that there is a distribution of \( b_0 \)s with individuals who are typical (average), low, and high in levels of behavior. Thus, in a sample of daily behavioral outcomes across many individuals, there are two kinds of variability in the behavioral outcome. There is within-person variability in behavior where daily NegBeh for a particular individual varies from day to day about that individual’s mean level of NegBeh. There is also between-person variability in behavior where individuals vary from each other on their mean levels of NegBeh. As we later show, we wish to understand both types of variability in behavior.
**Encountered situations.** An important feature of the CAPS conceptualization of personality is that individuals will exhibit different levels of a behavior or behave differently across the varied situations that they encounter in their everyday lives. Thus, encountered situations are the “ifs” in the if-then” contingencies. In Equation 1, perceived relationship threat can be operationalized either as the presence or absence of perceived daily conflict with one’s partner (e.g., a partner transgression) or as the degree to which the person feels threatened within the context of his or her relationship. In either case, perceived relationship threat represents the situational component and embodies possible daily relationship “situations,” such as low threat, average threat, or high threat, reflected in part by the partner’s actual relationship-threatening behavior.

As is the case for the behavioral outcome \( NegBeh \), this daily situational component, \( Threat \), is also measured on each of the 21 days across all the individuals in a sample. Now there are indexes of \( t \) for day and \( i \) for person. Moreover, as with the outcome \( NegBeh_{ti} \), \( Threat_{ti} \) also contains both within-person and between-person variability. There is within-person variability in \( Threat_{ti} \) such that daily threat ratings can vary from day to day about an individual’s mean level of threat across his or her 21 days. There also is between-person variability in \( Threat_{ti} \) such that individuals vary from each other on their mean levels of threat. This distinction becomes important because the CAPS model specifies that a person’s behavior will vary as a function of the varied situations the person experiences. Therefore, we wish to isolate the variability in \( Threat_{ti} \) that represents how much exposure to relationship threat changes from day to day (i.e., within-person variability). As we later show, it is this component of personality that will directly contribute to an individual’s unique “if... then” contingencies.

It is worth noting that the between-person variability in \( Threat_{ti} \) also represents an interesting personality component that can play a role in the CAPS framework and in our modeling approach. If within-person variability in \( Threat_{ti} \) reflects changes in daily situational exposure, between-person variability in \( Threat_{ti} \) reflects individual differences in the average tendency to perceive threat across the 21-day diary sampling period. These individual differences can be conceptualized as a constant influence of the person on his or her daily threat ratings. Some individuals will tend to report more relationship threat on average and some will report less. This between-person component of daily threat may reflect a “trait”
measure of relationship threat perception, akin to what is captured by facets of cross-sectional scales of neuroticism or extraversion scales. What is different from the traditional, cross-sectional trait inventories is that the “trait” between-person variability in \( \text{Threat}_{it} \) is based on the person’s actual daily reports of threat rather than a scale-based measure of threat perception tendencies. Although we do not do this here, an interesting step could be to include a single-time self-report scale assessing trait threat as a predictor along with the between-person component of \( \text{Threat}_{it} \).

Because within-person variability and between-person variability in a repeated-measures variable are independent parts of the variable’s total variability, links between each of these two types of variability and another repeated-measures outcome need not be the same in magnitude or even in sign. If the variance in \( \text{Threat}_{it} \) was not decomposed into its within-person and between-person parts, and the uncentered \( \text{Threat}_{it} \) itself was used as a predictor in the model, the resulting regression coefficient would reflect a potentially confounded blend of the two types of effects.

As a result of these two types of variability in \( \text{Threat}_{it} \), we will label the within-person and between-person components of daily relationship threat as \( \text{Threat}_w \) and \( \text{Threat}_b \), respectively. \( \text{Threat}_{witi} \) is the person-mean deviated threat scores (i.e., \( \text{Threat}_{witi} = \text{Threat}_{iti} - \text{Threat}_i \)) and \( \text{Threat}_{bi} \) is the person-means (i.e., \( \text{Threat}_i \)). The following set of Level 1 and Level 2 equations demonstrates this decomposition:

\[
\text{NegBeh}_{iti} = b_{0i} + b_{1i} \times \text{Threat}_{witi} + e_{iti} \quad \text{(Eq. 2)}
\]

\[
b_{0i} = \gamma_{00} + \gamma_{01} \times \text{Threat}_{bi} + u_{0i} \quad \text{(Eq. 2a)}
\]

\[
b_{1i} = \gamma_{10} + u_{1i} \quad \text{(Eq. 2b)}
\]

We return later to the interpretation of the parameters associated with \( \text{Threat}_w \) and \( \text{Threat}_b \).

If-then contingencies. A cornerstone of Mischel and Shoda’s CAPS model are the behavioral signatures that demonstrate stability of context (stimulus) and behavior (response) contingencies within an
individual. An individual’s behavioral signature is the if-then link between a specific situation (or exposure to a specific situation) and a specific behavior (or level of a behavior). Within the CAPS model, the specific situation is a stimulus of sorts that triggers a cascade of influences on cognitive-affective mediating units that in turn influence particular observed behavioral responses. In regression terms, a 1-unit increase in a person’s perception of relationship threat predicts a \( b_1 \)-unit shift in observed negative relationship behavior. The individual specificity of the chain of cognitive-affective links that mediates the situation and behavioral response is what allows for the fact that the same individual will behave differently over time and situation. Thus, what determines stability in an individual’s behavior is his or her behavioral signature.

In Equation 2, the typical individual’s behavioral signature is captured by the parameter \( \gamma_{10} \) (a fixed effect). Exposure or degree of exposure to a situation (i.e., relationship threat) on a particular day (i.e., \( \text{Threat}_{wi} \)) is associated with a behavioral reactivity to this situation. Extending this idea to the case of many persons, each with a \( b_1 \) coefficient of varying magnitude, allows for the fact that different individuals will respond differently to the same daily situation (the random effect, \( u_{1i} \)). These individual differences in behavioral reactivity to a situation are represented as a distribution across individuals (\( b_{1i} \)) and can potentially be explained by other between-person predictors. For example, we allow for the possibility that global relationship satisfaction attenuates behavioral reactivity to relationship threat.

**Findings From a Multilevel Model for Individuals**

For the present purposes, we are using the individual variation in day-to-day relationship threat (i.e., \( \text{Threat}_{wi} \)) to represent the changing situational factor. One person component of the CAPS model is represented by global relationship satisfaction, which measures how satisfied an individual generally feels about his or her relationship and is assumed to be stable over the course of the diary recording period. Another person component is an individual’s mean level of perceived relationship threat over the diary recording period (i.e., \( \text{Threat}_{bi} \)). We used this individual mean as a predictor of the intercept, capturing the association between the between-person variability in the daily negative behavior outcome and the between-person variability in daily relationship threat. Both subtracting out
each person’s mean relationship threat from his or her daily relationship threat ratings and controlling for mean relationship threat allows the slope of daily relationship threat to daily negative behavior (i.e., $\gamma_{10}$) to represent a pure within-person association, having purged the daily predictor of any between-person variance. The outcome of interest is a daily behavioral measure of negative behaviors expressed toward one’s partner. Consistent with the CAPS model, we expect the situational factor to interact with a person factor in predicting our outcome. That is, we expect a statistical cross-level interaction between daily perceptions of conflict and global perceptions of relationship satisfaction in predicting daily negative behaviors enacted. Specifically, we expect higher levels of relationship satisfaction to attenuate the effects of conflict on negative behaviors.

Before we turn to examination of the output, we review a visual depiction of the model under consideration. In Figure 1, within-person and between-person variables are separated by a dotted line.

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1. Due to the nature of the negative relationship behavior measure (i.e., a count variable with a positive skew), these kinds of count outcomes can be analyzed assuming a Poisson or negative binomial distribution (Atkins & Gallop, 2007) in Mplus. However, for ease of interpretation, we have reported results assuming normally distributed outcomes.
All the gammas coefficients label fixed effect paths whose point estimates we will soon see in Table 1. The daily outcome, negative relationship behaviors, has a filled solid circle on it to represent that a random effect variance component has been estimated for the intercept of the model, reflecting that individuals are allowed to vary from each other in intercept values (i.e., mean levels of negative partner behavior). The path representing the within-person fixed effect between daily relationship threat and daily negative behavior also has a filled solid circle on it, indicating that a corresponding random effect variance component has been estimated.

Table 1 contains the inferential statistics and estimated parameters for effects depicted in Figure 1 as well as some other parameters estimates not shown in the figure. The Mplus syntax for these results is presented in Appendix 1 (the corresponding HLM setup is in the top panel of Appendix 3). We first turn to the top section of the table, focusing on the fixed (average) effects. In particular, $\gamma_{10}$ represents the within-person effect of daily relationship threat on daily negative behavior. Because we have controlled for average tendency to perceive relationship threat ($\gamma_{02}$), the $\gamma_{10}$ effect can be interpreted as a pure within-person effect for the typical female partner: On days when there is a 1-unit increase in perceived relationship threat, there is a .40-unit increase in the negative behaviors she reports engaging in toward the male partner. We show that there are also significant individual differences in the magnitude of this within-person effect across female partners in the sample. The person factor of global relationship satisfaction ($\gamma_{01}$) has a negative influence on negative behaviors regardless of whether it is a high or low threat day. The $\gamma_{11}$ coefficient represents the daily relationship threat by global relationship satisfaction (i.e., cross-level) interaction, such that increases in relationship satisfaction counteract the daily effects of relationship threat. Finally, female partners who tended to perceived greater average (i.e., trait) levels of relationship threat across the 21-day diary period also tended to report higher levels of daily negative behavior.

Turning to the random effects, there remain significant individual differences (female intercept variance = .43) in overall levels of relationship behavior, taking into account the effects of the various predictors. There are also significant individual differences (female RelThreat variance = .31) in the degree to which female partners behaved negatively toward male partners on days when relationship
Table 1
Estimates From an Individual Multilevel Model of Daily Relationship Negative Behaviors as a Function of Daily Relationship Threat and Global Relationship Satisfaction

Outcome: Daily Relationship Negative Behaviors

<table>
<thead>
<tr>
<th>Model Parameters</th>
<th>Fixed Effects (intercept, slopes)</th>
<th>Estimate (SE)</th>
<th>Z</th>
<th>p</th>
<th>95% CI</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F Intercept, $\gamma_0$</td>
<td>1.55 (0.07)</td>
<td>23.66</td>
<td>&lt; 0.001</td>
<td>1.43</td>
<td>1.68</td>
<td></td>
</tr>
<tr>
<td></td>
<td>F Daily RelThreat, $\gamma_0$</td>
<td>0.40 (0.06)</td>
<td>6.58</td>
<td>&lt; 0.001</td>
<td>0.28</td>
<td>0.52</td>
<td></td>
</tr>
<tr>
<td></td>
<td>F RelSat, $\gamma_0$</td>
<td>-0.50 (0.12)</td>
<td>-4.03</td>
<td>&lt; 0.001</td>
<td>-0.74</td>
<td>-0.25</td>
<td></td>
</tr>
<tr>
<td></td>
<td>F Daily RelThreat*RelSat, $\gamma_1$</td>
<td>-0.40 (0.11)</td>
<td>-3.60</td>
<td>0.001</td>
<td>-0.62</td>
<td>-0.18</td>
<td></td>
</tr>
<tr>
<td></td>
<td>F RelThreat mean, $\gamma_2$</td>
<td>0.31 (0.13)</td>
<td>2.33</td>
<td>0.02</td>
<td>0.05</td>
<td>0.57</td>
<td></td>
</tr>
</tbody>
</table>

95% CI

<table>
<thead>
<tr>
<th>Random effects ((co-)variances)</th>
<th>Estimate (SE)</th>
<th>Z</th>
<th>p-value</th>
<th>95% CI</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 2 (between person)</td>
<td>F Intercept</td>
<td>0.43 (0.08)</td>
<td>5.51</td>
<td>&lt; 0.001</td>
<td>0.28</td>
<td>0.58</td>
</tr>
<tr>
<td></td>
<td>F RelThreat</td>
<td>0.31 (0.05)</td>
<td>5.86</td>
<td>&lt; 0.001</td>
<td>0.21</td>
<td>0.42</td>
</tr>
<tr>
<td></td>
<td>F Intercept RelThreat covariance</td>
<td>0.24 (0.06)</td>
<td>3.89</td>
<td>&lt; 0.001</td>
<td>0.12</td>
<td>0.36</td>
</tr>
<tr>
<td>Level 1 (within person)</td>
<td>F Residual</td>
<td>0.19 (0.006)</td>
<td>32.66</td>
<td>&lt; 0.001</td>
<td>0.18</td>
<td>0.20</td>
</tr>
</tbody>
</table>

Outcome: Daily Relationship Negative Behaviors

Note. F= female partner. N = 100 females; total days = 2,100. All p-values are two-tailed except in the case of variances, where one-tailed p values are used (because variances are constrained to be nonnegative).
threat increased. Taking $+/−2 SD$ about the fixed effect of relationship threat provides some sense of the range of the individual female slopes (approximately 95% of the samples slopes falls within the range of .21 to .59). There is a positive and significant conditional covariance between the random effects of female intercept and RelThreat slope. The covariances between the random effects take on a more substantive meaning when we turn to the dyadic multilevel context. Finally, there is a within-person residual that is assumed to be normally distributed with no autocorrelation—the variance of $e_{ii}$ is often referred to as $\sigma^2$.

The analytic approach described above is one way that the CAPS model can be empirically examined in a daily diary context using reports of both “situation” and “person” variables. In this particular model, perceived relationship threat served as the eliciting situation component, allowing us to capture varying daily contexts in which individuals find themselves. On average, individuals who perceive relationship threat on a particular day also display more negative relationship behaviors than on days when a threat is not perceived. The “person” factors of average levels of perceived threat and global relationship satisfaction can then influence aspects of the behavioral signature. Being generally satisfied with one’s relationship attenuates the if-then relationship. Moreover, individuals with higher average levels of perceived threat also tended to display more negative relationship behaviors on any given day, independent of whether or not a threat was perceived that day. Thus, we can see that the outcome of negative behaviors can change across days but in a consistent and predictable way based on known daily- and person-level contextual factors.

**Conceptualizing the Multilevel Model for Dyads**

We now turn to examining these data from a dyadic perspective, using data from both partners of each dyad (see Appendix 2 for Mplus syntax for these analyses). To do this, we extended the multilevel model for individuals presented above by utilizing dyadic multilevel modeling with multivariate outcomes (Laurenceau & Bolger, 2005; Raudenbush et al. 1995). At Level 1 (or the within-couple level), there are two outcomes for each couple (i.e., daily

2. Autocorrelated errors and other within-person error structures can be tested, but this was not done to simplify the presentation of results.
negative relationship behavior for male and female partners) being predicted by their corresponding daily ratings of perceived relationship threat. Therefore, the linear regression model that we started with above for a single individual is now a multivariate model estimated for a single couple:

\[ MNegBeh_t = b_{0M} + b_{1M} \times M\text{Threat}_t + e_t \]  
(Eq. 3a)

\[ FNegBeh_t = b_{0F} + b_{1F} \times F\text{Threat}_t + e_t \]  
(Eq. 3b)

We simultaneously estimate within-couple effects for male and female partners to accommodate the interdependent nature of dyadic data, where partners within the same dyad are likely to be more similar to one another than to a randomly selected partner because they share the same relationship. Additionally, we estimate male and female Level 1 residuals separately, thus providing separate variances and a covariance between the male and female residuals. This covariance represents the within-day interdependence between male and female partners in negative partner behavior that is not accounted for by perceptions of threat. For example, if male and female partners both woke up in a worse mood than usual on a particular day, which caused them to both have higher negative relationship behavior than usual (but morning mood was not measured and included in the model), then this would create correlated Level 1 partner residuals.

We also make use of the actor-partner interdependence framework (APIM; Kenny et al., 2006; see Figure 2) when examining cross-level effects. In this particular model, actor effects allow us to examine the effects of between-couple female predictors on within-couple female intercepts and slopes as outcomes (i.e., female actor effect) and effects of between-couple male predictors on within-couple male intercepts and slopes as outcomes (i.e., male actor effect). Partner effects allow us to examine the effects of between-couple female predictors on within-couple male intercepts and slopes (i.e., female partner effect) and effects of between-couple female predictors on within-couple male intercepts and slopes as outcomes (i.e., male partner effects), above and beyond any actor effects.
Similar to the individual model, we link (a) overall levels of behaviors as outcomes, (b) encountered or construed situations, and (c) if-then contingencies to particular parameters in our dyadic model. Moreover, we can also examine how these personality phenomena are influenced by partner variables (i.e., partner effects).

**Overall levels of behavior.** Similar to the individual model described above, $M_{NegBeh_i}$ and $F_{NegBeh_i}$ represent the distribution of reported negative relationship behaviors across the diary days for male and female partners. These outcomes are regressed on $M_{Threat_i}$ and $F_{Threat_i}$, respectively, representing the distribution of perceived relationship threat across the same 21 days for that male and female. Again, when $M_{Threat_i}$ and $F_{Threat_i}$ are mean centered, then $b_{0M}$ and $b_{0F}$ represent the male and female average (i.e., overall) levels of their outcomes, $M_{NegBeh}$ and $F_{NegBeh}$.

**Encountered situations.** Similar to the individual model, the perception of relationship conflict or threat reported by each partner

---

**Figure 2**

Multilevel model for dyads.
serves as the situation variable for each partner. These remain the “ifs” in the if-then contingencies. Because it is possible (and even likely) that both partners in a dyad may not perceive a threat or conflict on the same day, Equations 3a and 3b represent the effects of one’s own perception of relationship threat on one’s own subsequent behaviors.

As is the case in the individual model, the daily situational component, Threat_t, is also measured each of the 21 days across all male and female partners in a sample, and thus comprises both within-person (day-to-day) and between-person (person-to-person) variability. The index t still represents day, but i now represents couple. Therefore, we again isolated the within-person variability in Threat_t_i for both males and females by mean centering MThreat_t_i and FThreat_t_i, extracting the traitlike, between-person components of variability, or average levels of perceived threat, and making them Level 2 (between-couple) predictors (see Figure 2).

Because these two types of variability in Threat_t are present for both partners, we label the within-person and between-person components of daily relationship threat as MThreat_w and MThreat_b for the male partners and FThreat_w and FThreat_b for the female partners, respectively. The following set of equations depicts the dyadic multilevel model containing this decomposition:

\[
M\text{NegBeh}_t = b_{0im} + b_{tim} \times M\text{Threat}_{wti} + e_{tim} \quad (\text{Eq. } 4)
\]

\[
b_{0im} = g_{00m} + g_{01m} \times M\text{Threat}_{hti} + u_{0im} \quad (\text{Eq. } 4a)
\]

\[
b_{tim} = g_{10m} + u_{tim} \quad (\text{Eq. } 4b)
\]

\[
F\text{NegBeh}_t = b_{0if} + b_{tif} \times F\text{Threat}_{wtf} + e_{tif} \quad (\text{Eq. } 5)
\]

\[
b_{0i} = g_{00f} + g_{01f} \times F\text{Threat}_{hti} + u_{0if} \quad (\text{Eq. } 5a)
\]

\[
b_{ti} = g_{10f} + u_{tif} \quad (\text{Eq. } 5b)
\]
We return later to the interpretation of the parameters associated with male and female $\text{Threat}_w$ and $\text{Threat}_b$.

If-then contingencies. As described earlier, one way of examining the behavioral signatures of both partners is by estimating the effects of perceiving relationship threat on negative relationship behaviors. Just as with the individual model, the typical male and female behavioral signatures are captured by the parameters $g_{10m}$ and $g_{10f}$ in Equations 4 and 5. These parameters allow us to examine how the behavior of male and female partners differs in a context when a one-unit shift in threat is perceived, compared to when average threat is perceived. Although their overall responding may not show significant stability when looked at across threat-relevant situations, there may be stability in the different patterns of responding during the times in which threat is or is not perceived. These effects can be conceptualized as within-couple actor effects in which one person’s “situational construal” influences his or her own behavior. We have not included partner effects at Level 1.

Having Level 2 (i.e., between-couples) data from both partners allows us to examine more complex cross-level relationships in which the if-then contingencies are linked to person factors coming from both partners, as depicted in the following model:

\[
\begin{align*}
M_{\text{NegBeh}}_i &= b_{0im} + b_{lim} * M_{\text{Threat}}_{wit} + e_{lim} \\
&= g_{00m} + g_{01m} * M_{\text{Threat}}_{wit} + g_{02m} * M_{\text{RelSat}}_i + g_{03m} * F_{\text{RelSat}}_i + u_{0im} \\
&= g_{10m} + g_{11m} * M_{\text{RelSat}}_i + g_{12m} * F_{\text{RelSat}}_i + u_{lim} \\
F_{\text{NegBeh}}_i &= b_{0if} + b_{iff} * F_{\text{Threat}}_{wit} + e_{iff} \\
&= g_{00f} + g_{01f} * F_{\text{Threat}}_{wit} + g_{02f} * F_{\text{RelSat}}_i + g_{03f} * M_{\text{RelSat}}_i + u_{0if} \\
&= g_{10f} + g_{11f} * F_{\text{RelSat}}_i + g_{12f} * M_{\text{RelSat}}_i + u_{iff}
\end{align*}
\]
In the present example, $\text{RelSati}$ represents global relationship satisfaction that was measured for males ($M\text{RelSati}$) and females ($F\text{RelSati}$) at one time point, making them between-couple (i.e., Level 2) variables. Similar to the individual model, we can look at the association between female overall relationship satisfaction and female negative relationship behaviors (i.e., a cross-level actor effect), in which a female’s global evaluation of her relationship is associated with the overall level of negative behaviors she displays ($g_{02m}$). However, with data from both partners, we are also able to examine the effects of relationship satisfaction of the male partner on the female partner’s negative relationship behaviors (i.e., a cross-level partner effect), represented by the parameter $g_{03f}$ in Equation 7a. That is, the more satisfied the male partner is with his relationship, the fewer negative behaviors may be enacted toward him by his partner on a given day.

The if-then contingency can depend on relationship satisfaction, representing a person variable that can interact with a situation variable, such as perceived relationship threat. That is, a person’s global evaluation of his or her relationship may influence the way in which perceptions of threat lead to negative behaviors (i.e., cross-level statistical moderation). This is represented by the $g_{11m}$ and $g_{11f}$ actor effect parameters in Equations 6b and 7b, respectively. Additionally, partner relationship satisfaction can also have an influence on behavioral signatures, captured by cross-level partner effects $g_{03m}$ and $g_{03f}$ in Equations 6b and 7b, respectively. Figure 2 depicts the dyadic multilevel model represented in Equation sets 6 and 7.

**Findings From a Multilevel Model for Dyads**

Table 2 contains the inferential statistics and estimated parameters for effects depicted in Figure 2 as well as some other parameters not shown in the figure. The effects on the male outcome, negative behaviors, are reported first followed by the female effects, due to the multivariate outcome structure of our model. Similar to the individual model, $g_{10m}$ and $g_{10f}$ represent the within-couple actor effects of daily relationship threat on daily negative behavior for male and female partners, respectively. Just as with the individual model, this effect can be interpreted as the pure within-person effect for the typical male or female partner. For male partners, on days when there is a one-unit increase in his perceived relationship threat, there
Table 2
Estimates From a Dyadic Multilevel Model of Daily Relationship Negative Behaviors as a Function of Daily Relationship Threat and Global Relationship Satisfaction

Outcomes: Male and Female Daily Relationship Negative Behaviors

Model Parameters

<table>
<thead>
<tr>
<th>Fixed Effects (Intercept, Slopes)</th>
<th>Estimate (SE)</th>
<th>z</th>
<th>p</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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</tr>
<tr>
<td><strong>Male Outcome</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M Intercept, $\gamma_{00m}$</td>
<td>1.51 (0.06)</td>
<td>27.34</td>
<td>&lt; 0.001</td>
<td>1.39</td>
<td>1.61</td>
</tr>
<tr>
<td>M RelThreat slope, $\gamma_{01m}$</td>
<td>0.44 (0.07)</td>
<td>6.72</td>
<td>&lt; 0.001</td>
<td>0.31</td>
<td>0.56</td>
</tr>
<tr>
<td>M RelSat, $\gamma_{02m}$</td>
<td>-0.18 (0.08)</td>
<td>-2.29</td>
<td>0.022</td>
<td>-0.33</td>
<td>-0.03</td>
</tr>
<tr>
<td>F RelSat, $\gamma_{03m}$</td>
<td>-0.27 (0.09)</td>
<td>-2.87</td>
<td>0.004</td>
<td>-0.46</td>
<td>-0.09</td>
</tr>
<tr>
<td>M Daily RelThreat*RelSat, $\gamma_{11m}$</td>
<td>-0.35 (0.12)</td>
<td>-3.06</td>
<td>0.002</td>
<td>-0.58</td>
<td>-0.13</td>
</tr>
<tr>
<td>F Daily RelThreat*RelSat, $\gamma_{12m}$</td>
<td>-0.34 (0.10)</td>
<td>-3.46</td>
<td>0.001</td>
<td>-0.54</td>
<td>-0.15</td>
</tr>
<tr>
<td>M RelThreat Mean, $\gamma_{01m}$</td>
<td>0.30 (0.09)</td>
<td>3.42</td>
<td>0.001</td>
<td>0.13</td>
<td>0.47</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Female Outcome</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F Intercept, $\gamma_{00f}$</td>
<td>1.52 (0.05)</td>
<td>28.28</td>
<td>&lt; 0.001</td>
<td>1.42</td>
<td>1.63</td>
</tr>
<tr>
<td>F Daily RelThreat, $\gamma_{01f}$</td>
<td>0.36 (0.06)</td>
<td>6.33</td>
<td>&lt; 0.001</td>
<td>0.25</td>
<td>0.48</td>
</tr>
<tr>
<td>F RelSat, $\gamma_{02f}$</td>
<td>-0.27 (0.10)</td>
<td>-2.73</td>
<td>0.006</td>
<td>-0.46</td>
<td>-0.08</td>
</tr>
<tr>
<td>M RelSat, $\gamma_{03f}$</td>
<td>-0.48 (0.09)</td>
<td>-5.38</td>
<td>&lt; 0.001</td>
<td>-0.66</td>
<td>-0.31</td>
</tr>
<tr>
<td>F Daily RelThreat*RelSat, $\gamma_{11f}$</td>
<td>-0.25 (0.10)</td>
<td>-2.42</td>
<td>0.015</td>
<td>-0.45</td>
<td>-0.05</td>
</tr>
<tr>
<td>M Daily RelThreat*RelSat, $\gamma_{12f}$</td>
<td>-0.41 (0.11)</td>
<td>-3.71</td>
<td>&lt; 0.001</td>
<td>-0.62</td>
<td>-0.19</td>
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<tr>
<td>F RelThreat Mean, $\gamma_{01f}$</td>
<td>0.17 (0.11)</td>
<td>1.58</td>
<td>0.114</td>
<td>-0.04</td>
<td>0.39</td>
</tr>
</tbody>
</table>

(Continued)
Table 2 (Cont.)

<table>
<thead>
<tr>
<th>Random Effects ((co-)variances)</th>
<th>Estimate (SE)</th>
<th>z</th>
<th>p</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Level 2 (between couple)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M Intercept</td>
<td>0.24 (0.04)</td>
<td>6.75</td>
<td>&lt; 0.001</td>
<td>0.17</td>
<td>0.31</td>
</tr>
<tr>
<td>F Intercept</td>
<td>0.26 (0.04)</td>
<td>7.25</td>
<td>&lt; 0.001</td>
<td>0.18</td>
<td>0.33</td>
</tr>
<tr>
<td>M RelThreat</td>
<td>0.29 (0.04)</td>
<td>7.09</td>
<td>&lt; 0.001</td>
<td>0.21</td>
<td>0.37</td>
</tr>
<tr>
<td>F RelThreat</td>
<td>0.30 (0.05)</td>
<td>6.17</td>
<td>&lt; 0.001</td>
<td>0.21</td>
<td>0.40</td>
</tr>
<tr>
<td>M-F Intercept covariance</td>
<td>0.13 (0.03)</td>
<td>5.09</td>
<td>&lt; 0.001</td>
<td>0.08</td>
<td>0.19</td>
</tr>
<tr>
<td>M-F Slope covariance</td>
<td>0.14 (0.04)</td>
<td>4.04</td>
<td>&lt; 0.001</td>
<td>0.07</td>
<td>0.21</td>
</tr>
<tr>
<td><strong>Level 1 (within couple)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M Residual</td>
<td>0.20 (0.01)</td>
<td>31.49</td>
<td>&lt; 0.001</td>
<td>0.19</td>
<td>0.21</td>
</tr>
<tr>
<td>F Residual</td>
<td>0.20 (0.01)</td>
<td>32.52</td>
<td>&lt; 0.001</td>
<td>0.18</td>
<td>0.20</td>
</tr>
<tr>
<td>M-F Residual covariance</td>
<td>0.05 (0.01)</td>
<td>11.63</td>
<td>&lt; 0.001</td>
<td>0.05</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Note. M = male partner; F = female partner. N = 100 couples; total days = 2,100. All p values are two-tailed except in the case of variances, where one-tailed p-values are used (because variances are constrained to be nonnegative).
is a .44-unit increase in negative behaviors he reports engaging in toward his partner. For female partners, on days when there is a 1-unit increase in her perceived relationship threat, there is a .36-unit increase in negative behaviors she reports engaging in toward her partner. These significant increases in negative behaviors on days in which threats are perceived capture the presence of an if-then behavioral pattern (e.g., “If I perceive a threat in my relationship, then I behave more negatively toward my partner”).

Examining the effects of the between-couple contextual factor, global relationship satisfaction, (g02 for males and g03 for females), a dyadic model permits both actor and partner effects to be estimated. A male’s own global relationship satisfaction and his partner’s overall level of relationship satisfaction have negative influences on overall negative behaviors regardless of whether it is a high- or low-threat day. Additionally, because these factors are permitted to correlate, these parameters represent unique effects that have partialed out any shared variance between male and female partner global relationship evaluations. The g11 and g12 coefficients represent the daily relationship threat by global relationship satisfaction (i.e., cross-level) interaction for partners, such that increases in male relationship satisfaction attenuate both the daily effects of male relationship threat (actor effect) and the daily effects of female relationship threat (partner effect). Additionally, global levels of relationship threat were significantly associated with overall negative behaviors such that female and male partners who tended to perceived greater average levels of relationship threat averaged across the 21-day diary period also tended to report higher levels of their own daily negative behavior.

Similar to the random effects presented in the individual model, there were significant individual differences in overall levels of relationship behavior for both males and females, taking into account the effects of the various actor and partner predictors (i.e., intercept variance). There were also significant individual differences in the slopes (male and female RelThreat slope variance), reflecting variance in the relationships between male and female perceptions of threat and negative relationship behaviors enacted by males and females on those days.

Unique to the dyadic model, we are able to examine the covariances between male and female random effects. The variability levels in intercepts and slopes are significantly associated with one another across male and female partners (M-F intercept covariance = .13;
M-F slope covariance = .14). The male-female intercept covariance indicates whether male partners who have higher (lower) overall levels of negative behavior tend to be paired with female partners who have higher (lower) levels of negative behavior. The male-female slope covariance indicates whether male partners with stronger (weaker) behavioral signatures tend to be paired with female partners with stronger (weaker) behavioral signatures. One can attempt to explain these associations with other theoretically relevant covariates. Additionally, there is a positive and significant covariance between the male and female within-couple residual variance components capturing unexplained interdependence in the partner’s daily outcomes.

To summarize, this section illustrated how data obtained via dyadic daily diary methods allow researchers to parameterize some important aspects of the CAPS model as applied to individuals and dyads. Examining the CAPS model within a dyadic multilevel modeling framework permits exploration of if-then associations at the individual level and at the couple level. Partner effects can be examined to see how partners influence one another and create stable relationship patterns. Further aspects of the CAPS model can be investigated beyond those described above. For example, Bolger and Romero-Canyas (2007) described how reactivity to situations can be extended to multiple individuals, each with multiple situations and corresponding behavioral signatures.

Looking Toward the Future: Dynamical Systems as a Promising Theoretical and Methodological Framework

As argued by Reis et al. (2002) and implied by Zayas et al. (2002), the future of both relationship and personality research will need to include applications of statistical methods for the study of system processes and behavior. In this final section, we consider future directions that move toward conceptualizing personality and close relationship processes from a dynamical systems approach. While a system comprises a number of elements that are logically linked in time, a dynamical system is one in which past states of the system influence future states of the system (Boker, 2002). From this perspective, important features of some psychological systems are that when allowed to evolve over time, they become self-regulating and self-organizing in nature. These features allow systems to demonstrate both stability (e.g., homeostasis) and instability (i.e., change). A dynamical systems-based approach reflects an apprecia-
tion for the complex system behavior that is evident in personality
and close relationship phenomena.

*Systems Approaches to Personality*

An example of one process-oriented model of personality that is already
dynamic in its core is the Self-Regulation Model of Personality (Carver &
Scheier, 1990, 1998), which takes the view of the person as a complex
organization of self-regulating feedback loops. In this model, stability
and variability in an individual’s behavior is guided in part by present
versus desired status with respect to goals and the ongoing prioritization
and reprioritization of goals. Using a cybernetics-based approach
(Powers, 1973), Carver and Scheier describe two classes of feedback loop
systems: a discrepancy-reducing loop, which is approach oriented and
involves moving toward a desired goal, and a discrepancy-increasing
loop, which is avoidance oriented and involves moving away from
undesirable states. Thus, an individual’s behavior exhibits a predictable
pattern of self-regulation with respect to situationally salient goals.

Affect plays a feedback function as well—an ongoing signal to the
person of the rate of progress being made on a particular goal. Approach
and avoidance systems are hypothesized to be responsible for two sorts of emotional experience (e.g., Cacioppo, Gardner, &
Berntson, 1999; Carver, 2001; Watson et al., 1999). When a person is
progressing toward an incentive, the approach system is held to yield
positive affects such as excitement and enthusiasm (Fowles, 1994;
Gray, 1994a, 1994b). When a person is nearing a threat, the aversive
system is held to yield anxiety (Fowles, 1994; Gray, 1994a). We
should note, however, that these are not the only affects that can be
linked to these two systems. For example, disruption of movement
toward an incentive can yield frustration, anger, or sadness (Carver,
2004; Carver & Harmon-Jones, 2009).

In a laboratory experiment (Lawrence, Carver, & Scheier, 2002),
participants’ affect was measured as they were moving closer to a desired
goal (i.e., performing better over time on a computer task) or further
from it (i.e., performing worse over time on a computer task). Although
all participants ended with the same overall outcome, the trajectory
toward or away from their goal was significantly associated with their
change in mood. This exemplifies the importance of viewing the process
of goal-directed behavior over time. Had only the final position been
examined, without taking into account the trajectory toward that posi-
tion, it would be difficult to explain why two groups of participants who performed similarly were experiencing differences in mood. Affect-related feedback processes are posited as central mechanisms underlying regulation of system behavior.

Some aspects of this self-regulation personality model have also recently been extended to the domain of close relationships (Carver, Avivi, & Laurenceau, 2008). Each partner in a couple has relationship-focused goals that he or she seeks to approach and move closer to, as well as relationship-focused goals to avoid or withdraw from (which we will term “antigoals”). Regulation of behavior with respect to these goals is a process that is also continuous and iterative in nature. For example, couples often seek to move closer to states of closeness and intimacy and to move further from conflict or interpersonal distress. Inherent within this model is the notion that couples are constantly approaching multiple goals while simultaneously avoiding other goals, and these “relationship goals” are occurring concurrently with other, individual goals.

Carver and Scheier’s view involves the interaction between people’s dispositional motivation-based sensitivities, the goal they are presently working toward, and the perception of the distance between them and the desired goal. These varying elements render this a complex feedback system to examine empirically in the everyday life of individuals and dyads. A complete examination of Carver and Scheier’s self-regulation model necessitates a dynamical systems conceptualization and corresponding methodological framework. They draw from a control-theoretic framework (Powers, 1973) for conceptualizing the important components underlying a self-regulating system. Behavior responds to the discrepancies in goal attainment. If there is a perceived discrepancy between goal and present circumstances, the system induces behavior to change circumstances to more closely approximate goal attainment. This is a discrepancy-reducing system, a dynamical system reflecting time-varying processes that affect outcomes. Artificial feedback control dynamical systems are exemplified by cruise-control systems in cars.

Control-theoretic methodological and analytic tools have rarely been applied to the study of control processes in psychology, much less personality (or close relationships). However, there is some emerging work that is promising. Molenaar and colleagues (Molenaar & Ram, 2010) detailed the use of time-series methods to model optimal control in the context of psychotherapy interventions with
individuals (Sinclair & Molenaar, 2008) and control of insulin and glucose levels in diabetic patients. Other work has been drawing from engineering-based control system methods to develop adaptive interventions that optimize effectiveness and efficiency (Rivera, Pew, & Collins, 2007). Moreover, recent work has examined questions involving self-regulation using dynamic systems models. For example, Bisconti, Bergeman, and Boker (2006) examined adjustment to conjugal loss by modeling intraindividual variability with daily well-being scores over a 3-month period and were able to identify an oscillating pattern with damping that occurs over time. Specifically, there was evidence that emotional social support led to higher increasing trends in well-being as well as greater damping to equilibrium.

The CAPS model, also dynamic and systems based at its core, suggests that the interaction of cognitive and affective processes (developed from past experience) and the current situation will predict behavior in the future. Can dynamical systems modeling extend investigation of aspects of the CAPS model? Our discussion of behavioral signatures above makes the implicit assumption that these signatures are stable over a relatively long-term time frame, but there may also be changes in those signatures. How can this be examined? A form of dynamical systems modeling known as functional data analysis (Ramsay & Silverman, 2002) allows for the strength of an individual’s behavioral signature parameter to change over time. This type of analysis requires intensive longitudinal assessments to be conducted over a relatively long-term time frame.

An example of this type of methodological design is a burst design (Nessleroad, 1991; Sliwinski, 2008), where a researcher might collect 21-day intensive daily diary assessment periods over several 6-month periods. Applying these notions to the illustrative example above, a functional data analytic approach coupled with a daily diary burst design would allow researchers to track whether a husband’s behavioral reactivity to perceived relationship threats changes over time. This approach might reveal that some male partners have behavioral signatures reflecting relatively high threat reactivity early on in a relationship that decreases somewhat over the first 12 months, increases dramatically at the birth of the first child, and then steadily decreases again as the child matures to middle childhood. Modeling stability and change at different time scales (over days vs. over years) in an individual’s data becomes the focus of the dynamical analysis approach (Ram & Gerstorf, 2009).
Turning to the study of close relationship processes, recent work has conceptualized an individual’s experience of daily intimacy from the framework of a self-regulating dynamical system and how couples can demonstrate coregulation of intimacy (Boker & Laurenceau, 2006). This approach facilitates (a) the integration of both the trait (i.e., equilibrium) and state (i.e., fluctuation) nature of intimacy and (b) exploration of how partners in close relationships mutually influence each other’s course of intimacy. Considering a dyad (e.g., marriage) as a coupled system, one might hypothesize a self-regulating intimacy process in each individual partner and a coupling between these dynamic processes. To empirically test these ideas, Boker and Laurenceau (2006) used second-order differential equations to formalize a model of self-regulation in both partners’ variables measured over time. The two key regulatory parameters produced from these second-order differential equations are a parameter controlling frequency (of oscillations) and a parameter controlling damping (how quickly the process returns to equilibrium). Moreover, the model allowed them to examine how the regulating intimacy behavior of one partner may influence the regulating intimacy behavior of the other. They found support for the hypothesis that in a well-adjusted marriage, the regulation of intimacy toward one’s desired equilibrium level should operate to prevent each partner from experiencing long-term extremes in levels of intimacy (i.e., too little intimacy or too much intimacy). We believe that this direction of work on conceptualizing and examining the regulatory processes underlying intimacy processes shows promise for understanding better the ups and downs of intimate relationship life.

Using a conceptually similar methodology, Ferrer and Nesselroade (2003) examined affective processes and interdependencies in husband-wife dyads using daily diaries over 182 consecutive days. The authors also introduced time into the model and examined lagged effects (e.g., t−1, t+1). Although we did not examine lagged effects in the set of analyses on the simulated data described earlier due to a desire to present a more basic model, lagged effects can easily be integrated into our model, allowing researchers to determine whether events or processes that occur at one time point can influence partner or actor effects later on. In nonexperimental research, lagged effects can help establish causal directionality of
relationships between variables by incorporating temporal sequence links (Cole & Maxwell, 2003).

Dynamical systems approaches can accommodate other important behavioral phenomena. Models of bifurcations and cusp catastrophes have the potential to explain sudden changes in behavior (Kellert, 1993). A common characteristic of some dynamical systems is that complex patterns of behavior and sudden shifts in behavior can be explained using relatively few variables associated through a system of two or three equations. A conceptualization of personality and relationship systems should accommodate this type of variation in behavior as well as the smoother, oscillating forms of variability. Moreover, dynamical systems can also demonstrate sensitivity to initial conditions (Kellert, 1993), which may prove useful in understanding why there is a tendency for the level of negativity at the start of couple conflict discussion to predict how negative the interaction becomes over time (Gottman, Coan, Carrere, & Swanson, 1998).

Concluding Comments

The examination of how personality processes and close relationships influence one another requires intensive sampling and complex statistical modeling. In part due to the complexity required to examine these questions, much of the work on how personality plays a role in close relationship processes remains theoretical and empirically unexamined. The main aim of the simulation described here was to demonstrate methodologically and analytically a way in which personality can be studied within a romantic relationship context using daily diary methods. We also explore future directions, drawing from dynamic system modeling concepts and methods.

Using a daily diary methodology, models such as the CAPS can be tested by creating interactions between stable personality variables and situational variables that may change over time. By examining the interaction between relationship satisfaction and daily relationship threat, we were able to see the ways in which personality influences relationship outcomes, such as negative behaviors enacted toward one’s partner, and how this association may differ as a function of the situation in which the partners find themselves. Although we did not collect real data on this issue and therefore cannot apply the results we observed to the literature of marital
processes, we hope it is clear that researchers are able to examine these dynamic relationship processes through the application of currently used research methodologies, such as daily diary methods and multilevel modeling.

Appendix 1

Mplus Multilevel Model Syntax for Individual Data (Table 1 Estimates)

TITLE: Multilevel model for individual data (Table 1 estimates);
DATA: FILE = jopdyadic1.dat;
DEFINE: xbf = CLUSTER_MEAN (xf);
VARIABLE: NAMES = ym yf xm xf wm wf clus;
USEVAR = yf xf wf clus xbf;
BETWEEN = wf xbf;
CLUSTER = clus;
WITHIN = xf;
CENTERING = GROUPMEAN (xf);
ANALYSIS: TYPE = TWOLEVEL RANDOM;
MODEL:

%WITHIN%
sf | yf ON xf;
yf;
%BETWEEN%
yf ON xbf wf;
sf ON wf;
[yf sf];
yf sf;
yf WITH sf;

OUTPUT: sampstat cinterval;

Note. Capitalized terms refer to Mplus-specific commands and options and lower case terms refer to user-defined variables or options.

y = daily relationship negative behaviors.
x = daily relationship threat (within).
xb = mean daily relationship threat (between).
w = global relationship satisfaction.
f = female partner, m = male partner.
Appendix 2

Mplus Syntax Multilevel Model for Dyadic Data
(Table 2 Estimates)

TITLE: Multilevel model for dyadic data (Table 2 estimates);
DATA: FILE = jopdyadic1.dat;
DEFINE: xbf = CLUSTER_MEAN (xf);
xbm = CLUSTER_MEAN (xm);
VARIABLE: NAMES = ym yf xm xf wm wf id;
USEVAR = id yf xf wf ym xm wm xbf xbm;
BETWEEN = wf xbf wm xbm;
CLUSTER = id;
WITHIN = xf xm;
CENTERING = GROUPMEAN (xf xm);
CENTERING = GRANDMEAN (xbf xbm);
ANALYSIS: TYPE = TWOLEVEL RANDOM;
MODEL:

%WITHIN%
slopf | yf ON xf;
slopem | ym ON xm;
yf; ym; yf WITH ym;

%BETWEEN%
yf ON xbf wf wm;
ym ON xbm wm wf;
slopf ON wf wm;
slopem ON wm wf;
[yf slopf ym slopem];
yf slopf ym slopem;
slopf WITH slopem yf ym;
slopem WITH yf ym;
yf WITH ym;

OUTPUT: sampstat cinterval;

Note. Capitalized terms refer to Mplus-specific commands and options and lower case terms refer to user-defined variables or options.

y = daily relationship negative behaviors.
x = daily relationship threat (within).
xb = mean daily relationship threat (between).
w = global relationship satisfaction.
f = female partner, m = male partner.
Appendix 3
HLM Models for Individual (Table 1 Estimates) and Dyadic Data (Table 2 Estimates)

REFERENCES


