Special Issue: Nonlinear Effects and Dynamics in Close Relationships

JSPR

Close TIES in relationships: A dynamic systems approach for modeling physiological linkage

Journal of Social and Personal Relationships
2022, Vol. 39(10) 3059–3084

DOI: 10.1177/02654075221082594
journals.sagepub.com/home/spr
SAGE

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Abstract
We explore complex dynamic patterns of autonomic physiological linkage (i.e., statistical interdependence of partner's physiology; PL), within the sympathetic and parasympathetic nervous systems (SNS and PNS), as potential correlates of emotional and regulatory dynamics in close relationships. We include electrodermal activity (EDA) as an indicator of SNS activation and respiratory sinus arrhythmia (RSA) as an indicator of regulatory and/or homeostatic processes within the PNS. Measures of EDA and RSA were collected in 10-second increments from 53 heterosexual couples during a mixed-emotion conversation in the laboratory. We used the R statistical package, *rties* (Butler & Barnard, 2019), to model the dynamics of EDA and RSA with a coupled oscillator model and then categorized couples into qualitatively distinct profiles based on the set of parameters that emerged. We identified two patterns for EDA and three patterns for RSA. We then investigated associations between the PL patterns and self-report measures of relationship and conversation quality and emotional valence using Bayesian multilevel and logistic regression models. Overall, we found robust results indicating that PL profiles were credibly predicted by valence and relationship quality reported prior to the conversations. In contrast, we found very little evidence suggesting that PL patterns predict self-reported conversation quality or valence following the conversation. Together, these results suggest that PL across autonomic subsystems may reflect different processes and therefore have different implications when considering interpersonal dynamics.

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Keywords

Physiological linkage, coregulation, close relationships, *rties* package, coupled oscillator model

Extensive evidence suggests that the quality of social relationships is critical to health and well-being (Sbarra & Coan, 2018). This is especially true in marriage or marriage-like relationships, which create an interpersonal context for much of life's emotional ups and downs (Robles et al., 2014). A growing body of evidence suggests that understanding how emotional and regulatory dynamics unfold in the context of close relationships is central to understanding when and why relationships impact well-being (Sbarra & Coan, 2018; Schoebi & Randall, 2015), as well as how emotional and regulatory dynamics contribute to relationship functioning (Butler & Barnard, 2019; Helm et al., 2014). Thus, interpersonal emotional processes may be both a potential precursor and consequence of relationship quality, with implications for well-being.

Emotional processes within an individual can be conceptualized as a dynamic system comprised of interrelated parts that interact over time to give rise to emotional states (Chow et al., 2005). More specifically, emotion can be understood as a self-organizing system of interacting subcomponents, including subjective experience, physiology, and behavior that change together in a loosely coupled way to coordinate responses to threats and opportunities in the environment (Thayer & Lane, 2000). This situation is complicated by the fact that emotional processes are not bounded by the individual but extend into close relationships and social interactions. Emotional processes are also not static, but play out over time, both within and between people (Timmons et al., 2015). As such, research on emotion is expanding to include the interpersonal nature of emotion systems in which the subcomponents of one person's emotion system interact not only within the individual but across partners as well (Butler, 2011; Butler & Randall, 2013; Reed et al., 2015).

In the current study, we focus on one aspect of interpersonal systems, physiological linkage (PL), which is the statistical interdependence of social partners' physiology, as a biological substrate for—or manifestation of—emotional interdependence within the relationship. Specifically, PL may both contribute to and arise from the biopsychosocial health of the partners and the relationship. For example, partners in a satisfying, stable relationship may automatically enter into a coregulatory pattern of PL that contributes to optimal physiological functioning when interacting with each other (Reed et al., 2015; Saxbe et al., 2020). At the same time, the repeated experience of coregulatory PL may contribute to their overall sense of security and satisfaction (Sbarra & Hazan, 2008). Prior empirical findings are mixed, however, with greater PL sometimes associated with positive relational and health variables (Helm et al., 2014), sometimes associated with negative ones (Levenson & Gottman, 1983), and sometimes unrelated (Reed et al., 2013). To fully understand if, when, and how PL is relevant to psychological, relational, and physical health in close relationships, we need to start unpacking the factors that may be contributing to the contradictory findings in the literature.

Modeling distinct patterns of physiological linkage

One factor that is likely limiting our understanding of PL is methodological. Most work on PL uses statistical approaches such as cross-correlations or multilevel modeling that provide simple overall estimates of the "quantity" of PL. For example, Thorson et al. (2018) introduced the stability-influence model (a specific version of a multilevel model) which can be used to estimate whether social partner's physiological states are predicted by each other (e.g., PL), while controlling for within-person self-regulatory processes. Importantly, however PL can also take qualitatively distinct temporal patterns that require more complex models to assess (Ferrer & Helm, 2013; Li et al., 2021; Reed et al., 2015).

Such distinct patterns arise from at least three common characteristics of dynamic systems, including interpersonal emotion systems. First, physiological signals can operate like a thermostat, where social partners' joint physiological state oscillates around an optimal level (i.e., homeostasis; Chow et al., 2005; Saxbe et al., 2020). These oscillations can occur at different frequencies and partners can have different phase relationships (e.g., when one partner is high, the other can be high or low). Second, positive and negative feedback processes either work to amplify physiological signals away from or dampen them toward homeostatic levels (Butler, 2011). For example, during a conflict, partners' may reciprocate each other's negative emotions such that both partners' anger spirals upward (amplification: Levenson & Gottman, 1983). Conversely, one partner may effectively regulate their own anger, thus interrupting that upward spiral and returning both partners to a more stable state (damping). Third, partners' physiologies may be more or less coupled, meaning that each person's frequency, phase and amplification-damping can either be due entirely to within-person self-regulatory processes (e.g., uncoupled; Sels et al., 2020) or can be driven at least partially by mutual influence (e.g., coupled; Ferrer & Helm, 2013; Thorson et al., 2018).

Considered together, these dynamic properties of physiology give rise to qualitatively distinct temporal patterns of PL. We are aware of six patterns that have been previously studied (illustrated in Figure 1) including (1) simple-disengaged (Panel (a)), where partners' physiologies oscillate together, but little or no coupling is present (i.e., the pattern is likely arising primarily due to contextual or within-person processes; Reed et al., 2015; Li et al., 2021); (2) in-phase (Panel (b)): where partners' physiology converges (i.e., when one partner is high (or low) on some indicator of physiology, so is the other partner; Reed et al., 2013); (3) anti-phase (Panel (c)): where partners' physiology diverges (i.e., when one partner is high (or low) on some indicator of physiology, their partner is the opposite; Gates et al., 2015); (4) simple coregulation (Panel (d)): where partners' physiology is coupled in a way that restores homeostasis (Helm et al., 2014); (5) co-dysregulation (Panel (e)): where partners' physiology is coupled in a way that disrupts homeostasis (Reed, et al., 2015); and (6) complex coregulation (Panel (f)): a complex pattern involving shifting dynamics that may reflect partners' striving toward a homeostatic state, but having not yet achieved it (e.g., Li et al., 2021).

It is important to note that there are infinite possible patterns, and although they are mutually exclusive within a given time frame, a couple could move through a variety of them in sequence across a longer time frame. Indeed, the goal of the current work is to

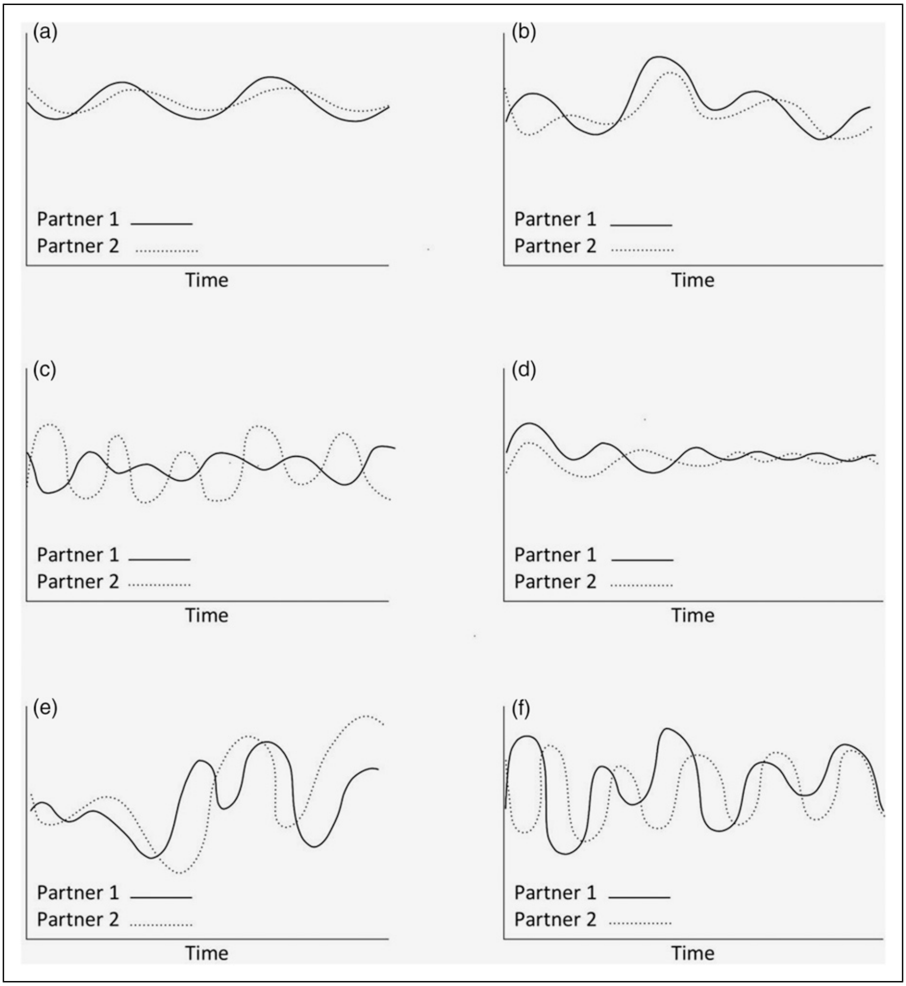

Figure 1. Examples of six physiological linkage patterns that have been studied previously. Panel (a) reflects a simple-disengaged pattern where partners' physiologies oscillate together, but little or no coupling is present. Panel (b) reflects an in-phase pattern (e.g., when one partner is high, so is the other and vice versa). Panel (c) reflects an anti-phase pattern (e.g., when one partner is high, the other is low and vice versa). Panel (d) reflects simple coregulation, where both partners show mutual damping in a way that restores homeostasis. Panel (e) shows mutual amplification, which results in less stability and suggests co-dysregulation. Panel (f) reflects complex coregulation, a pattern involving shifting dynamics where both partners' physiologies counterbalance without achieving homeostasis.

encourage others to take a more dynamic modeling approach to uncover the many nuanced PL patterns that may be occurring and contributing to biopsychosocial well-being. Currently, only a small body of empirical literature distinguishes between different patterns of PL (Butler & Barnard, 2019; Li, et al., 2021; Reed, et al., 2015), while much of the literature uses methods that blur these distinctions. This may be one reason that greater linkage has been both associated with negative outcomes such as conflict (Gates et al., 2015) and inflammation (Wilson et al., 2018), as well as positive relationship indicators such as higher relationship satisfaction (Helm et al., 2014) and empathy (Chatel-Goldman et al., 2014).

Using a coupled oscillator model to investigate physiological linkage

We used *rties* (Butler & Barnard, 2019), a new statistical package in the open-source programming language R, to assess distinct patterns of PL. The *rties* package simplifies the use of dynamic models for exploring interpersonal processes such as PL by implementing a coupled oscillator (CO) model. Variations of CO models have been previously used in the literature on emotional and regulatory dynamics in close relationships (Boker & Laurenceau, 2006; 2007; Reed et al., 2015; Steele et al., 2014). In general, they are based on differential equations and represent oscillatory phenomena. When applied to PL, they can represent the frequency of each partner's physiological oscillations, the damping or amplification of their oscillations (e.g., whether the oscillations are diminishing and becoming more stable, or growing larger and less stable), and the coupling between partners (e.g., mutual influence). In other words, they can be used to assess all six of the PL patterns reviewed above, as well as an infinite number of other possibilities.

We are aware of only two prior studies that considered qualitative differences between interpersonal patterns and their correlates with biopsychosocial well-being, and only one of those focused on physiological measures. The first study, conducted by Reed et al. (2015), looked at the association between coregulation (vs. co-dysregulation) of emotional experience and body weight in heterosexual couples while they discussed body-weight relevant topics during a 20-minute conversation. Three distinct interpersonal emotional patterns emerged. A simple-disengaged pattern (Figure 1(a)) surfaced for couples where both partners were of healthy weight and was interpreted as evidence for a lack of emotional engagement in the topic, due to their healthy status. The second pattern was a simple coregulatory one (Figure 1(d)), where both partners' signals displayed mutual damping across time. This pattern was exhibited by couples where the man was heavier than the woman and was interpreted as a coregulatory pattern, whereby the partners were emotionally perturbed by the conversation topic but were able to return to equilibrium. The final pattern was co-dysregulation (Figure 1(e)), which was exhibited by couples where both partners were overweight, or the woman was heavier than the man, and was interpreted as evidence that these couples were unable to mutually regulate their emotions during the conversation topic.

The second study is the only published study to use the *rties* package to implement a CO model. Li et al. (2021) examined the association between couple relationship functioning and patterns of PL among same-sex male couples across four different conversational contexts that each lasted 10 minutes. Results revealed two distinct patterns using inter-beat interval (IBI) as an indicator of PL. A simple-disengaged pattern

(Figure 1(a)) was more common in the sample and was interpreted as reflecting a lack of engagement between partners due to its association with lower self-reported relationship quality and prevalence during neutral contexts. The second pattern was a Complex/Coregulatory one (Figure 1(f)), which was associated with higher reports of love, regardless of conversational context, as well as higher sexual satisfaction during an emotionally arousing body image conversation. This pattern was interpreted as evidence that these couples, especially in an emotionally provocative context, were strongly engaged in the interaction and attempting to mutually regulate but had not yet returned to homeostasis within the time of the interaction.

Parasympathetic and sympathetic nervous systems

A second factor that may be contributing to the mixed findings regarding PL is that most work does not consider distinctions between the two branches of the autonomic nervous system (ANS), which has been the predominant focus of PL research (Palumbo et al., 2017), due to the ability to extract high time resolution data using relatively non-invasive measures (Timmons et al., 2015). There are two branches nested within the ANS: the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). These two systems innervate many of the same organs (e.g., the heart) but may reflect different processes and therefore have different implications when considering linkage (Palumbo et al., 2017).

The SNS is responsible for "fight or flight" (sometimes referred to as "approach or avoid") responses. This increased arousal leads to immediate action in the face of threat/stress or reward (Palumbo et al., 2017). In contrast, the PNS is responsible for homeostatic functioning through the "rest and digest" response. More specifically, the PNS functions to maintain a state of physiological equilibrium in situations where stress is not immediately present (Porges, 2003). Importantly, these two branches do not function in isolation from one another, but rather work *together*, often in a reciprocal nature regulating the body in response to environmental demands. In other words, a shift in activation of the ANS reflects a coordinated adjustment between both the SNS and PNS to maintain homeostasis in an individual (Berntson et al., 1991). When extending this to the context of close relationships, partners may up-regulate or down-regulate their own physiological responses, either consciously or automatically, to maintain equilibrium at the interpersonal level (i.e., coregulation), or partners' physiological responses may coactivate, resulting in increased amplification away from their equilibrium (i.e., co-dysregulation).

Most existing literature has either used an indicator that is not specific to one branch (e.g., heart rate; Ferrer & Helm, 2013), included measures of only one branch (Reed et al., 2013; for an exception, see Danyluck & Page-Gould, 2019), or used a composite that includes measures from both branches (e.g., Chen et al., 2020). Assessing PL in this way leaves us with an incomplete story since it is unlikely that both physiological systems operate similarly across a variety of contexts. For example, it is possible that PL in the PNS is more likely during predominately positive contexts, such as sharing good news or empathy. Porges' polyvagal theory provides some support for this idea, arguing that PNS activity may reflect social engagement (Porges, 2003, 2011). For example, higher respiratory sinus arrhythmia (RSA) has been associated with mental health outcomes such as socioemotional well-being and better emotional and attentional regulation (Isgett et al., 2017; Porges, 2011), and lower cardiovascular reactivity during conflict discussion has been associated with indicators of greater marital quality (Robles et al., 2014). In contrast, SNS activity mainly reflects general arousal, rather than valence (Mauss & Robinson, 2009; Palumbo et al., 2017). So, PL in the SNS might be higher during contexts involving heightened arousal such as stress or conflict, or during moments requiring increased attention and engagement. For example, higher in-phase PL in the SNS may either represent partners' mutual experience of positive emotions (e.g., capitalization supports; Gable et al., 2004) or negative emotions (e.g., conflict escalation; Timmons et al., 2015), depending on the situation. In support of these speculations, a recent meta-analysis found that PL in the SNS and PNS were differentially associated with relationship outcomes (Mayo et al., 2021), which points strongly to the need for further work comparing PL of both branches within a single study.

To address these issues, we used RSA as an indicator of the PNS, which has been shown to demonstrate PL in romantic couples (e.g., Gates et al., 2015; Helm et al., 2014) and is the only known non-invasive, pure measure of PNS activity. We also used electrodermal activity (EDA) as an indicator of the SNS, which has also been shown to demonstrate PL in romantic couples and is known to be a pure indicator of the SNS (Chatel-Goldman et al., 2014; Coutinho et al., 2019). The use of these two measures allowed us to differentiate between SNS and PNS linkage between partners and their potential associations with relationship and conversation quality measures, as well as emotional valence.

Exploratory research questions

Our research questions are mainly exploratory due to the dearth of existing research using modeling approaches that can distinguish different PL patterns (Li et al., 2021; Reed et al., 2015). Additionally, while the potential for a bidirectional relationship between PL and relationship quality has been acknowledged (Saxbe et al., 2020; Sbarra & Coan, 2018), existing research has yet to directly consider dynamic temporal patterns of PL as both predictors and outcomes of relationship factors. Nevertheless, the extant research discussed above led us to have some general expectations for what we would find. First, we expected at least two patterns of PL to emerge for each of RSA and EDA. In line with the two prior studies reviewed above, we expected a "Simple/Disengaged" pattern to be associated with lower relationship and conversation quality (Li et al., 2021; Reed et al., 2015). Second, we expected either a simple coregulatory pattern (e.g., initial perturbation followed by damping to stability; Reed et al., 2015) or a complex one (e.g., shifting dynamics that may reflect partners' striving toward a homeostatic state, but having not yet achieved it; Li et al., 2021) to be associated with higher relationship quality and more engagement in the conversation. Finally, we also considered the possibility of a co-dysregulatory pattern, which we would expect to be associated with lower relationship and conversation quality.

The present study used secondary data from 53 romantic couples engaged in a mixed-emotion conversation to compare patterns of PL, based on RSA and EDA, as both potential outcomes and predictors of self-reported relationship and conversation quality or emotional valence. More specifically, we focused on the following research questions:

1) Does relationship quality or emotional valence prior to the conversation predict different patterns of PL across RSA and EDA?
2) Do patterns of RSA or EDA PL predict conversational quality or emotional valence following the conversation?

Method

Participants and procedure

The data comes from a larger study of health behavior and weight change across 6 months in self-identified heterosexual romantic couples during their first year of cohabitation. Participants were recruited from a southwestern university and the surrounding area in 2013–2014 via advertisements posted on Craigslist and university listservs, flyers posted at churches, the county marriage license building, and local businesses, as well as word of mouth. The data for the present study comes from the baseline questionnaire and laboratory session and includes the 53 couples who had usable data from both partners on all relevant measures. Figure 2 provides the inclusion/exclusion criteria and a flowchart showing the steps that led to the final sample for the current study.

All participants included in the current study were in a self-identified, heterosexual relationship with their current romantic partner. Participants were on average 26 years old (SD = 10 years; range = 18–69 years), had been in a romantic relationship together for 2 years (SD = 1.40 years; range = 1 month to 6 years), were predominantly not married (86%), and were very satisfied with their relationship (M = 2.59, SD = 0.89, scale ranged from −3 to +3). Twenty-five percent (n = 27) identified as Latinx, and approximately 47% (n = 50) were undergraduate students. Additional demographic information is provided in Table 1. All study procedures and materials were approved by the University of Arizona Institutional Review Board.

Couples participated in a telephone screening and those who were eligible completed the baseline questionnaire. Participants were then scheduled for a laboratory session. Upon arrival, participants reported on their current emotions and then engaged in a conversation with their partner about a series of topics including: the importance of a healthy lifestyle, things the partners do that help/hinder each other to be healthy, things they would like the other person to change, and something for which they would like more support from their partner. Couples were given 5 minutes to discuss each topic but could move on if they finished with a topic sooner. During the conversation, autonomic physiological measures were assessed continuously for both participants. Immediately following the conversation, participants again reported on their emotional experience, as well as items regarding their perceptions of the quality of the conversation.

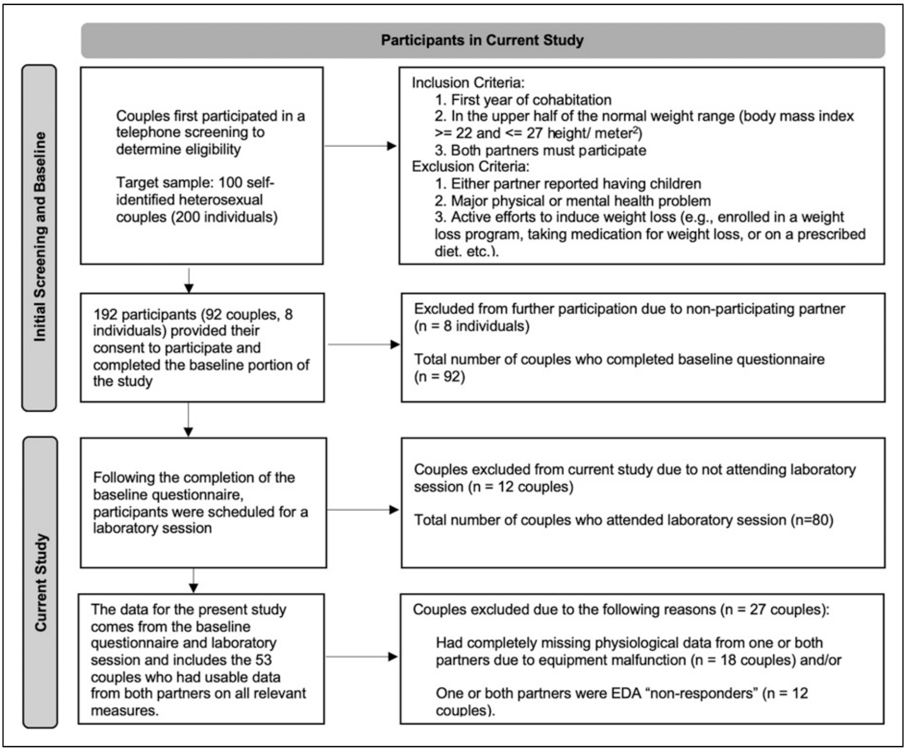

Figure 2. A flowchart outlining criteria for original study as well as decisions made in the current study that resulted in 53 self-identified heterosexual couples.

Measures

See Table 2 for summary statistics and alphas for all self-report measures.

Autonomic physiology measures

Electrodermal activity and electrocardiography were measured using a MindWare BioNex 8SLT Chassis and processed using MindWare's (MindWare Technologies, Gahanna, OH) customized software. IBI time series measured from the electrocardiography were further processed using the approach detailed in Allen et al. (2007) to estimate RSA using a 16-second moving average window with a 4-second overlap (for a discussion of this approach, see Schafer et al., 2015). This approach for assessing RSA allows for modeling rapid change, which is important given the dynamic process of interest. Pilot analyses showed that a 16-second moving window was the shortest period that also gave stable RSA estimates. Specifically, the average respiration rate was 12.2 breaths per minute, meaning that 16 seconds allowed for three full breaths as the basis for each

Table 1. Demographic information.

Variable		Women (n = 53), %	Men (n = 53), %
Ethnicity	European American	39.62	35.85
	African American	1.89	0
	Asian American	7.54	1.89
	Native Hawaiian or Pacific Islander	0	1.89
	Non-Hispanic White	32.08	32.08
	Other	18.87	28.30
Education	Graduate degree	7.54	5.66
	Undergraduate degree	26.42	28.30
	Some college	52.83	41.51
	Professional program	1.89	1.89
	High school	11.32	20.75
	Less than high school	0	1.89
Yearly household income	\$0–\$25,000	73.58	73.58
	\$25,000–\$50,000	15.09	15.09
	\$50,000–\$75,000	7.55	9.43
	\$75,000+	3.77	1.89

Table 2. Summary of self-report variables.

			Mean (SD)		Alpha (α)	
Measure category	Measure	Scale range	Women	Men	Women	Men
(Prior) valence	Positive	0 to 4	2.14 (0.69)	2.25 (0.70)	.81	.80
	Negative	0 to 4	0.33 (0.35)	0.30 (0.41)	.63	.68
(Post) valence	Positive	0 to 4	2.30 (0.97)	2.61 (0.80)	.87	.83
	Negative	0 to 4	0.49 (0.56)	0.30 (0.32)	.77	.57
Relationship quality	Love	0 to 6	5.28 (0.59)	5.16 (0.58)	.78	.85
	Ambivalence	0 to 6	1.01 (0.90)	1.15 (1.09)	.80	.88
	Conflict	0 to 6	2.08 (1.02)	1.94 (1.00)	.70	.80
	Relationship stress	0 to 3	0.49 (0.49)	0.53 (0.55)	.83	.86
	Satisfaction	−3 to 3	2.71 (0.66)	2.48 (1.05)	.78	.77
Conversation quality	Disengagement	−3 to 3	−1.99 (1.07)	−1.68 (1.31)	.63	.75
	Emotional connection	−3 to 3	1.48 (1.10)	1.54 (1.09)	.60	.66
	Attachment anxiety	−3 to 3	−2.11 (1.41)	−2.22 (1.16)	.81	.74
	Attachment avoidance	−3 to 3	−2.34 (0.92)	−2.04 (0.92)	.50	.63

estimate of RSA. Visual inspection confirmed that the resulting RSA values were normally distributed around 6.1 ln(HFPower) with a range of 0.9–11.2, representing a fairly typical distribution for adult RSA. We then aggregated both RSA and EDA into 10-second increments to smooth the signals. Finally, the raw time series were linearly detrended to meet the assumptions of a CO model and these detrended signals for RSA and EDA were used as input variables for the modeling of PL (see *Data Analytic Plan*). Mean baseline EDA and RSA were 5.31 (*SD* = 4.05) and 6.38 (*SD* = 1.66), respectively. Mean conversation EDA and RSA were 10.81 (*SD* = 4.52) and 6.02 (*SD* = 1.19), showing that SNS activity increased and PNS activity slightly decreased during the conversation compared to baseline.

Emotional experience measures

Participants reported the extent to which they felt 10 discrete emotions both upon arrival at the lab and immediately following the conversation using a 5-point face-valid scale (0 = *Not at all* to 4 = *A very large amount*). Of the 10 emotions, five were classified as positive (e.g., happy) and five were classified as negative (e.g., anxious). Mean composite scores were created for positive emotion upon arrival, negative emotion upon arrival, positive emotion during the conversation, and negative emotion during the conversation.

Relationship quality measures

Love, Ambivalence, and Conflict: Relationship quality was assessed using Braiker and Kelley's (1979) Love and Relationships Questionnaire, including love, ambivalence, and conflict subscales. Participants rated all 20 items on a 7-point scale ranging from 0 (*Not at all*) to 6 (*Very much*). The 10-item love subscale included items such as "How committed do you feel toward your partner?" The 5-item ambivalence subscale included items such as "How confused are you about your feelings toward your partner?". The 5-item conflict subscale included items such as "How often do you feel angry or resentful toward your partner?"

Acute Relationship Stress: As another indicator of relationship quality, we used the Multidimensional Stress Scale for Couples (Bodenmann et al., 2008) to measure relationship stress within the past 7 days. Participants rated 10 items on a four-point scale ranging from 0 (*No burden/Stress*) to 3 (*Significant burden/Stress*). The situations included such things as "Difference of opinion with partner" and "Unsatisfactory distribution of duties and responsibilities."

Relationship Satisfaction: As the final indicator of relationship quality, we used two items from the Kansas Marital Satisfaction Scale (Schumm et al., 1986) to measure relationship satisfaction. Participants rated both items on a seven-point scale ranging from −3 (*Very Unsatisfied*) to 3 (*Very Satisfied*).

Conversation quality measures

After the conversation, participants reported things that they might have thought, felt, or done during the conversation. Two sets of questions assessed feelings of disengagement and emotional connection. An additional two sets of questions asked about momentary feelings of attachment anxiety and avoidance. Although it is more common to consider attachment as a between-person trait, empirical work shows that attachment experiences can also be temporarily primed (Bryant & Hutanamon, 2018) and vary day to day (Haak et al., 2017). All four measures were rated on a 7-point scale (-3 = *Very much disagree* to 3 = *Very much agree*). The 3-item disengagement subscale included items such as "I found it difficult to concentrate and kept getting distracted." The 3-item emotional connection subscale included items such as "I felt very emotionally connected to my partner." The attachment anxiety and attachment avoidance subscales both included three items and examples include "I worried about being abandoned" and "I felt my partner getting close to me, so I started pulling away."

Data analytic plan

Appropriateness of a coupled oscillator model

To investigate whether a CO model was appropriate for the present study, we first visually inspected the raw RSA and EDA data for evidence of periodic oscillations. As depicted in Figure 3, both EDA and RSA show obvious oscillations over time, making a CO model appropriate.

Assessing distinct patterns of physiological linkage

We used the *rties* package (version 5.0.0; Butler & Barnard, 2019) available in the R Statistical Platform (version 3.6.3; R Core Team, 2020) to operationalize linkage for EDA and RSA with a CO model. In this report, we provide a high-level description of our analyses. Supplemental materials provide the data and details to replicate our analyses, and explanations for all decisions we made. In addition, interested readers can consult the vignettes accompanying the *rties* package for extensive documentation for every step of an analysis using the package.

Assessing PL requires repeated observations over time from social partners. Such data violate the assumptions of the General Linear Model because the observations, and hence the residuals, are likely to be correlated (Kenny et al., 2006; Singer & Willett, 2003). The most common way to approach this is to use multilevel modeling, which models the interdependence as part of the error structure. Theories about how socioemotional processes impact health, however, emphasize that interpersonal dependencies should be the focus of our inquiry, not relegated to error. Thus, we take a different approach and put the dependencies in the foreground with a CO model that can represent interpersonal dynamics, allowing us to directly consider the dynamics

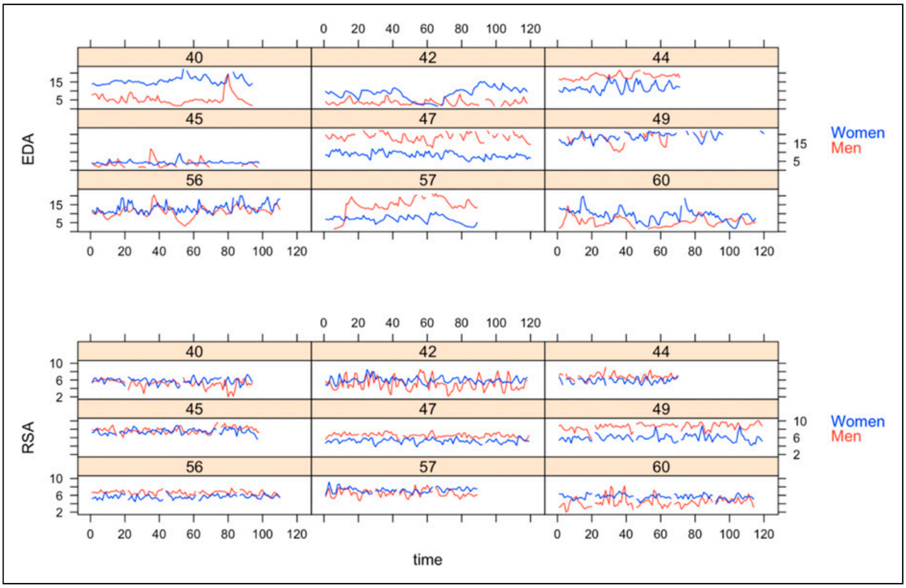

Figure 3. Representative plots of couples' raw physiological activity (y-axis) over time in 10-second units (total time on x-axis = 21 minutes).

as predictors and outcomes of other variables of interest. With multilevel modeling they would need to be treated as moderators, which is less direct and more prone to unstable results arising from issues such as low power and collinearity.

The first step in our method is to fit a CO model to each couple's detrended physiological signals separately for EDA and RSA, one couple at a time (e.g., ideographically). In the next step, the estimates of the eight CO parameters for each couple are extracted. The parameters are (1) female frequency, (2) female damping, (3) female coupling for frequency (e.g., male impact on female frequency), (4) female coupling for damping (e.g., male impact on female damping), and (5–8) parallel parameters for the male partner. Each couple's set of 8 parameters are then used as input to a latent profile analysis (LPA), which clusters couples based on the similarities of their CO parameter estimates. This approach is similar to latent growth curves, but uses the parameters of the CO model, rather than intercepts and slopes, as the input to the clustering.

We decided a priori to consider LPA solutions with 2, 3, or 4 profiles and chose the solution based on a combination of (1) how evenly distributed the number of couples in each profile was, (2) how well separated the profiles were, and (3) whether the resulting profiles were qualitatively distinct in terms of dynamics based on visual inspection. No fit statistics were used (e.g., AIC and BIC) since simulation studies show they only work well for large samples combined with large effect sizes (Tein et al., 2013).

Models for addressing research questions

In the next step, we used the LPA cluster membership for each couple as an outcome of relationship quality and emotional valence *prior* to the conversation, and as a predictor of conversation quality and emotional valence *following* the conversation. We used the R statistical package, *brms* (version 2.11.5; Bürkner, 2017), to estimate models for EDA and RSA PL separately for each relationship or emotion variable (i.e., a total of 26 models) using Bayesian modeling.

We used Bayesian modeling rather than a frequentist approach for the following reasons: First, Bayesian allows direct probability statements about the parameter estimates, while a frequentist approach can only reject, or fail to reject, the null hypothesis (Wagenmakers et al., 2018). As such, Bayesian provides more informative results. Specifically, it combines a prior distribution and the information gained from the data (e.g., the likelihood) to generate a posterior distribution that contains complete information about the parameter of interest (e.g., its expected value and dispersion). One way to summarize the posterior distribution is the highest density interval (HDI), which provides a probability range for a given parameter (Kruschke, 2018). In our results, we report the center of the 95% HDI for each parameter of interest (e.g., the posterior mean), which is the most likely value of the parameter in the population, given the model and the data. We also report the boundaries of the 95% HDI, which are the range of values for which there is a 95% probability that the population parameter is within them.

A second advantage of Bayesian is that the HDIs are not dependent upon each other as separate significance tests are in a Frequentist analysis, so controlling for multiple comparisons is irrelevant. Thus, we can simplify by considering each relationship quality or emotional valence measure in a separate model, without concerns for controlling multiple comparisons.

Finally, Bayesian is more robust than Frequentist methods when applied to small samples, such as in the present study. With inadequate data, the HDIs will become very wide, accurately reflecting the limited evidence for or against any conclusions about parameter values. Thus, with inadequate data, one will correctly conclude that nothing new has been learned, over and above the prior. In contrast, even a small sample may contain reliable information, and thus, if the HDIs do not include zero, they can be trusted as valid evidence, unlike a frequentist perspective where they cannot be disentangled from Type I error.

Profiles as Outcomes (RQ1): To address RQ1, we fit an initial 14 models across EDA and RSA (i.e., 7 models each) using valence and relationship quality measures prior to the conversation as predictors of the profile membership. We started with the full model and included both partner's reports (e.g., women's conflict and men's conflict) as well as the interaction term (women's conflict × men's conflict) as predictors in each model. When a credible interaction was not found (i.e., the HDI included 0), we estimated a main effects only model and report those results. If the interaction HDI did not include zero, we compared the full model to the main effects model using leave-one-out cross-validation (Vehtari et al., 2017). In cases where cross-validation indicated equivalent predictive accuracy on held out data, we chose the full model including the interaction term. Otherwise, we chose the main effects only model.

Profiles as Predictors (RQ2): To address RQ2, we fit an initial 12 models across EDA and RSA (i.e., six models each) using the PL profiles to predict valence and conversation quality following the conversation. Eight of our outcome variables were zero inflated and for those we used a hurdle Gamma likelihood distribution, which is a two-part model that first estimates the probability of the outcome being zero using logistic regression, and then models the non-zero observations using a Gamma distribution (Atkins et al., 2013). For the remaining four outcomes, we specified a skew normal distribution.

Results

Physiological linkage profiles for electrodermal activity

The adjusted R^2 for the CO model fit to each couples' EDA data ranged from 0.42 to 0.86, showing that the CO model fit the data fairly well for all couples. The length of the average oscillation period was 4.2 minutes. The average conversation lasted 7.5 minutes, allowing for about 2 EDA cycles per typical conversation.

As described in the Supplemental Materials, we chose a 2 profile LPA solution for EDA. Figure 4 displays the temporal trajectories of the EDA profiles plotted across 11 minutes (i.e., the time by which 75% of couples' conversations had ended). Profile 1

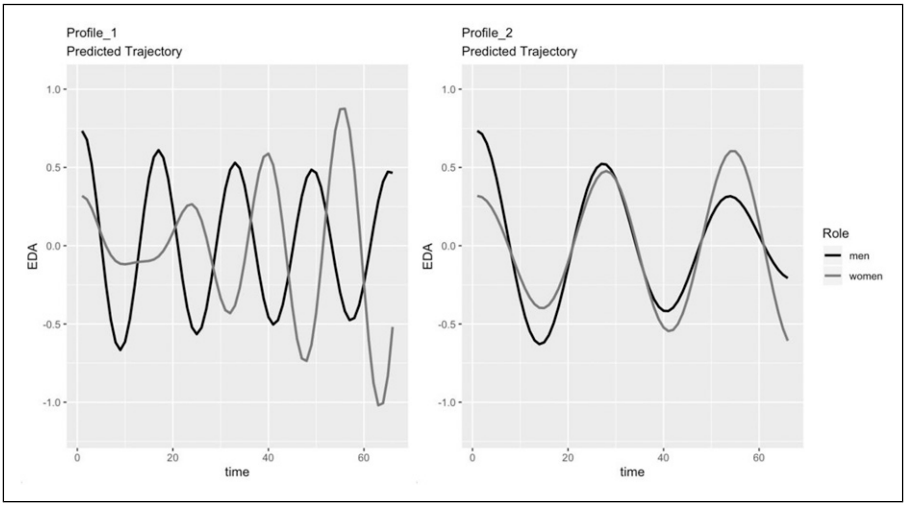

Figure 4. Estimated electrodermal activity trajectories in 10-second units for the two profiles (total time on x-axis = 11 minutes). Profile 1 included 18 couples and was characterized as a "Complex/Coregulatory" profile. Profile 2 included 35 couples and was characterized as a "Simple/ Disengaged" profile.

included 18 couples and was characterized as a Complex/Coregulatory pattern. Profile 2 included 35 couples and was characterized as a Simple-Disengaged pattern.

Physiological linkage profiles for respiratory sinus arrhythmia

The adjusted R^2 for the CO model fit to each couples' RSA data ranged from 0.59 to 0.88, showing that the CO model fit the data fairly well for all couples. The length of the average oscillation period was 2.7 minutes, allowing for about three RSA cycles per typical conversation.

As described in the Supplemental Materials, we chose a three profile LPA solution for RSA. Figure 5 displays the RSA trajectories plotted across 11 minutes (i.e., the time by which 75% of couples' conversations had ended). Profile 1 included 14 dyads and was characterized as a Complex/Coregulatory—Fast profile, similar to Profile 1 for EDA. Profile 2 included 18 couples and was characterized as a Complex/Coregulatory—Slow profile. Profile 3 included 21 couples and was characterized as a Simple-Disengaged pattern.

RQ1: Does prior relationship quality or valence predict profiles?

Relationship Quality and EDA: We found no evidence of interactions between partners' reports of relationship quality. However, we found evidence for credible main effects of men's ambivalence (posterior mean = 0.52, 95% HDI: 0.04–1.03) and relationship stress (posterior mean = 1.04, 95% HDI: 0.03–2.15), such that Profile 2 (i.e., the "Simple/Disengaged" profile) was more likely when men reported higher ambivalence and relationship stress. The remaining relationship quality measures were not credible predictors of EDA profile membership.

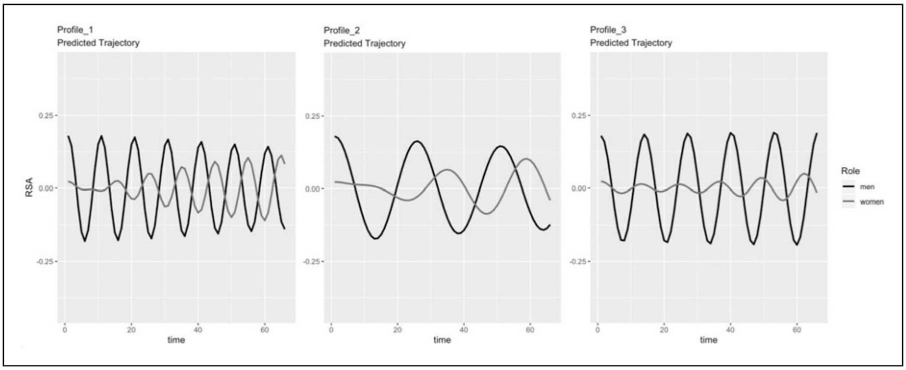

Figure 5. Estimated respiratory sinus arrhythmia trajectories in 10-second units for the three profiles (total time on x-axis = 11 minutes). Profile 1 included 14 couples and was characterized as a "Complex/Coregulatory—Fast" profile. Profile 2 included 18 couples and was characterized as a "Complex/Coregulatory—Slow" profile. Profile 3 included 21 couples and was characterized as a "Simple/Disengaged" profile.

Relationship Quality and RSA: Partner's reports of love credibly interacted to differentially predict RSA profile membership (posterior mean = 2.08, 95% HDI: 0.21–4.10). As shown in Figure 6, Profile 1 (i.e., the "Complex/Coregulatory—Fast" profile) was most likely when women reported lower average love and men reported higher love. In contrast, the probability of being in Profile 3 (i.e., the "Simple/Disengaged" profile) was most likely when both partners reported lower average love.

We did not find any evidence of interactions between partners' other reports of relationship quality, but lower relationship quality reported by women was associated with a higher probability of being in Profile 1 (i.e., the "Complex/Coregulatory—Fast" profile). Specifically, we found evidence for credible main effects of women's ambivalence (posterior mean was −0.70, 95% HDI: −1.38 to −0.07), conflict (posterior mean was −0.59, 95% HDI: −1.21 to 0.01), and relationship stress (posterior mean was −2.08, 95% HDI: −3.61 to −0.72). Further, lower relationship quality reported by men was associated with a higher probability of being in Profile 3 (i.e., the "Simple/Disengaged" profile). Specifically, we found evidence for credible main effects of men's ambivalence

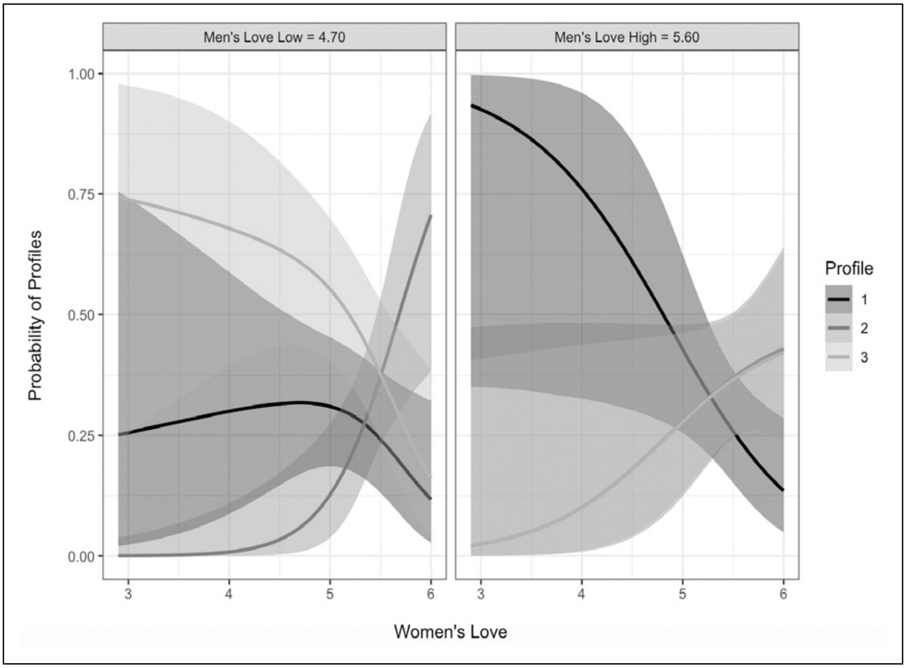

Figure 6. The credible interaction of partner's reports of love predicting respiratory sinus arrhythmia profile membership. Profile 1 (i.e., the "Complex/Coregulatory—Fast" profile) was most likely when women's average love was low, but men's average love was high, and the slight overlap in probabilities suggests this is a moderate effect. Profile 3 (i.e., the "Simple/Disengaged" profile) was most likely when both partners reported low average love, and the overlap in probabilities suggests this is a small to moderate effect.

(posterior mean was 0.59, 95% HDI: 0.07–1.15), conflict (posterior mean was 0.74, 95% HDI: 0.12–1.40), acute relationship stress (posterior mean was 1.52, 95% HDI: 0.30–2.86) and relationship satisfaction (posterior mean was −0.84, 95% HDI: −1.77 to −0.08).

Valence and EDA: Partner's reports of positive valence prior to the conversation credibly interacted to differentially predict EDA profile membership (posterior mean = 1.69, 95% HDI: 0.44–3.11). As shown in Figure 7, Profile 1 (i.e., the "Complex/Co-regulatory" profile) was more likely when women reported high and men reported low average positive emotional valence at baseline. Results for negative valence were unstable and driven by ceiling effects, so we dropped them from further consideration.

Valence and RSA: Partner's reports of positive valence prior to the conversation credibly interacted to differentially predict RSA profile membership (posterior mean = 1.97, 95% HDI: 0.55–3.52). As shown in Figure 8, Profile 3 (i.e., the "Simple/Disengaged") was most likely when both partners reported lower average positive emotional valence at baseline. Baseline negative emotional valence was not a credible predictor of RSA profile membership.

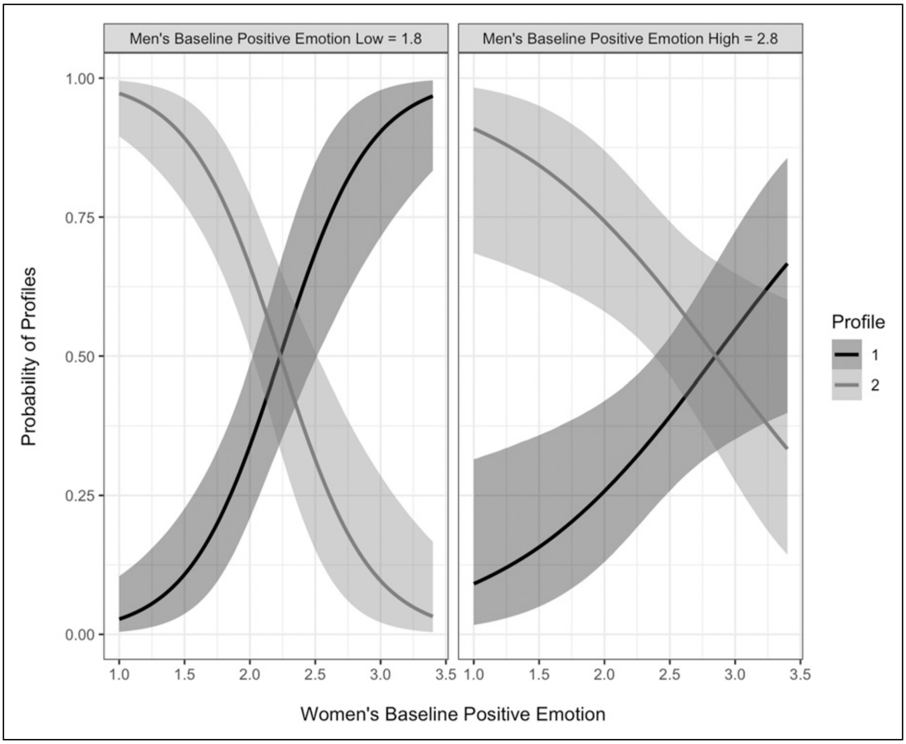

Figure 7. The credible interaction of partner's reports of positive emotional valence prior to the conversation predicting electrodermal activity profile membership. Profile 1 (i.e., the "Complex/Coregulatory" profile) was most likely when women reported high and men reported low average baseline positive emotion. The clear separation in profile probabilities suggests this is a large effect.

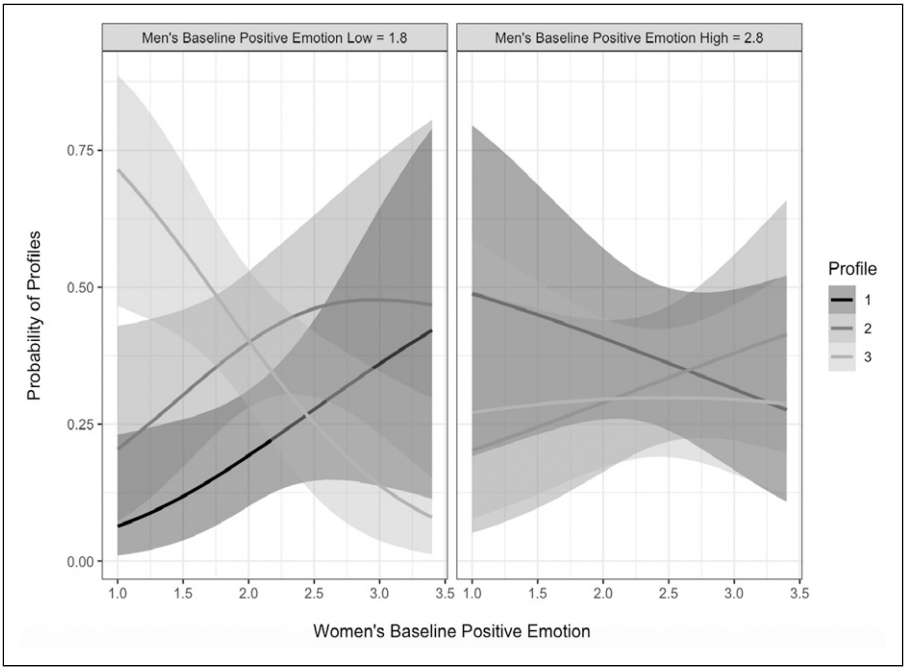

Figure 8. The credible interaction of partner's reports of positive emotional valence prior to the conversation predicting respiratory sinus arrhythmia profile membership. Matched low baseline positive emotion was associated with a higher probability of being in Profile 3 (i.e., the "Simple/Disengaged" profile). The clear separation in profile probabilities suggests this is a large effect.

RQ2: Do profiles predict conversation quality or valence following conversation?

The only credible effect was that the main effect of profile membership based on EDA dynamics was a credible predictor of negative valence following the conversation. The posterior mean difference between the two profiles in their report of negative valence was 0.42 (95% HDI: 0.03–0.82). Specifically, couples in Profile 2 (i.e., the "Simple/Disengaged" profile) reported credibly higher negative valence following the conversation.

Discussion

We investigated complex patterns of PL using a CO model within the sympathetic and parasympathetic nervous systems (SNS and PNS). We then considered these distinct patterns of PL as both potential outcomes and predictors of relationship and conversation quality, as well as emotional valence. Although our study was largely exploratory, we did have some general expectations based on the small existing literature and so we discuss our findings in terms of expected, unexpected and exploratory results.

Expected findings

Simple/Disengaged: We observed a simple pattern of PL across both EDA and RSA that was more common than the other patterns. This simple pattern was largely in-phase for EDA and anti-phase for RSA. These "Simple/Disengaged" patterns were associated with worse relationship and conversation quality, as well as less favorable emotional valence. These findings are consistent with Li et al. (2021) who also observed a simple pattern of PL that was more common and associated with lower relationship quality. Our work builds upon this finding by showing that "Simple/Disengaged" patterns of PL may be associated with worse correlates across both autonomic systems, suggesting that this pattern may reflect a lack of engagement between partners and therefore a lack of coregulation. We expect this pattern may have been common due to many couples not being perturbed by the content of the conversations while also reflecting resistance to emotional engagement when the topics were upsetting, hence connecting it to lower relationship quality.

Complex/Coregulatory: We identified one complex pattern of PL within the SNS and two within the PNS. The "Complex/Coregulatory" pattern for EDA was similar to one of the patterns observed by Li et al. (2021) where the partners appeared to counterbalance each other. Guided by previous work (Li et al., 2021; Reed et al., 2015) we expected this pattern to be associated with higher relationship and conversation quality, as well as more favorable emotional valence. Our results are largely consistent with this expectation, although the patterns observed in the previous studies showed evidence of mutual damping, while the EDA pattern in the current study showed some amplification for one partner and damping for the other. This coregulatory pattern is consistent with the idea that more satisfied couples exhibit a pattern where one partner damps when the other amplifies, resulting in regulated fluctuations around an optimal set point that maintains co-stability (Gates et al., 2015; Timmons et al., 2015).

Unexpected findings

The two "Complex/Coregulatory" patterns we observed for RSA suggested coregulatory processes, in that the women amplified to counterbalance the men, but they differed in their oscillatory frequency, with couples in Profile 1 exhibiting a faster frequency than couples in Profile 2. Additionally, while the women in these two profiles both exhibited amplification across time, this was much more evident for the women in Profile 1. Further, Profile 1 was most likely for couples where women reported lower relationship quality and when partners reported mismatched levels of love. One explanation for this finding may be that the combination of increasing frequency and women's amplification may result in a form of dyadic destabilization (e.g., co-dysregulation), rather than coregulation.

Another unexpected finding was the similarity of temporal trajectories between Profile 1 for both EDA and RSA. While we found this pattern to be associated with positive indicators of relationship quality when the pattern was within the SNS, we found the opposite when the pattern occurred within the PNS. Together, these results suggest that PL in the PNS and SNS may reflect different processes and therefore have different implications when considering interpersonal dynamics. For example, amplified anti-phase PL in the SNS may reflect mutual emotional activation and engagement, while in the PNS, a similar pattern may reflect more intense regulation in response to distress. Clearly, this is a central question that will need to be addressed by future research.

Exploratory findings

Although we did not set out to assess sex differences, given the lack of prior literature, we did observe somewhat consistent sex differences in the main effects that arose for patterns of PL based on RSA. Specifically, the Complex/Coregulatory—Fast profile was most likely when women reported higher ambivalence, conflict, and acute relationship stress. In contrast, the Simple/Disengaged profile was most likely when men reported higher ambivalence, conflict, and acute relationship stress. One potential explanation for these observed differences lies in demand-withdraw interaction patterns arising from power differences (Holley et al., 2010). From this perspective, women in committed, heterosexual relationships tend to be identified as the more demanding/influencing partner who desires change, whereas men are often identified as the withdrawing/influenced partner due to social norms that reinforce male dominance. In the context of the current study, women reporting higher negative relationship quality may have played the regulatory/demanding role, showing either amplified or damped physiological activation throughout the interaction to counterbalance to their male partners, thus making the Complex/Coregulatory—Fast pattern of PL we observed more likely. In contrast, men reporting higher negative relationship quality may have been predisposed to withdrawing or disengaging from the interaction, making the Simple/Disengaged pattern of PL more likely.

Another way of thinking about these results is that couples exhibiting the Simple/Disengaged pattern of PL may have been less attentive to each other during the conversation, resulting in higher stability of their individual physiological responses (i.e., little to no mutual influence). In contrast, for the Complex/Coregulatory patterns of PL, at least one or both partners' physiological responses were less stable across time (e.g., they either amplified or damped). Although we referred to these patterns as "coregulatory" based on prior literature, they are not necessarily good or bad, but may reflect highly coupled patterns that result from partners actively attending and responding to one another. In line with this, recent work by Thorson and West (2018) found that the more people were physiologically influenced by their partner, the less stable they were in their own physiological responding. Taken together, these results suggest that certain patterns of PL may show more coupling and mutual influence at the cost of one's own individual stability. Whether this decrease in stability is good or bad likely depends on the relational and emotional context.

Overall, we found robust results indicating that the PL profiles were credibly predicted by emotion and relationship quality reported prior to the conversations. In contrast, we found very little evidence suggesting that PL patterns predict self-reported conversation quality or emotional valence after the fact. Taken together, these results suggest that PL may be more a reflection of tonic relationship quality, rather than an immediate contributor to acute relational perceptions. Given the exploratory nature of our study, however, we do not want to place too much emphasis on this pattern of findings. Future work using experimental methods will be important for unpacking the potentially bi-directional connections between PL and relationship quality.

Limitations/future directions

Our sample was relatively small because we needed at least some useable data from both partners on all relevant measures, primarily White and reported high relationship satisfaction. We also acknowledge that the measures used to represent relationship quality, conversational quality, and emotional valence are not prevalent in the current literature since the study was designed almost a decade ago. All these factors limit the generalizability of our results. Additionally, couples engaged in a mixed-emotion conversation, making it impossible to untangle PL during positive versus negative emotional exchanges. This is a major limitation because, as others have alluded to, the implications of PL patterns likely depend on the context within which they occur (Li et al., 2021; Timmons et al., 2015). For example, in the seminal research done by Levenson and Gottman (1983), it was only during conflictual interactions (vs. neutral) that PL was associated with reduced marital satisfaction. In our study, some couples may have experienced predominately positive (or negative) emotion, while others were relatively neutral. In this scenario, the same pattern of PL may reflect quite different regulatory dynamics due to the emotional context of the conversation (e.g., capitalization, empathy, and conflict). For example, when disclosing success to one's partner (i.e., capitalization support; Gable et al., 2004), an in-phase pattern of PL may arise due to shared positive emotions, ultimately increasing well-being. In contrast, situations that produce mutual hostility (e.g., conflict), an in-phase pattern of PL, may represent an escalation of negative emotion, ultimately contributing to relational distress. Future work could include discrete conversation topics eliciting different dominant emotions, with enough time points in each to model the dynamics separately by topic.

Finally, while the range of relationship length was between 1 month and 6 years, most couples in this sample had been in a relationship for less than a year. This range limited our ability to assess whether relationship length influenced patterns of PL. Future studies might intentionally recruit couples with more variability in relationship length to assess whether the higher interdependence that comes with a longer relationship influences whether couples will exhibit Complex/Coregulatory or Simple/Disengaged patterns of PL. Similarly, the lengths of the conversations in this study—and the two prior studies that assessed PL patterns—were all in the range of 10–20 minutes. Future work will be needed to consider both shorter and longer time frames since PL dynamics may emerge in different ways at different time scales, but that question is unexplored in the literature.

Despite these limitations, the present study demonstrates the ability of CO models to represent a variety of complex PL patterns and shows that different patterns have different relational and emotional correlates. Future work using similar modeling but incorporating experimental designs for manipulating factors such as emotional context, relational behaviors, and partner's perceptions will be important in unpacking the subtleties of PL and its connections to interpersonal well-being.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This research was supported in part by Grant 1R21HL109746-01A1 from the National Heart, Lung, and Blood Institute awarded to the third author.

Open research statement

As part of IARR's encouragement of open research practices, the authors have provided the following information: This research was not pre-registered. The data and materials used in the current study are publicly posted. The data and materials can be obtained at: https://osf.io/vnscy/?view_only=7ff85a17eb624df398e1ef3695e6ae56.

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