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New Frontiers in Ambulatory Assessment: Big Data Methods for Capturing Couples' Emotions, Vocalizations, and Physiology in Daily Life

Adela C. Timmons[1], Brian R. Baucom[2], Sohyun C. Han[1], Laura Perrone[3], Theodora Chaspari[4], Shrikanth S. Narayanan[4], and Gayla Margolin[1]

Abstract

With the increasing use of smartphone technologies and wearable biosensors, we are currently undergoing what many have termed a "data revolution," where intensive, multichannel data are passively collected over long time frames. Such procedures are transforming the way psychologists conceptualize research and have the potential to spur important advances in the study of close relationships. This proof-of-concept study from the Couple Mobile Sensing Project, a partnership between psychologists and engineers, combines big data and ambulatory assessment methodologies to study multimodal, microprocesses in couples' everyday lives. These data collection procedures are designed to test how characteristics of everyday behavioral, physiological, and vocal interactions are integrated within and across individuals. We present two mini-illustrations to show how these data can be synchronized across modalities and partners and can be linked to generalized relationship dimensions. Discussion highlights the potential and challenges of capturing multimodal, multiperson, real-time, naturally occurring social phenomena.

Keywords

ambulatory assessment, big data, wearable technology, social relationships, couples

In a society of ever-evolving technology, new methods of communicating, being entertained, and making money have revolutionized popular culture and the business world. These changes also have broad implications for the ways researchers think about and approach data. The term "big data," first popularized in the early 2000s, has been used to describe a new era of scientific research where technology is harnessed to collect vast amounts of data across multiple settings (Laney, 2001; Manyika et al., 2011). Big data are relevant to many disciplines, including engineering, economics, and medicine. Within psychology, the use of big data is diverse, with some psychologists mining data via social media (e.g., Kern et al., 2014) and others using mobile sensing devices to track GPS locations (e.g., Epstein et al., 2014) or physiological states (e.g., Edmondson, Arndt, Alcantar, Chaplin, & Schwartz, 2015). Despite growing interest in these methods, they continue to be the "wild west" of psychological research, with ongoing debate regarding what constitutes big data and how to creatively apply them in specific contexts. The current article illustrates the feasibility of collecting big data via ambulatory assessment methods and presents proof-of-concept examples as a starting point for using such data to understand relationship phenomena.

The Rise of Big Data

The digitalization of modern life, starting in the 1970s and evolving ever-rapidly since, has resulted in the proliferation of large and easy-to-collect repositories of data, though methods for making use of this information have lagged behind. As the value of these repositories became apparent within the business sector, interest in big data increased precipitously. Citations referencing big data exploded in 2011, as scientists caught on to the big data craze (Gandomi & Haider, 2015). Although big data are clearly powerful, some argue that big data are a buzz term lacking clear definition. Defining big data

[1] Department of Psychology, University of Southern California, Los Angeles, CA, USA
[2] Univeristy of Utah, Salt Lake City, UT, USA
[3] Department of Psychology, Stony Brook University, New York, NY, USA
[4] Department of Electrical Engineering, University of Southern California, Los Angeles, CA, USA

Corresponding Author:
Adela C. Timmons, Department of Psychology, University of Southern California, SGM 921, 3620 South McClintock Avenue, Los Angeles, CA 90089, USA.
Email: adelatim@usc.edu

is indeed difficult; although the primary characteristic of big data is size, the term incorporates more than sheer volume. Laney (2001) described big data in terms of "three Vs," which included volume, variety, and velocity. Volume, referring to the size of the data set, suggests that big data contain a large number of data points, though no consensus exists regarding how big is big enough. Variety refers to the heterogeneity of data formats collected, which can include survey, text, audio, and so on. Velocity concerns the speed at which data are collected and the need for efficient processing systems. When data are characterized by high volume, variety, and velocity, big data methods are needed for "insight extraction," which is the process of obtaining information from the data (Gandomi & Haider, 2015). Insight extraction includes both data management (i.e., recording, cleaning, and aggregating data) and analysis (i.e., applying traditional statistical methods and machine-learning techniques).

Ambulatory Assessment Methodologies

In contrast to big data methodology, ambulatory assessment, or ecological momentary assessment, has been used in research as early as the 1940s, though it gained popularity over the past 25 years (Shiffman, Stone, & Hufford, 2008). Ambulatory assessment is a broad term that refers to data collected in naturalistic settings. These methods increase ecological validity by investigating events in vivo and in situ (Laurenceau & Bolger, 2005; Mehl & Conner, 2012), that is, by capturing phenomena when they actually occur, rather than attempting to induce behaviors in the lab or asking participants to report on how they usually behave or feel. For example, couple researchers commonly ask spouses to have discussions in the laboratory, while the researchers record their behavior. While a well-established and valid method for researching couples, investigators readily acknowledge that couples may be subdued in an artificial environment. By capturing spontaneously occurring interactions, such as displays of affection or conflict episodes, ambulatory assessment provides information on what precipitates these events and how they progress over time, move across locations, and whether they naturally diminish, maintain, or escalate.

Ambulatory assessment methods have evolved in concert with technological advances, moving from paper and pencil diaries to Internet-based surveys, personal digital assistants, and smartphones. The explosion of affordable and easily available phone applications has made it increasingly feasible to collect multimodal data in daily life, including GPS, texting frequency, or time on the Internet. One such application is the electronically activated recorder (EAR), which collects audio snippets in daily life (Mehl & Holleran, 2007; Mehl, Pennebaker, Crow, Dabbs, & Price, 2001). Recordings obtained from the EAR have been transcribed and coded to obtain information on how everyday speech relates to other factors such as relationship functioning or coping with illness (e.g., Robbins et al., 2011; Robbins, Lopez, Weihs, & Mehl, 2014). Audio files can also be used to extract indices of vocal quality, such as fundamental frequency (f_0), which is an index of pitch associated with emotional arousal (e.g., Russell, Bachorowski, & Fernandez-Dols, 2003). The f_0 collected during laboratory-based discussions has been associated with families' emotional expressions (Baucom et al., 2012), while home-based toddler f_0 has been used to map the escalation of temper tantrums (Green, Whitney, & Potegal, 2011). To our knowledge, however, no study has examined f_0 data from couples as they go about daily life.

In addition to phone applications, wearable biosensors have been developed to collect data on physiological arousal conveniently and inconspicuously outside of the laboratory (e.g., Goodwin, Velicier, & Intille, 2008; Poh, Swensen, & Picard, 2010). Such sensors can collect data on electrodermal activity (EDA), a measure of sweat in skin glands linked to activation of the sympathetic nervous system, and electrocardiogram (ECG), a measure of heart rate associated with both parasympathetic and sympathetic activity (Hugdahl, 1995). ECG data can also be used to estimate high-frequency heart rate variability (HF-HRV), an index of vagal tone thought to reflect parasympathetic activation and emotion regulation ability (e.g., Porges, Doussard-Roosevelt, & Maiti, 1994; Thayer, Hansen, & Johnsen, 2010). Contrasted with other physiological measures such as cortisol, ECG and EDA are particularly informative because they are quick responding and can be linked to observable moment-to-moment changes in behavior or emotion. By capitalizing on new technologies to obtain multimodal, ambulatory assessment data in the natural environment, couple researchers can assess how observable and under-the-skin moment-to-moment processes are related to each other and how they interact with external stimuli.

Considering Interpersonal Context

Beyond monitoring individual-level psychological functioning, ambulatory big data methods can be used to investigate how romantic partner's behaviors, emotions, and physiology are interconnected in daily life. Considerable evidence suggests that people exist in a web of social relationships and that the way individuals feel and behave is closely linked to the feelings, behaviors, and physiological reactions of those with whom they are close (e.g., Beckes & Coan, 2011; Hofer, 1984; Sbarra & Hazan, 2008). Research on physiological linkage, or covariation in partners' physiology over time, suggests that physiological arousal is regulated in part by social relationships and that this process is related to various dimensions of generalized relationship functioning, such as relationship satisfaction (Timmons, Margolin, & Saxbe, 2015). While such processes can be studied in lab environments, ambulatory big data could allow researchers to model webs of interconnectivity as people move about their daily lives. For example, it would be possible to model how physiological linkage fluctuates as partners naturalistically separate and reunite. Moreover, if linkage is meaningfully related to interpersonal processes—rather than partners reacting to the same external stimuli—we would expect it to be linked to measures of interpersonal functioning, such as anxious and avoidant attachment, which characterizes peoples' tendencies toward seeking increased closeness or toward emotional withdrawal, respectively.

Putting It All Together: Using Ambulatory Big Data to Study Couple Processes

Although big data are typically obtained by collecting small amounts of information on a large number of people, an equally valid method is to collect a large amount of information on a relatively small number of people. Sampling frequently, the earmark of ecological momentary assessment, allows researchers to model how processes of interest develop over time. Historically, ecological momentary assessment studies have used only self-report data to assess mood and behavior, but some studies have combined self-report data with one additional measure, for example, Robbins, Lopez, Weihs, and Mehl (2014) used the EAR to study language use in couples coping with illness, and Hasler and Troxel (2010) used actigraphy to test linkage in couples' sleep timing. For measuring physiology in couples' daily lives, researchers typically have focused on blood pressure (e.g., Holt-Lunstad, Birmingham, & Light, 2014; Smith, Birmingham, & Uchino, 2012) or cortisol (e.g., Papp, Pendry, Simon, & Adam, 2013; Saxbe & Repetti, 2010). In our view, a valuable next step is to incorporate the three Vs into ecological momentary assessment. In the framework described below, we (1) collect a large number of data points (e.g., EDA collected at 8 Hz for one couple over 1 day results in over 1 million data points), (2) obtain a variety of data types (EDA, ECG, audio, etc.), and (3) sync our data over time, so that temporal patterns can be modeled. In presenting these data, we demonstrate how these methods can provide a detailed window into social processes, linking different moment-to-moment experiences within and across people and testing how these micropatterns relate to overall relationship functioning.

Present Study

In the current article, we present proof-of-concept data from the Couple Mobile Sensing Project, a collaboration between psychologists and engineers that aims to capture physiological, emotional, and behavioral processes of interacting couples in the home environment. Our goal here is to describe our procedures for collecting ambulatory big data from couples and to briefly summarize the feasibility and validity of such data. In our first example, we present qualitative data from one couple mapping moment-to-moment fluctuations in EDA, positive emotion, and f_0 within and across partners. In our second example, we demonstrate how ambulatory big data can be used to investigate theoretically based questions. Specifically, to demonstrate how patterns of social connectivity fluctuate as people go about daily life, we test how linkage in partners' EDA differs when couples naturalistically separate and reunite—a question that cannot be addressed with lab-based data. To demonstrate that these patterns reflect important social processes, we test anxious and avoidant attachment style as moderators of linkage in physiology. Because physiological linkage is theorized to be an interpersonal process that occurs when partners are interacting, we hypothesize that linkage will occur only when the partners are together (Hypothesis 1). Furthermore, because insecurely attached individuals may be more interpersonally reactive than securely attached individuals, we hypothesize that anxious (Hypothesis 2) and avoidant (Hypothesis 3) attachment will be associated with heightened linkage. As exploratory analyses, we test parallel models examining the moderating role of partner attachment and also test gender as a moderator of these associations. In addition, we provide information on participants' compliance and reactivity to the procedures as well as exploratory analyses testing links between physiology and contextual variables (e.g., mood and exercise).

Method

Participants

Participants consisted of 80 young adults (38 opposite-sex and 2 female same-sex couples; $M_{\text{age}} = 22.7$; standard deviation $[SD] = 3.0$) who were in a relationship for at least 2 months ($M = 34.8$ months; $SD = 26.1$); 40% of couples were cohabitating. For ethnic/racial status, 28.7% identified as Hispanic/Latino, 26.3% Caucasian, 15.0% African American, 8.8% Asian American, 1.3% Native American or Pacific Islander, and 20.0% multiracial. The majority of participants (63.7%) were enrolled in college or technical school, and 71.3% were employed, with 28.4% working full time (see the Online Supplemental Materials, section A, for additional details about the sample).

Procedures

Overview. On the day of data collection, couples met the experimenter at the laboratory at 10:00 a.m. Each partner was outfitted with two physiological monitors. Experimenters also lent each partner a smartphone that alerted them to take hourly surveys and collected audio recordings. Couples were instructed to go about their day as usual, to spend at least five waking hours together, and to wear the monitors at all times. The next morning, partners returned to the lab to provide an hour-by-hour account of how they spent their day and complete a questionnaire assessing reactivity to and comfort with the procedures. Compensation was US$100; all procedures were conducted in compliance with American Psychological Association (APA) ethical standards.

Equipment

Smartphones. Nexus 5 phones were programmed with hourly alarms to notify participants to complete phone-based surveys (via the application Survelytics), to collect minute-by-minute GPS coordinates to measure partners' proximity to each other (via the application GPS Logger), and to capture 3-min audio recordings (via the application RecForge II) once every 12 min. Recording start times across the two partners never overlapped such that 50% of their time together was recorded. To avoid recording any conversations involving unconsented individuals, participants were instructed to disable the audio recording feature when in the presence of third parties. Prior to returning the phones, couples were allowed to listen to and delete any recordings they wished to remain private; only one couple elected to do so and subsequently did not request any deletions. Phone recordings were not monitored in real time; however, research assistants who later transcribed the recordings were trained to identify reportable events in the files (e.g., physical aggression), which, had they occurred, were to be reported to the principal investigator. Phones were stripped of identifying information between uses, and password locks prevented participants from changing settings or leaving personal information beyond the prearranged recordings.

Actiwave. The Actiwave is a physiological sensor that records ECG, time, and movement. The Actiwave (attached to one electrode on the chest bone and another a few inches to the left) is worn under a shirt. Sampling rate was set to 32 Hz to accommodate software constrains related to file sizes and to ensure battery life over the sampling duration.

Q sensor. The *Q* sensor is a physiological sensor that collects EDA, movement, and body temperature through a watch-like device worn on the inside of the nondominant hand. Sampling rate was set to 8 Hz.

Measures

Hourly phone surveys. The 12-item surveys assessed recent (within the past hour) stress, general mood states (happy, sad, nervous, and angry), and various relationship dimensions (feelings of annoyance and emotional closeness with partner; expressed annoyance to partner). Example questions include: "How stressed were you in the last hour?" and "In the last hour, how happy were you?" Participants responded on a scale from 0 (*not at all*) to 100 (*extremely*). Factors that could impact physiology, for example, exercise, caffeine, or alcohol consumption, were assessed via dichotomous "yes" versus "no" response options.

ECG and EDA. We used Matlab (Version R2013b) to process ECG and EDA, first applying a low-pass filter and then using computer algorithms to detect movement artifacts, which were visually inspected and revised. Skin conductance responses and interbeat intervals were identified using Ledalab (Version 3.4.4) and BioSig (Version 3.1.0), respectively (Benedek & Kaernbach, 2010; Vidaurre, Sander, & Schlögl, 2011). Minimum amplitude of skin conductance responses was set to .02 μs (Dawson, Schell, & Filion, 2000). HF-HRV was calculated with frequency spectral analysis using a Fourier transformation in Kubios (Tarvainen, Niskanen, Lipponen, Ranta-aho, & Karjalainen, 2014). Additional details on data cleaning procedures are provided in the Online Supplemental Materials (section B).

Audio-based measures. For our sample audio file presented here, we calculated the f_0 of each person once every 5 s. Values for f_0 were only obtained for time intervals in which participants spoke. Similarly, human coders provided ratings for every 5-s interval in which the participant provided audible sound (e.g., laughing and sighing). Three coders independently rated the positive emotional intensity of each partner using a scale from 0 (*not at all positive*) to 100 (*extremely positive*); Type 2 mixed Intraclass Correlation Coefficient (ICC) was .88 for the female and .91 for the male (Shrout & Fleiss, 1979). Final coded scores represent the average across coders for each partner every 5 s.

Exit questionnaire and interview. The exit questionnaire, assessing the degree of reactivity to the procedures, contains 17 items (e.g., "How much did filling out the phone surveys change the way you interacted with your partner?"), with quantitative items scored on a scale of 0 (*not at all*) to 4 (*extremely*). In addition, the experimenter conducted an interview to obtain more detailed information about the activities the participants engaged in over the course of data collection. For each hour, the couples reported on their activities, whether they were together, whether they interacted, and whether they were with other people. We also asked couples to report when they ate, if and when they exercised, if and when they had conflict, and when they went to sleep and woke up the next morning.

Attachment style. Avoidant and anxious attachment style was measured with the Experiences in Close Relationships—Revised Questionnaire (Fraley, Waller, & Brennan, 2000). The questionnaire contains anxious (i.e., fear of losing the partner's love; Cronbach's $\alpha = .95$ for females and .93 for males) and avoidant (i.e., preferring not to show true feelings to the partner; Cronbach's $\alpha = .95$ for females and .93 for males) subscales. The response scale ranges from 1 (*strongly disagree*) to 7 (*strongly agree*). Subscale scores represent the mean across items.

Results

Descriptive Statistics and Compliance

Table 1 presents descriptive statistics for all 29 measures in this study; correlations matrices are presented in the Online Supplemental Materials (section C) for females (Supplemental Table C1) and males (Supplemental Table C2). On average, couples provided survey data for 14.4 hr ($SD = 1.0$). Of the 1,133 possible surveys (based on the number of hours participants were awake), participants provided 1,025 reports (90.5%). Electronic time stamps obtained from the phone application showed that 90.5% of surveys were initiated within 15 min of the alarm and that the surveys took an average of 1 min and 56 s to complete ($Mdn = 1$ min 20 s; 90.0% in <3 min). The participants wore the *Q* sensor for 92.9% and the Actiwave for 95.3% of the sampled hours. Reasons for removing the monitors included bathing (41.6%), monitors were uncomfortable (37.5%), engaging in an activity (other than bathing) that could damage the monitors (7.5%), monitor fell off (7.5%), participant felt embarrassed (3.8%), or other (10.0%). Table 2 summarizes

Table 1. Descriptive Statistics.

Measures	Entire Sample				Females				Males			
	M (*SD*)	Min., Max.	Percentage of Hours	Percentage of People/ Couples	*M* (*SD*)	Min., Max.	Percentage of Hours	Percentage of People/ Couples	*M* (*SD*)	Min., Max.	Percentage of Hours	Percentage of People/ Couples
Interpersonal context												
Close with partner	67.1 (30.8)	0, 100	95.2	100	60.9 (33.5)	0, 100	92.9	100	73.9 (26.0)	0, 100	97.8	100
Annoyed with partner	7.6 (16.6)	0, 100	38.9	86.3	9.1 (19.1)	0, 100	40.3	90.48	6.0 (13.7)	0, 100	37.4	81.6
Expressed annoyance	—	—	16.6	72.5	—	—	20.5	73.8	—	—	12.3	57.9
Conflict with partner	—	—	12.0	66.7	—	—	—	—	—	—	—	—
With partner	—	—	83.0	100	—	—	—	—	—	—	—	—
Interacting with partner	—	—	74.9	100	—	—	—	—	—	—	—	—
GPS distance (m)	1,084.2 (3,711.9)	0.3, 2,334.0	—	—	—	—	—	—	—	—	—	—
Texted or called partner	—	—	17.9	61.3	—	—	—	—	—	—	—	—
With other people	—	—	42.8	93.8	—	—	42.9	92.9	—	—	42.8	97.4
Mood												
Stressed	13.4 (22.1)	0, 100	52.8	88.8	13.7 (22.7)	0, 100	52.4	90.5	13.1 (21.5)	0, 100	53.2	86.8
Stress source: partner	—	—	9.7	48.8	—	—	10.6	57.1	—	—	8.8	39.5
Stress source: other person	—	—	3.8	33.8	—	—	4.3	33.3	—	—	3.3	34.2
Stress source: work/ school	—	—	15.8	45.0	—	—	16.6	66.7	—	—	14.9	34.2
Stress source: other	—	—	30.2	85.0	—	—	28.3	95.2	—	—	32.5	84.2
Happy	67.8 (27.7)	0, 100	97.7	100	63.7 (29.1)	0, 100	97.6	100	72.3 (25.5)	0, 100	97.8	100
Sad	4.9 (13.7)	0, 100	31.3	73.8	5.9 (16.2)	0, 100	30.0	76.2	3.9 (10.1)	0, 100	32.7	71.5
Nervous	6.6 (13.9)	0, 100	40.8	87.5	7.0 (16.6)	0, 100	41.0	90.5	6.2 (13.2)	0, 100	40.5	84.2
Angry	6.4 (15.4)	0, 100	36.0	87.5	7.7 (17.3)	0, 100	37.5	90.5	4.9 (12.8)	0, 100	34.4	84.2
Substances												
Caffeine	—	—	9.4	52.5	—	—	10.3	57.1	—	—	8.4	47.4
Alcohol	—	—	6.0	21.3	—	—	5.2	19.1	—	—	6.9	23.7
Tobacco	—	—	1.9	5.0	—	—	0.4	2.4	—	—	3.5	7.9
Other drugs	—	—	5.4	12.5	—	—	2.9	7.7	—	—	7.8	18.2
Physical activity												
Exercise	—	—	26.2	76.3	—	—	27.1	76.2	—	—	25.2	76.3
Q activity level	164.0 (3.1)	1,40.5, 1,76.1	—	—	162.6 (3.9)	140.51, 76.1	—	—	165.5 (2.1)	155.6, 173.6	—	—
Physiology measures												
SCL (μs)	7.7 (9.0)	0, 50.5	—	—	5.8 (8.1)	0.1, 38.5	—	—	9.8 (9.5)	0, 50.5	—	—
fSCRs	0.9 (1.8)	0, 12.8	—	—	1.0 (2.2)	0, 12.8	—	—	0.7 (1.2)	0, 11.2	—	—
aSCRs (μs)	0.7 (0.7)	0, 3.9	—	—	0.6 (0.7)	0, 3.9	—	—	0.8 (0.8)	0, 3.4	—	—
IBI (ms)	879.9 (138.3)	4,33.3, 1,506.3	—	—	869.8 (129.6)	476.1, 1,293.1	—	—	891.1 (146.7)	433.3, 1,506.3	—	—
HF-HRV (ln ms^2)	3.38 (0.3)	2.2, 4.0	—	—	3.89 (0.3)	2.3, 3.4	—	—	3.4 (0.3)	2.2, 4.0	—	—
Q temperature (C)	37.6 (1.2)	34.9, 39.5	—	—	37.5 (1.2)	34.9, 39.5	—	—	37.6 (1.2)	34.9, 39.5	—	—

*Note. M*s and *SD*s are not provided for dichotomously scored variables. Descriptive data for audio (still in processing) are not presented. Percentage of hours = the percentage of hours each construct was endorsed at all; percentage of people/couples = the percentage of people or couples who endorsed the construct at all (not applicable for physiological and GPS estimates measured continuously); m = meters; *Q* = *Q* sensor; SCL = skin conductance level; μs = microsiemens; fSCRs = frequency of skin conductance responses; aSCRs = average amplitude of skin conductance responses; IBI = interbeat interval; ms = milliseconds; HF-HRV = high-frequency heart rate variability; ln ms^2 = natural log milliseconds squared; C = Celsius; shaded regions = significant gender differences in mean values; *SD* = standard deviation.

Table 2. Self-Reported Reactivity to the Study Procedures.

	Percentage of Entire Sample					
Question	Not At All	A Little	Some	A Lot	Extremely	*M* (*SD*)
How typical was the day of data collection in terms of how you usually interact with your romantic partner?	2.5	0	25.0	55.0	17.5	2.9 (0.8)
How much did filling out the hourly phone surveys change the way you interacted with your romantic partner?	31.3	37.5	21.3	8.8	1.3	1.1 (0.9)
How much did you change your behavior knowing some of your conversations were being recorded?	52.5	33.8	11.3	2.5	0	0.6 (0.8)
How disruptive (i.e., interfered with your daily activities) was it to complete the hourly phone surveys?	41.8	43.0	11.4	3.8	0	0.8 (0.8)
How disruptive (i.e., interfered with your daily activities) was it to wear the wrist monitor?	51.3	27.5	17.5	2.5	1.3	0.8 (0.9)
How disruptive (i.e., interfered with your daily activities) was it to wear the chest monitor?	48.8	33.8	11.3	5.0	1.3	0.8 (0.9)
How uncomfortable was it to wear the wrist monitor?	31.3	30.0	25.0	10.0	3.8	1.3 (1.1)
How uncomfortable was it to wear the chest monitor?	37.5	30.0	21.3	8.8	2.5	1.1 (1.1)

Note. Endorsement did not differ by gender with two exceptions: males ($M = 1.45$) reported that wearing the chest monitor was more disruptive than did females ($M = .97$), $t(37) = 2.48$, $p = .02$, and males ($M = .68$) reported that the chest monitor was more uncomfortable than did females ($M = .50$), $t(37) = 3.86$, $p < .001$. 0 = *not at all*; 1 = *a little*; 2 = *some*; 3 = *a lot*; 4 = *extremely*; *SD* = standard deviation.

participants' self-reported reactivity to the procedures; 97.5% reported the day was *somewhat* to *extremely* typical. Close to 70% reported minimal (either *not at all* or *a little*) reactivity to the surveys; approximately 80% also reported minimal reactivity to the phone recordings and monitors. Table 3 presents results of exploratory three-level models testing how fluctuations in physiology relate to ongoing contextual variables, tested at $p < .01$ to adjust for multiple comparisons (see the Online Supplemental Materials, section D, for further details). Results showed that physiology was linked to contextual variables in generally expected directions (e.g., increased skin conductance level when stressed).

Illustrative Data

Example 1. Figure 1 presents a graphic illustration of the volume, variety, and velocity of data captured during a brief, 3-min segment of couple interaction. The top of the figure provides context for the couple for the three time-linked modalities of assessment: human coding of couple interaction for positive emotion (Panel A), EDA (Panel B), and f_0 (Panel C). Human coding for positive emotion was based on both speech content and tone; breaks signify no speech or sound during the interval. This visual example is provided to illustrate the potential, complexity, and power of big data. Even after collapsing into 5-s intervals, information from these three modalities across two partners translates into 216 data points for 3 min; if extended for a 12-hr day with 10 samples per hour, this would amount to 25,920 data points per couple. Such data, though requiring considerable forethought about storage, processing, synchronization, and analytics, are ideal for testing covariation in signals across people and identifying predictors of that covariation.

Example 2. To provide an example of analyses that can be conducted using ambulatory big data methods, we present three-level models testing linkage in female and male hourly EDA on the opposite-sex couples. Power analyses for the hypotheses were conducted using Monte Carlo simulations (Mathieu, Aguinis, Culpepper, & Chen, 2012). To adjust for confounding influences on EDA, hours elapsed since starting the study; exercise; body temperature; time spent together; and consumption of caffeine, tobacco, alcohol, and other drugs were added to all models as covariates (see the Online Supplemental Materials, section D, for details and complete results). To test whether linkage in EDA was greater during hours that the partners were together, we entered "with partner" as a Level 1 moderator of covariation in EDA. In support of Hypothesis 1, partner presence moderated linkage in EDA ($b = .26$, $p = .02$). As seen in Figure 2, Panel A, linkage in EDA was significant when couples were together but not when apart. Next, we examined anxious attachment as a Level 2 moderator of the association between partner (x-axis) and self (y-axis) EDA (Panel B). In support of Hypothesis 2, anxious attachment moderated the association between self and partner EDA ($b = .13$, $p = .01$) such that linkage in EDA was heightened in individuals with greater anxious attachment. Similarly, avoidant attachment moderated the association between partner and self EDA ($b = .20$, $p < .01$). Moreover, this effect was moderated by gender ($b = -.17$, $p < .05$); for both males and females, avoidant attachment was associated with increased linkage, and this effect was stronger in males. Effects for partner attachment were not significant. These analyses, which highlight EDA data, are a starting point for examining questions about physiological linkage in reference to global interpersonal styles; similar questions could be investigated via other modalities and with other global dimensions, for example, relationship satisfaction.

Table 3. Exploratory Tests of Hourly Associations Between Physiological Measures and Moods, Interpersonal Context, and Other Contextual Variables.

Mood, Interpersonal Context, and Other Contextual Variables	EDA									ECG					
	SCL			fSCRs			aSCRs			IBI			HF-HRV		
	b	*p*	[95% CI]	*b*	*p*	[95% CI]	*b*	*p*	[95% CI]	*b*	*p*	[95% CI]	*b*	*p*	[95% CI]
Interpersonal context															
Close with partner	0.04	.63	[−0.14, 0.23]	0.00	.86	[−0.03, 0.04]	0.01	.18	[−0.01, 0.03]	−0.06	**.00**	[−0.09, −0.03]	−0.03	.07	[−0.06, 0.00]
Annoyed with partner	0.00	.99	[−0.25, 0.26]	0.00	.88	[−0.04, 0.05]	−0.00	.82	[−0.03, 0.02]	0.02	.28	[−0.02, 0.07]	0.01	.56	[−0.03, 0.06]
Expressed annoyance	−1.04	.09	[−2.24, 0.16]	−0.07	.49	[−0.27, 0.13]	−0.09	.14	[−0.21, 0.03]	−0.07	.54	[−0.27, 0.13]	−0.08	.42	[−0.29, 0.12]
Conflict with partner	1.50	.25	[−1.03, 4.03]	0.17	.41	[−0.23, 0.58]	−0.05	.65	[−0.28, 0.17]	−0.16	.27	[−0.44, 0.13]	−0.05	.74	[−0.36, 0.26]
With partner	−3.01	**.00**	[−4.22, −1.79]	−0.10	.29	[−0.31, 0.09]	0.06	.33	[−0.06, 0.17]	−0.08	.40	[−0.27, 0.11]	−0.28	**.00**	[−0.48, −0.09]
Interacting with partner	−1.13	**.00**	[−1.63, −0.62]	−0.02	.51	[−0.11, 0.06]	0.04	.15	[−0.01, 0.08]	−0.15	**.00**	[−0.23, −0.08]	−0.04	.36	[−0.12, 0.04]
GPS (m)	0.31	**.00**	[0.10, 0.53]	0.01	.52	[−0.02, 0.05]	−0.00	.64	[−0.02, 0.02]	0.02	.32	[−0.02, 0.05]	0.03	.11	[−0.01, 0.06]
Texted or called partner	2.12	**.00**	[0.84, 3.41]	0.04	.74	[−0.18, 0.25]	0.06	.38	[−0.07, 0.18]	0.02	.89	[−0.20, 0.23]	0.30	**.00**	[0.07, 0.52]
With other people	0.72	.01	[0.21, 1.23]	0.15	**.00**	[0.06, 0.23]	0.05	.06	[−0.00, 0.10]	−0.13	**.00**	[−0.21, −0.05]	−0.02	.68	[−0.10, 0.07]
Mood															
Stressed	0.36	**.00**	[0.14, 0.57]	0.04	.07	[−0.00, 0.08]	0.02	.13	[−0.00, 0.04]	−0.02	.41	[−0.05, 0.02]	0.02	.39	[−0.02, 0.06]
Stress source: partner	−0.26	.73	[−1.74, 1.21]	−0.22	.08	[−0.46, 0.03]	0.03	.68	[−0.13, 0.20]	0.11	.42	[−0.16, 0.38]	−0.02	.87	[−0.30, 0.26]
Stress source: other person	1.28	.18	[−0.61, 3.17]	0.15	.36	[−0.17, 0.49]	0.11	.32	[−0.10, 0.31]	−0.17	.34	[−0.52, 0.18]	−0.17	.36	[−0.53, 0.19]
Stress source: work/school	0.64	.42	[−0.91, 2.20]	0.07	.57	[−0.18, 0.33]	−0.00	.98	[−0.17, 0.16]	−0.02	.92	[−0.30, 0.27]	−0.16	.28	[−0.46, 0.13]
Stress source: other	−0.94	.11	[−.2.09, 0.20]	0.03	.78	[−0.17, 0.22]	−0.06	.38	[−0.18, 0.07]	−0.02	.87	[−0.23, 0.19]	0.22	.05	[−0.00, 0.43]
Happy	−0.08	.41	[−0.27, 0.11]	0.00	.83	[−0.03, 0.04]	−0.00	.85	[−0.02, 0.02]	−0.06	**.00**	[−0.09, −0.03]	−0.04	.04	[−0.07, −0.00]
Sad	0.33	**.00**	[0.12, 0.54]	−0.03	.33	[−0.09, 0.03]	0.04	.04	[0.00, 0.07]	−0.01	.72	[−0.07, 0.04]	−0.02	.55	[−0.08, 0.04]
Nervous	0.27	.10	[−0.05, 0.60]	0.03	.28	[−0.03, 0.09]	0.01	.57	[−0.02, 0.04]	−0.02	.46	[−0.07, 0.03]	0.02	.45	[−0.04, 0.08]
Angry	0.09	.51	[−0.17, 0.35]	0.03	.18	[−0.01, 0.08]	−0.00	.80	[−0.03, 0.02]	−0.00	.93	[−0.05, 0.04]	0.05	.05	[0.00, 0.10]
Substances															
Caffeine	−0.51	.51	[−2.06, 1.02]	−0.00	.99	[−0.26, 0.26]	0.05	.54	[−0.10, 0.20]	−0.22	.10	[−0.47, 0.04]	0.03	.85	[−0.24, 0.29]
Alcohol	1.30	.18	[−0.59, 3.18]	−0.03	.87	[−0.34, 0.29]	0.09	.32	[−0.09, 0.28]	−0.54	**.00**	[−0.85, −0.23]	−0.69	**.00**	[−1.01, −0.37]
Tobacco	0.88	.64	[−2.78, 4.54]	−0.03	.93	[−0.64, 0.59]	0.01	.95	[−0.35, 0.37]	−0.77	.01	[−1.38, −0.16]	−0.64	.05	[−1.28, 0.00]
Other drugs	5.42	.03	[0.59, 10.25]	−0.23	.59	[−1.05, 0.60]	0.54	.02	[0.09, 0.98]	−0.75	**.00**	[−1.27, −0.23]	−0.36	.21	[−0.91, 0.20]
Physical activity															
Exercise	1.22	**.00**	[0.77, 1.67]	0.11	**.00**	[0.04, 0.19]	0.10	**.00**	[0.06, 0.15]	−0.30	**.00**	[−0.37, −0.23]	−0.06	.14	[−0.14, 0.02]
Q activity level	0.13	.31	[−0.12, 0.38]	−0.03	.15	[−0.07, 0.01]	0.03	.01	[0.01, 0.05]	−0.06	**.00**	[−0.10, −0.02]	0.03	.16	[−0.01, 0.07]
Physiology measures															
SCL (µs)	—			—			—			—			—		
fSCRs	1.95	**.00**	[1.57, 2.33]	—			—			—			—		
aSCRs (µs)	4.52	**.00**	[3.89, 5.16]	−0.27	**.00**	[−0.38, −0.16]	—			—			—		
IBI (ms)	−1.29	**.00**	[−1.69, −0.89]	−0.13	**.00**	[−0.20, −0.06]	−0.11	**.00**	[−0.15, −0.07]	—			—		
HF-HRV (ln ms^2)	−0.05	.01	[−0.09, −0.01]	−0.00	.59	[−0.01, 0.00]	−0.00	.01	[−0.01, −0.00]	.03	**.00**	[0.03, 0.04]	—		
Temperature (C)	0.35	**.00**	[0.20, 0.50]	−0.01	.58	[−0.03, 0.02]	0.03	**.00**	[0.01, 0.04]	.06	**.00**	[0.04, 0.09]	−0.04	**.00**	[−0.06, −0.02]

Note. Three-level models (observations nested in people nested in couples) testing associations on Level 1. When testing how physiology relates to self-reported mood states or feelings toward one's dating partner, we statistically adjusted for hours elapsed since starting the study, exercise, body temperature, the consumption of caffeine, alcohol, tobacco, and other drugs (entered as Level 1, time-varying covariates), and gender (entered on Level 2). Further analytic details are provided in the Online Supplemental Materials (section D). m = meters; *Q* = *Q* sensor; SCL = skin conductance level; µs = microsiemens; fSCRs = frequency of skin conductance responses; aSCRs = average amplitude of skin conductance responses; IBI = interbeat interval; ms = milliseconds; HF-HRV = high-frequency heart rate variability; ln ms^2 = natural log milliseconds squared; *C* = Celsius; *SD* = standard deviation; CI = confidence interval; EDA = electrodermal activity; ECG = electrocardiogram.
Significance (noted in boldface) tested at $p < .01$ to adjust for multiple comparisons.

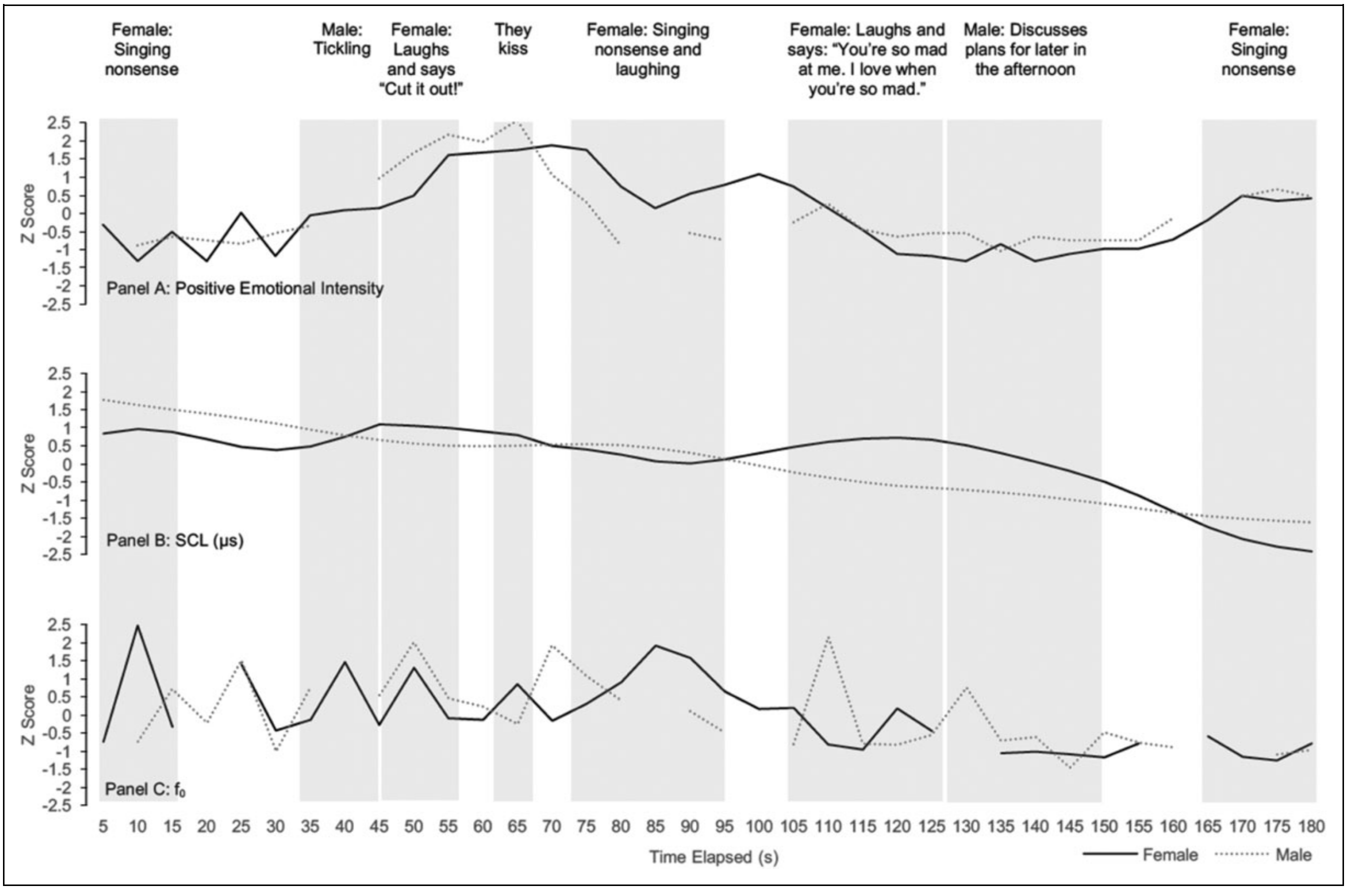

Figure 1. Male and female positive emotional intensity, SCL, and f_0 during one spontaneously occurring positive interaction across 3 min. Panel A: positive emotion, Panel B: SCL, and Panel C: f_0. SCL = skin conductance level; μs = microsiemens; f_0 = fundamental frequency; s = seconds. Because indices were measured on different scales, standardized values are plotted here. Blank spaces represent pauses in speech. The text at the top marks highlights in the conversation (not all aspects of the conversation are labeled). Shaded regions identify portions of time corresponding to the text listed at the top.

Discussion

The current study is an illustration of the application of ambulatory big data methods for studying couple processes. With technological innovations in data acquisition, big data are increasingly ubiquitous. Although ambulatory big data methods have the potential to advance our understanding of social–psychological phenomena, they raise important questions regarding data quality, privacy, and ethics. Within this "brave new world" of big data, researchers must take advantage of these innovations while also ensuring the quality of the data. In this study, we first examined the acceptability of these procedures to participant couples. By and large, they provided data when prompted and they wore the biosensors as instructed. Exit interviews suggested that the data collected were reasonably typical of their daily interactions. Second, our exploratory analyses testing links between physiological and contextual variables provide initial evidence of the validity of collecting physiological data in the home environment. Third, our two examples demonstrated how these methods can specifically be used to capture social processes.

Illustrative Examples

Data from our first example demonstrate how everyday interactions can be captured via ambulatory big data methods. Although this example reflects just one couple, it provides a tangible, visual model of how ambulatory big data can be used to map fluctuating, multimodal, and interconnected dimensions of a naturally occurring interpersonal dynamics. Results of our second example provide evidence that data obtained with ambulatory big data methods are useful for testing theoretically driven questions about couple processes. Results showed that physiological linkage occurred only when couples were together, suggesting that linkage is related to individuals' ongoing social dynamics. This analysis, while preliminary, provides an example of how contextual, everyday occurrences, such as reuniting with a close partner, are linked to physiological arousal in daily life. In addition, results showed that linkage was heightened in people with anxious (Hypothesis 2) and avoidant (Hypothesis 3) attachment. Anxiously attached individuals may be more likely to track the shifting moods of others, yearn for increased connection, and to seek reassurance, while avoidantly attached individuals may avoid social

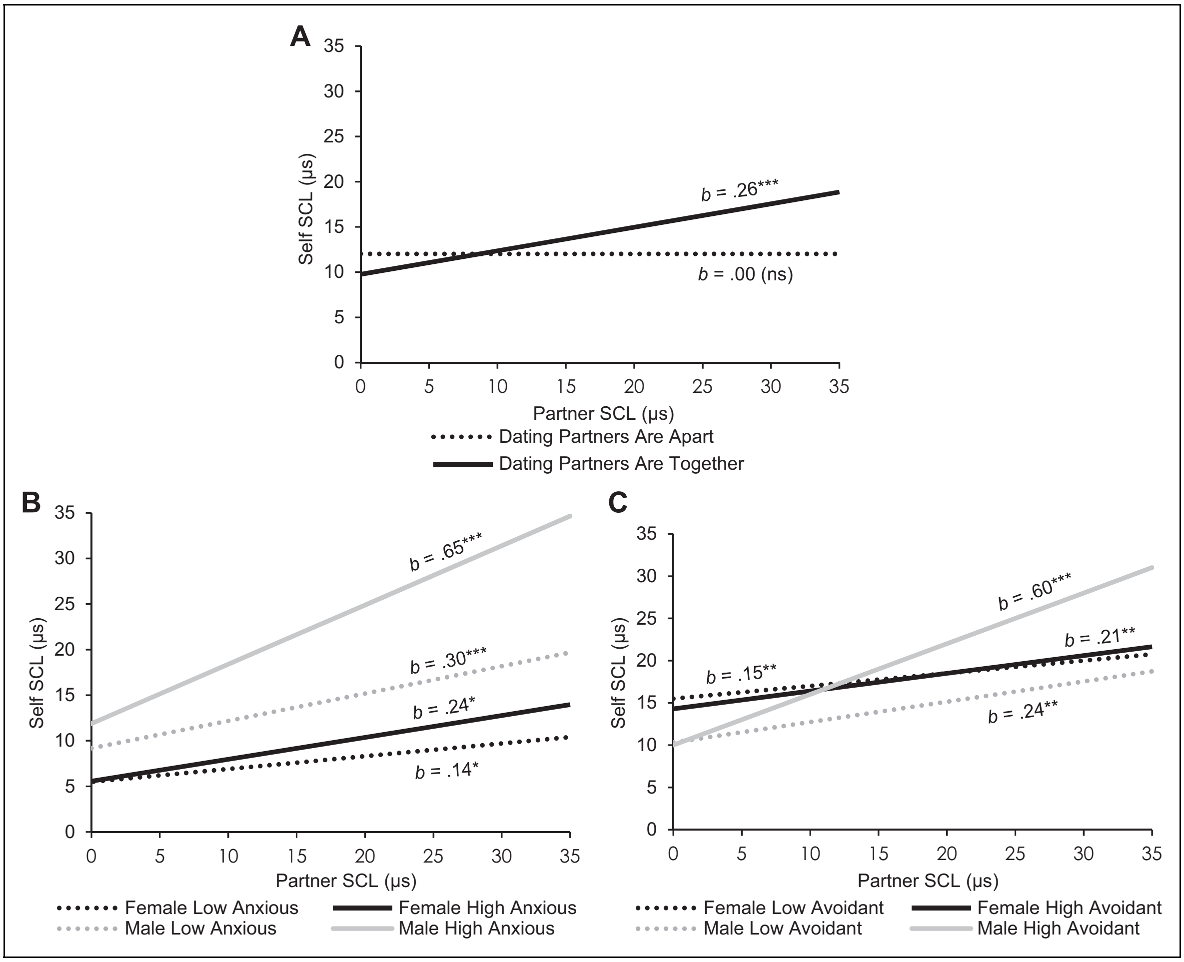

Figure 2. Panel A: linkage in SCL when dating partners are together versus apart, Panel B: linkage in SCL moderated by self-anxious attachment, Panel C: linkage in SCL moderated by self-avoidant attachment. SCL = skin conductance level; μs = microsiemens; low anxious = anxious attachment at $M - 1$ SD; high anxious = anxious attachment at $M + 1$ SD; low avoidant = avoidant attachment at $M - 1$ SD; high avoidant = anxious avoidant at $M + 1$ SD; SD = standard deviation.*$p < .05$. **$p < .01$. ***$p < .001$.

connection. Perhaps both anxious and avoidant attachment are characterized by heightened reactivity to others, with anxiously attached individuals coping by seeking increased connection and avoidantly attached individuals creating distance from others. Together, these findings illustrate how ambulatory big data can be used for hypothesis-driven testing and the types of questions, for example, partners reuniting, that cannot be investigated with lab-based data; methods such as this provide a new framework for testing the intersection between interpersonal functioning and physiology.

Data Processing and Quantitative Analysis

Although ambulatory big data hold promise, it is important to note that there are a number of limitations and challenges associated with using these methods, especially in terms of data processing and analysis. Ambulatory big data are time- and resource-intensive, often costing more than laboratory-based studies in terms of participant compensation and equipment fees. With the vast amount of data collected, data processing is an enormous task often requiring cross-disciplinary collaboration. To process our data, we worked with engineers to develop code for automated artifact processing. We are also in the process of manually transcribing the audio files, which will allow us to analyze word content. Although these methods are time-consuming, we anticipate that technologies for automatizing these tasks will continue to emerge and subsequently decrease processing time. Once data are processed, researchers must choose an appropriate time interval and analytic strategy that can handle multiple levels of nestedness and intensive repeated measurements. Here, we used 5-s time intervals to capture moment-to-moment links in physiology and behavior in our first example and then aggregated our measures to test how linkage varied according to hourly partner proximity in our second example; the time interval chosen and length of the sampling period should be matched to the phenomenon that is being studied. In fact, one exciting aspect of collecting a repository of data like the one we present here is the ability to choose and change the time scale examined based upon the aims of specific projects. Another advantage of these methods is that data can be analyzed using multiple analytic frameworks. In our second example, we showed how data can be aggregated for use with regression-based models, such as multilevel modeling, which can be particularly useful for theory-driven projects. Alternatively, an evolving frontier for using data sets such as this is to use machine learning and other exploratory methods to detect and predict events of interest, outside of what might be tested theoretically; both frameworks could provide important insights about interpersonal processes and could work in tandem to advance relationship science.

Data Security, Ethics, and Privacy

As big data increase in popularity, it has become increasingly important to consider the potential ethical and legal implications of collecting these types of data sets. Because data such as audio recordings are identifiable, great care is needed to ensure that the participants are fully consented to the procedures and that the data are protected from security breaches. Accordingly, it is paramount that information cannot be accessed if the mobile device is misplaced and that data are removed from the devices prior to use. Application locks and passwords should be installed to prevent participants from leaving identifying data for other participants, for example, by taking pictures or leaving videos on the smartphones. In terms of the audio recordings, each state has different laws regarding consent to capture recordings of conversations that occur publicly or privately. Procedures used in specific studies should be developed in accordance with local laws and with Institutional Review Board (IRB) oversight. Another potential ethical issue is what to do if reportable events are caught on the recordings, for example, if violence occurs. As is routinely done, participants should be made aware of the mandated reporting laws, and researchers should have established protocols for responding to these events should they occur.

Potential Impacts: Intervention and Future Directions

The methods presented here represent a first step in using ambulatory big data to collect naturally occurring social processes involving two partners in a close relationship. Beyond the examples we present, there are a number of exciting directions for data sets such as this, for example, testing lagged effects and cross correlations to identify how perturbations in one domain influence another domain, in oneself or in one's partner. These data could also be used to determine how everyday, small-scale couple interactions either buffer or amplify stress and how these processes cumulate in health outcomes (Burman & Margolin, 1992; Robles & Kiecolt-Glaser, 2003). In addition to testing social–psychological theories, ambulatory big data provide detailed information about when and where to intervene within a chain of events, which can be translated into microsocial points of intervention; machine learning algorithms in particular could be useful for designing just-in-time adaptive interventions (e.g., Graham & Bond, 2015) to detect events of interest in the moment and intervene before problems occur or before they escalate.

Conclusion

In sum, ambulatory big data methods have unique applicability for capturing biopsychosocial processes in close relationships. Understanding covariation across response modes and people is an often-stated aspiration in relationship science; the methods described here are a starting point for what is likely to be continued and rapid evolution in testing models integrating biological, emotional, behavioral, and auditory data. The increasing availability of such methods, accompanied by their lower costs and greater comfort, is likely to advance relationship science, with particular insight into interpersonal dynamics and health. A repeating, significant challenge for relationship researchers is how to capture the interactions of greatest interest, which often go beyond laboratory-based observations. Data collection "in the wild," such as that described here, can be applied to many relationship contexts—not just couples—to test theories and advance our understanding of social phenomena.

Authors' Note

The contents are the responsibility of the authors and do not necessarily represent the official views of the NIH.

Declaration of Conflicting Interests

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Supplemental Material

The supplemental material is available in the online version of the article.

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Author Biographies

Adela C. Timmons is a doctoral candidate in Clinical and Quantitative Psychology at the University of Southern California. She received her BA in Psychology at the University of Kansas (2011) and her MA in Clinical and Quantitative Psychology at the University of Southern California (2013). She is interested in quantitative methods for modeling biopsychological processes in families and couples in daily life.

Brian R. Baucom, PhD, is an Assistant Professor of Clinical and Quantitative Psychology in the Department of Psychology at the University of Utah. His research focuses on cognitive, behavioral, and emotional mechanisms by which romantic relationships impact psychological and physical well-being as well as mechanisms of change in couple-based psychotherapies.

Sohyun C. Han is a doctoral candidate in Clinical Psychology at the University of Southern California. Her research interests include psychophysiology and family/couple conflict. Han received an MA in Clinical Psychology from the University of Southern California.

Laura Perrone received her BA in Psychology at Pomona College (2014) and is currently pursuing a PhD in Clinical Psychology at Stony Brook University. She is interested in the impact of early adversity on individuals' risk and resilience and the role of protective factors within the family context.

Theodora Chaspari received a diploma in Electrical and Computer Engineering from the National Technical University of Athens, Greece (2010) and a master's degree from the University of Southern California (2012), where she is currently pursuing a PhD degree. Since 2010, she has been a member of the Signal Analysis and Interpretation Laboratory. Her research interests lie in the area of biomedical signal processing, speech analysis, and behavioral signal processing.

Shrikanth S. Narayanan is Niki and C. L. Max Nikias Chair in Engineering at the University of Southern California, and Professor of Electrical Engineering, Computer Science, Linguistics, Psychology, Neuroscience and Pediatrics. He directs the Signal Analysis and Interpretation Laboratory and the Ming Hsieh Institute. He is a Fellow of IEEE, the Acoustical Society of America, International Speech Communication Association, National Academy of Inventors, and the American Association for the Advancement of Science.

Gayla Margolin, PhD, is a professor of Psychology and Pediatrics at the University of Southern California where she studies the intergenerational transmission of family aggression. Her research investigates how aggression alters everyday interactional processes in couples and families and aims to identify points of intervention.

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