HHS Public Access
Author manuscript
Biol Psychol. Author manuscript; available in PMC 2022 November 30.

Published in final edited form as:
Biol Psychol. 2021 May ; 162: 108074. doi:10.1016/j.biopsycho.2021.108074.

Capturing emotion coherence in daily life: Using ambulatory physiology measures and ecological momentary assessments to examine within-person associations and individual differences

Natalia Van Doren[a,*], **Chelsea N. Dickens**[b], **Lizbeth Benson**[b], **Timothy R. Brick**[b,c], **Lisa Gatzke-Kopp**[b], **Zita Oravecz**[b,c]

[a]Department of Psychology, The Pennsylvania State University, 370 Moore Building, University Park, PA, 16802, United States

[b]Department of Human Development and Family Studies, The Pennsylvania State University, Health and Human Development Building, University Park, PA, 16802, United States

[c]Institute for Computational and Data Sciences, The Pennsylvania State University, 224B Computer Building, University Park, PA, 16802, United States

Abstract

While emotion coherence has long been theorized to be a core feature of emotion, to date, studies examining response coherence have been conducted in laboratory settings. The present study used a combined approach of ambulatory physiology measures and ecological momentary assessment conducted over a 4-week period to examine the extent to which emotional experience and physiology show coherence in daily life within-persons; and whether individual differences in response coherence are associated with between-person differences in well-being, negative emotionality, and gender. Results revealed that, on average, individuals exhibited coherence between subjective experience and physiology of emotion, but that there was substantial between-person variation in coherence in daily life. Exploratory analyses revealed no credible link between levels of response coherence and well-being, negative emotionality, or gender. Findings contribute to the literature by demonstrating a novel methodological approach to measuring coherence in daily life and supporting the generalizability of coherence to ecologically valid contexts.

[*]Corresponding author. nataliavandoren@psu.edu (N. Van Doren).

Declarations
The second author is currently employed as a paid part-time intern for Janssen R&D, a pharmaceutical company of Johnson & Johnson. Though the company has no vested interest in this manuscript, the author wishes to note the involvement in the spirit of transparency.

Declaration of Competing Interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data
Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.biopsycho.2021.108074.

Keywords

Emotion coherence; Emotion concordance; Response coherence; EMA; Well-being

1. Introduction

Functionalist models of emotion suggest that coherence across physiological, experiential, and behavior response systems supports effective responding to environmental challenges which may, over time, be associated with greater well-being (Ekman, 1992; Levenson, 2014; Mauss, Levenson, Mccarter, Wilhelm, & Gross, 2005; Plutchik, 1980). Although there is disagreement in the literature with respect to average levels of emotion coherence (Barrett, 2006), researchers generally agree that individuals differ in the extent to which they exhibit emotion coherence (also called concordance; Hollenstein & Lanteigne, 2014). A growing body of work suggests that individual differences in emotion coherence are associated with multiple indicators of adaptive function. Studies have reported associations between greater emotion coherence and subjective well-being (Brown et al., 2019; Mauss et al., 2005, 2011; Sommerfeldt, Schaefer, Brauer, Ryff, & Davidson, 2019), physical health (Sommerfeldt et al., 2019), emotion regulation (Lohani, Payne, & Isaacowitz, 2017), and body awareness (Sze, Gyurak, Yuan, & Levenson, 2010). However, little is known about the specific processes that contribute to coherence, and very little research has examined the implications of coherence outside of the laboratory setting. The current study utilizes an intensive sampling design incorporating ambulatory measures of autonomic physiology and participant self-reports over a 28-day period to examine whether coherence in emotional arousal is observed in the daily context (i.e., in the absence of experimentally induced affective states), and whether coherence in this context is associated with individual differences in psychological well-being.

Researchers have long recognized that emotion is experienced across multiple levels of analysis including physiological (e.g., heart rate), cognitive (e.g., subjective experience), and behavioral manifestations (e. g., facial expression). The most commonly used physiological measures in emotion research are electrodermal activity (EDA) and heart rate (HR), both of which show rapid dynamic reactivity (on the order of seconds) to emotional stimuli and are proposed to facilitate behavioral actions congruent with the emotion (Mauss & Robinson, 2009). EDA reflects sympathetic nervous system activity, while HR contains both sympathetic and parasympathetic influence (Berntson, Cacioppo, & Quigley, 1993). Manifestations of emotion across these levels of analysis are subjectively experienced as concurrent processes, but researchers have long sought to understand their sequential relation to one another. Early theoretical models proposed that subjective emotional state was *induced by* a physiological response to a stimulus, thus asserting that coherence between these levels of analysis was a defining quality of emotion (James, 1894). Though some studies of emotion coherence examine coherence between physiology and behavior (e.g., Crowell et al., 2014), many studies of emotion coherence frequently examine the extent of association between physiological reactivity and self-reported subjective emotional state in the context of an experimental emotion induction. One study found that emotion induction using both film and music stimuli produced relatively coherent associations between physiology and self-report across 5 basic emotions (Friedman, Stephens, & Thayer, 2014), although some studies report differences in coherence across emotion categories, with stronger coherence in high-arousal emotion conditions such as fear (Egeren, Feather, & Hein, 1971; Grossberg & Wilson, 1968).

Subsequent theoretical models, however, demonstrate that subjective emotional experience is a complex product of physiological signals and cognitive processing of historical and contextual cues that enables one to apply an affective label to their experiential state (Schachter & Singer, 1962). In contrast to earlier models, the Schachter-Singer framework proposes that discrete emotions are not bound by unique physiological signatures, but that patterns of physiological arousal could be associated with a range of emotional states that could vary significantly in valence while being similar in arousal (e.g., excitement/anger). Consistent with this framework, research supports associations between physiological arousal and emotional experience, but has failed to identify emotion-specific physiological signatures (Quigley & Barrett, 2014). Changes in EDA have been shown to reflect general changes in arousal that are not necessarily reflective of emotional valence (Bradley & Lang, 2000a, 2000b; Greenwald, Cook, & Lang, 1989; Lang, Greenwald, Bradley, & Hamm, 1993). In other words, increases in EDA may reflect a change in affective state from a low-arousal emotion (e.g., contentment) to a high-arousal emotion (e.g., excitement) but does not reliably differentiate among high-arousal emotions (e.g. excitement/anger/fear). Similarly, several studies have identified coherence between HR and self-reported arousal (Greenwald et al., 1989; Lang et al., 1993). In addition, core affect theories suggest that individual differences in arousal focus—the degree to which one attends to the arousal dimension of affective experience—is linked to greater interoceptive accuracy (Barrett, Quigley, Bliss-Moreau, & Aronson, 2004). These findings are consistent with the supposition that arousal contributes to, but does not dictate the nature of the emotional state, suggesting that coherence between physiology and self-reported specific emotion is not necessarily likely, while coherence between physiology and self-reported arousal may be more in line with prior findings. Component process models of emotion also suggest that response synchronization is an adaptational function of emotion (Scherer, 2005). For example, subjective awareness of arousal may aid in monitoring internal states, underscoring the role of awareness of arousal as part of the multicomponent emotion response. The present study adds to this literature by examining coherence in emotional arousal based on physiology and self-report measures.

More recently, research has documented the extent of individual differences in emotion coherence across channels, suggesting that coherence itself may be a meaningful marker of emotional function beyond the extent of emotional reactivity in individual response domains (Mauss et al., 2005; Rattel, Mauss, Liedlgruber, & Wilhelm, 2020). Indeed, a recent study found that individuals with a higher degree of within-person coherence across physiological and subjective response to a stress condition were characterized by better emotional and physical health (Sommerfeldt et al., 2019). However, the mechanisms through which greater coherence relates to greater well-being have generally not been well-elaborated in the literature, either theoretically, or empirically. Given that most prominent theories of emotion suggest a significant contribution of peripheral physiological activation in the experience and construction of subjective emotion (Damasio, 1994; Ekman, 1977;

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Oatley & Johnson-Laird, 1987; Plutchik, 1980), it is possible that individual differences in emotion coherence arise from individual differences in body attunement. Physiological research indicates that individuals differ in the extent to which they are interoceptively aware (Garfinkel, Seth, Barrett, Suzuki, & Critchley, 2015). Because awareness of physiological reactivity is an important precursor to emotional labeling (Barrett & Fossum, 2001) and subjective emotional state (Garfinkel et al., 2014), the extent to which individuals are aware of changes in their physiological arousal may be a necessary component of emotional coherence. Indeed, a recent study of individuals high in body awareness found evidence of coherence between heart rate and emotional intensity, where emotional intensity was a measure of the extent of deviation from neutral regardless of the directional valence (Brown et al., 2019). Building on this line of work, we propose that the extent of coherence between physiological arousal and subjective arousal awareness is an important component of emotion coherence and examine it in the daily context.

1.1. Measurement context

Examination of emotion coherence further requires consideration of the alignment between the theoretical construct and its measurement. Some researchers have argued that the analytical approaches used in many studies are not appropriate to test the core tenants of emotion coherence (cf. Levenson, 2014; Mauss et al., 2005). Specifically, traditional analysis techniques rely on between-person comparisons that assess whether individuals with relatively higher levels of physiological arousal report relatively stronger emotions. This approach does not truly examine emotion dynamics, and whether moments *when* an individual experiences an increase in physiological arousal are associated with concurrent changes in emotional experience. Studies that have employed a within-person analysis framework have more consistently identified evidence of coherence (Brown et al., 2019; Mauss et al., 2005; Rattel et al., 2020; Sommerfeldt et al., 2019; Sze et al., 2010; Wu, Svoboda, Bae, & Haase, 2020). However, the extent to which these findings reflect coherence as a generalized trait are limited by the restricted contexts in which coherence is assessed.

Specifically, despite the centrality of functionalist theoretical accounts of emotion coherence in the literature (Ekman, 1992; Levenson, 2003; Rosenberg & Ekman, 1994), focal hypotheses arising from these theories (e.g. that coherence is adaptive) have been examined exclusively in laboratory settings in the context of experimental manipulations of emotion condition. This context may only provide limited insight into the implications of coherence in daily life. For instance, laboratory conditions establish strong and consistent context cues about the nature of the emotion being induced, whereas typical daily life often requires people to navigate emotional experiences in more ambiguous contexts.

In order to advance our understanding of emotion coherence, research needs to examine individuals in naturalistic settings. The advent of new technologies makes possible the measurement of autonomic physiological activity over long intervals and without restrictions on movement or location through the use of wearable devices (Kleckner, Feldman, Goodwin, & Quigley, 2020). Coupled with the ability to deploy psychological surveys directly to the participants' smartphones, researchers are well positioned to examine emotion coherence in everyday life through ecological momentary assessment (EMA; Shiffman, Stone, & Hufford, 2008). EMA studies are generally geared towards learning about life as it is lived by collecting repeated measures on momentary experiences, from many participants. The intensive longitudinal data yielded in EMA studies enables researchers to examine processes at the within-person level by observing the associations between an individual's self-reported emotion and concurrent physiological activity repeatedly over time (Bolger & Laurenceau, 2013). Accordingly, utilizing intensive longitudinal data that consists of both subjective self-reported experiences and in-vivo physiological recording provides an opportunity for the measurement of coherence in daily life that may be more representative of normative emotional responding.

2. The present study

To advance the knowledge base of coherence in daily life, the present study used EMA data to assess coherence of physiological activity and subject arousal awareness in a sample of adults measured over a 28-day period. A wrist-worn device measured HR and EDA continuously throughout the day, and participants were prompted 6 times per day to complete self-report questionnaires on their own smartphones. Data were analyzed using linear mixed-effects modeling, cast in Bayesian statistical framework (Gelman, 2013), to (1) determine whether emotion coherence in daily life, in terms of emotional arousal, was evident at the within-person level similar to what has been observed in laboratory/experimental studies, and (2) which physiological channels show coherence with subjective awareness of arousal. HR is a consciously accessible physiological marker that has been consistently examined in research on body awareness and interoception (Sze et al., 2010). EDA is also considered a robust marker of affective arousal (Braithwaite, Broglia, & Watson, 2014; Sommerfeldt et al., 2019). Finally, we (3) examined potential between-person moderators of emotion coherence. Based on previous findings, we hypothesized that coherence will be higher among women (Kring & Gordon, 1998; Rattel et al., 2020), and that individuals with higher coherence have higher subjective well-being and lower trait negative emotionality (e.g., Brown et al., 2019; Sommerfeldt et al., 2019).

3. Methods

We analyzed data from a larger EMA study that explored people's everyday life experiences, with special focus on psychological well-being and the dynamics of emotion. All scripts for data analyses are available via OSF at the following link: https://osf.io/scgev/?view_only=f2aba20f81064ccf87942321d60a0c5d. All procedures were approved by the IRB (protocol #00001017).

3.1. Participants

The sample consisted of twenty-five participants (17 women, 8 men) ranging from 21 to 66 years of age (*M* = 32.2, *SD* = 10.40). Participants were recruited from the community adjacent to a large, Northeastern university. The majority of the participants were White (84 %, *n* = 21) with the remaining participants identifying as Asian (8 %, *n* = 2) and Latino/a (8 %, *n* = 2).

3.2. Procedure

After consenting to participate in the study, participants completed a battery of baseline questionnaires consisting of demographic and psychological items. They also provided their phone numbers to the research assistants and were enrolled in SurveySignal text messaging service (Hofmann & Patel, 2014) for delivery of the daily self-report survey prompts (with a link to a Qualtrics web survey). Participants reported their normal waking hours, and these hours were divided into 6 blocks. Daily surveys were timed so that one survey was delivered during each time block, and no two surveys were delivered within half an hour of one another. These surveys were prompted 6 times each day for 28 days, and consisted of items related to core affect (valence and arousal), love, meaning of life, accomplishment, and flow. Surveys expired after 60 min to ensure participant compliance within the specified time window. Current analyses focus on the single item assessing self-reported momentary arousal. Participants received payment in accordance with their response rates to EMA prompts and could earn a maximum payment of $200.

3.3. Apparatus and measures

3.3.1. Baseline measures

3.3.1.1. Psychological well-being.: The PERMA-Profiler (Butler & Kern, 2016) was used to quantify five elements of psychological well-being, namely: positive emotion, engagement, relationship satisfaction, meaning of life, and accomplishment, based on Seligman's (2011) theoretical model. The PERMA-Profiler captures the five PERMA elements as trait-level factors using three items each, such as "*In general, how often do you feel joyful?*" for positive emotion. Items are rated on a Likert scale from *0* = *Never* to *10* = *Always*. In the current study, the mean across all domains was taken to represent a single, well-being composite score, with a possible range of 0–10. The PERMA-Profiler has exhibited high internal consistency in prior work (Butler & Kern, 2016; Ryan et al., 2019), and in the present study (Cronbach's alpha = 0.95). Scores in our sample ranged from 4.56 to 9.56 ($M = 7.72$; $SD = 1.35$), and were sample-mean centered to facilitate multilevel modeling.

3.3.1.2. Negative emotionality.: The PERMA-Profiler was also used to quantify negative emotionality, via three items*: "In general, how often do you feel sad?", "In general, how often do you feel anxious?", and "In general, how often do you feel angry?"*. Items were rated using the same scale as noted above and were averaged across items to create a total score, with a possible range of 0–10. Scores in our sample ranged from 2.00 to 7.67 ($M = 4.17$; $SD = 1.68$). Scores were sample-mean centered to facilitate multilevel analyses. Cronbach's alpha was 0.74.

3.3.2. Daily measures

3.3.2.1. Self-reported momentary arousal.: At each of the 6 daily prompts participants were asked "How awake/active do you feel right now?" This item was rated on a visual sliding scale from 0 = *Not at all* to 100 = *Extremely*. The overall mean level of arousal across the sample was 69.17 ($SD = 13.86$).

3.3.2.2. Physiological indices of arousal.: The Empatica E4 wristband (Empatica, Milan, Italy) was used to collect physiological measures of interest, heart rate and electrodermal activity, throughout the 4-week data collection period. Details of collection are described below.

3.3.2.3. Heart rate (HR).: Heart rate estimated from blood volume pulse (BVP) was measured using a photoplethysmogram (PPG) sensor mounted on the underside of the E4 watch. The E4 PPG sensor uses green and red light. Both the green and red LEDs are oriented towards the skin and absorbed by the blood in different ways, and are combined to optimize maximizing the estimation of heart rate (Empatica, 2020). Measured light during green exposure contains most of the information on HR and is characterized by a sequence of valleys, whose time occurrences are used to estimate the heart beats. Measured light during red exposure contains a reference light level which is used to cancel motion artifacts. Changes in pulse rate are linearly related to the timing of individual heart beats, and are therefore used to estimate HR (Pietilä et al., 2017; Tamura, Maeda, Sekine, & Yoshida, 2014). BVP was sampled at 64 Hz and a second-by-second estimate of HR was generated for analysis. The overall mean heart rate across the sample was 83.99 ($SD = 4.04$).

3.3.2.4. Electrodermal activity (EDA).: Electrodermal activity was derived from a sensor made of two aluminum nodes mounted on the wristband and resting on the palmar side of the wrist. Changes in electrical potential across the nodes reflect fluctuations in cutaneous sweat glands, which are innervated by the sympathetic nervous system. EDA was sampled at 4 Hz, and a second-by-second time series of EDA level measured in μSiemens was generated for analysis. The overall mean EDA level across the sample was 1.96 ($SD = 2.19$).

3.4. Data processing

To facilitate alignment with the EMA data, the physiological data streams were downloaded from the Empatica cloud platform and processed using R version 3.6.0 and R Studio version 1.2.1335 (R Core Team, 2019; R Studio Team, 2020). Data processing was performed using the data.table, lubridate, plyr, and zoo packages (Dowle & Srinivasan, 2019; Grolemund & Wickham, 2011; Wickham, 2011; Zeileis & Grothendieck, 2005). First, we filtered out occasions based on physiologically invalid temperature or heart rate data, specifying the same parameters used by Li et al. (2019). Specifically, we excluded any occasions where the value for temperature was less than 30 degrees Celsius or greater than 43 degrees Celsius, or where the value for heart rate was less than 30 beats per minute or greater than 200 beats per minute. We then isolated the 1-min segment of physiological data immediately preceding the EMA prompt and calculated the arithmetic mean over the entire minute. If valid physiological data were not available for the entire 1-min interval, that interval was treated as missing.

Compliance was satisfactory both in terms of E4 wear time and self- reported survey responses. Across the study period, on average, participants reported arousal levels for $M = 157.20$ (93.57 %) of the EMA prompts they received ($SD = 8.39$, min = 129, max = 166). We consider missing physiological data only in reference to occasions where EMA data were provided. Across the study period, on average, 122.25 (77.41 %) of EMA prompts responded to by participants had valid physiological data in the 1-minute interval prior to the EMA prompt (*SD* = 23.77, min = 80, max = 152). On average, participants had complete EMA and physiological data for *M* = 122.03 (72.64 %) (*SD* = 23.84, min = 80, max = 152) of the 168 total possible occasions designated by the study protocol.

3.5. Data analysis

All analyses were performed in R version 4.0.0 and R Studio version 1.2.5042 (R Core Team, c; R Studio Team, 2020) using the brms package (Bürkner, 2017, 2018). The brms package implements parameter estimation in the Bayesian framework by calling Stan software (Stan Development Team, 2017).

To facilitate analysis of within-person covariation, the processed EDA and HR data were person-mean centered. Specifically, for each person we calculated the mean value of their EDA and HR scores across all occasions preceding an EMA. Then the person-level mean for each marker was subtracted from each raw score for that marker, yielding scores reflecting whether the person's EDA or HR was higher (positive values) or lower (negative values) than their usual on that specific occasion.

To answer our research questions of whether coherence between arousal and physiological indices is evident at the daily level, and whether these associations vary based on person-level characteristics, we chose a linear mixed-effects modeling approach fit in the Bayesian framework. This approach enables the ability to examine within-person associations of two variables (self-reports and physiology) while allowing for between person differences in the intercept and slope and inclusion of predictors of between-person differences (well-being, negative emotionality, and gender). A comparable method has been used to assess coherence between physiology and self-reports of emotion in prior work to accommodate time-series data where the self-reports of emotion may not map on to the precise timing of peak physiological arousal (Sommerfeldt et al., 2019). We opted for implementing the models in the Bayesian statistical framework as it is computationally more stable with small sample sizes. In the Bayesian framework we were able to fit the fully specified random effects structure to our data, which was not possible when we attempted to fit the model in the frequentist framework. Failure to include a random slope in the model due to model non-convergence would have meant that the strength of concordance between physiological arousal and self-report arousal could not vary across persons in the sample, which is often not a tenable assumption. In the Bayesian framework, prior probability distributions on the model parameters need to be selected, and may vary in how informative they are—that is, how much influence they have on the result. In our analyses, we used the default priors in the brms package, which are meant to be weakly informative (i.e., they provide a rough scale to the model; Bürkner, 2017, 2018). First, we specified base models without person-level predictors to test whether there was coherence between self-reported and physiological arousal indicators. These models were specified as follows:

$$Arousal_{it} = \beta_{0i} + \beta_{1i} HR_{it} + \varepsilon_{it}$$

and

$$Arousal_{it} = \beta_{0i} + \beta_{1i}EDA_{it} + \varepsilon_{it}$$

where

$$\beta_{0i} = \gamma_{00} + u_{0i}$$

$$\beta_{1i} = \gamma_{10} + u_{1i}$$

where γ_{00} is the fixed intercept, representing the average expected level of self-reported arousal in the sample; u_{0i} is the random effect for the intercept, representing the extent of between-person variability in that intercept; γ_{10} is the fixed slope for the physiological variable (EDA or HR) and represents the average effect for individuals in the sample; u_{1i} is the random effect for the slope, representing the extent of between-person variability in the slope of the physiological variable; and ε_{it} stands for some zero mean residual error.

We then added person-level predictors, namely well-being, negative emotionality, and gender, into the model in order to assess the extent to which these variables influence both self-reported arousal and coherence between physiological and self-reports of arousal.

$$Arousal_{it} = \beta_{0i} + \beta_{1i}HR_{it} + \varepsilon_{it}$$

and

$$Arousal_{it} = \beta_{0i} + \beta_{1i}EDA_{it} + \varepsilon_{it}$$

where

$$\beta_{0i} = \gamma_{00} + \gamma_{01}WellBeing_i + \gamma_{02}NegEtmotion_i + \gamma_{03}Gender_i + u_{0i}$$

$$\beta_{1i} = \gamma_{10} + \gamma_{20}WellBeing_i + \gamma_{30}NegEtmotion_i + \gamma_{40}Gender_i + u_{1i}$$

where γ_{01}, γ_{02}, and γ_{03} represent the main effects of well-being, negative emotionality, and gender, respectively, on arousal; γ_{20}, γ_{30}, and γ_{40} represent the cross-level interactions of well-being, negative emotionality, and gender, respectively, with the physiological variables. The rest of the terms are as defined for the equations above. The interaction effects indicate the extent to which these between-person variables are associated with the within-person coherence between physiological and self-reported arousal. Missing values for one or more predictors on a given occasion are often handled through listwise deletion in a multilevel modeling framework, regardless of whether the model is fit using frequentist of Bayesian statistics. Data were not imputed prior to or during model fitting because we did not have reason to suspect that values were not missing at random in these data.

As an assumption check, we calculated the intraclass correlation (ICC) for self-reported arousal to ensure that there was sufficient variability at both the within- and the between-person levels. The ICC was about 0.34, indicating that 34 % of the variation in arousal is due to between-person differences, which leaves the remaining 66 % at the within-person level. We consider this sufficient to continue multilevel modeling on these data.

We hypothesized that the physiological measures would be positively associated with self-reported arousal. We further expected that the cross-level interactions would be significant such that higher coherence (or a stronger positive relationship) between the physiological measures and the self-reports of arousal would be associated with greater psychological well-being, lower negative emotionality, and gender (women higher) at the person level. Due to the small sample size to detect between-person effects, the inclusion of person-level predictors is purely exploratory.

4. Results

4.1. Coherence between heart rate and self-reports

Coefficient estimates for the base model estimating the within-person relationships between HR and self-reported arousal are shown in Table 1. Model parameters were estimated by calculating distributions that give the most probable values of these parameters, using Monte Carlo algorithms that sample random values from them. These distributions are called posterior distributions and they combine information from the priors (see defined above) and the likelihood function of the data. Two chains of samples, each updating the results of the previous sample, were run, using different starting values. The first 2000 samples from each chain were used to “warm up” the sampling algorithm and were discarded afterwards. Another 5000 were run in each chain after warm-up, and these 10,000 samples were used to estimate the mean for a point estimate (shown in column 2), the standard error (based on the standard deviation of the posteriors, column 3) and the lower and upper limits of the central 95 % credible interval (column 4). The true parameter falls in this credible interval with 95 % probability.

The intercept, describing the expected level of arousal at a self-report survey for a perfectly average person when all predictors are at mean levels, is just over 70 (γ_{00HR} = 70.07, *SE* = 2.93) on a scale from 0 to 100. Between-person differences in this expected level had a standard deviation of just under 15 (u_{0iHR} = 14.90; *SE* = 2.32). More importantly, in line with our hypotheses, results revealed coherence between HR and self-reported arousal, such that when individuals experienced elevated heart rate in the one-minute period prior to the EMA survey, they tended to report higher levels of arousal (γ_{10HR} = 0.23; *SE* = 0.04). The strength of this association varied between participants (u_{1iHR} = 0.17; *SE* = 0.04), as depicted in Fig. 1. Person-mean centering focuses the plot on the differing within-person associations between physiological and self- reported arousal and does not provide a visualization of between-person variability in the intercept for arousal. Lines with steeper slopes indicate that, for some individuals, this association is much stronger. Lines with shallower slopes indicate that, for some individuals, this association is much weaker. In other words, for some participants, a given increase in physiological arousal results in a greater change in self-reported arousal, while in others the same increase results in a smaller change in self- reported arousal.

Next, we added well-being, negative emotionality, and gender to the model in order to examine whether coherence between HR and self-reported arousal was moderated by these person-level predictors. In the full model (Table 2), coherence between HR and self-reported arousal was evident even after accounting for person-level predictors (γ_{10HR}= 0.26; *SE* = 0.05). There was also a main effect of person-level psychological well-being on arousal, such that individuals with higher levels of psychological well-being generally had higher momentary self-reports of arousal (γ_{01HR} = 7.78; *SE* = 1.99). There were no main effects for negative emotionality or gender on self-reported arousal. Contrary to our expectations, we did not find a credible effect on psychological well-being on the strength of HR coherence (γ_{20HR} = −0.05; *SE* = 0.04). In addition, there were no credible interaction effects for negative emotionality or gender on the relationship between HR and self-reported arousal (see Table 2).

4.2. Coherence between electrodermal activity and self-reports

Results for the base model estimating the within-person relationships between EDA and self-reported arousal are shown in Table 3. Similar to the HR models, the intercept was just under 70 (γ_{00EDA} = 69.87; *SE* = 2.93), with a standard deviation of just under 15 (u_{0iEDA} = 14.77; *SE* = 2.36). Regarding coherence between EDA and self-reported arousal, results revealed that there was a credible association between within-person changes in EDA and self-reports of arousal, such that when individuals' EDA levels were higher than average in the one-minute period prior to the EMA survey, they reported higher levels of arousal (γ_{10EDA} = 0.68; *SE* = 0.23). In addition, the strength of this association varied between participants (u_{1iEDA} = 0.81; *SE* = 0.22), suggesting substantial individual differences in coherence (Fig. 2).

To examine whether coherence between self-reported arousal and EDA was moderated by person-level predictors, we added well-being, negative emotionality, and gender to the model. Results (Table 4) revealed that after controlling for covariates, evidence of coherence between EDA and self-report arousal remained credible (γ_{10EDA} = 0.81; *SE* = 0.28). Consistent with the HR models, there was also a main effect of person-level psychological well-being on arousal, such that individuals with higher levels of psychological well-being had higher momentary self-reports of arousal (γ_{01EDA} = 7.79; *SE* = 2.00). There were no main effects for negative emotionality or gender on self-reported arousal. Finally, we did not find credible effects of psychological well-being, negative emotionality, or gender on the strength of EDA coherence.

5. Discussion

The present study examined whether coherence between physiological arousal and the subjective experience of arousal can be found in daily life. We used ecologically valid EMA methodology, including smartphone based self-report surveys to assess momentary arousal levels and second-by-second, unobtrusive, in-vivo physiological recording to assess concurrent physiological markers of affective arousal. Results indicated that individuals, on average, displayed coherence between physiology and subjective experience of arousal. Furthermore, findings were consistent across both HR and EDA, suggesting that coherence may manifest in both channels. In addition, we examined whether hypothesized individual differences in between-person baseline factors are related to daily coherence.

Our study presents the first analysis of emotion coherence in daily life, and adds to the literature by providing preliminary support that coherence does occur outside of the laboratory in ecologically valid contexts that aim to capture the normative range of emotions and emotional intensity that individuals typically experience. The use of an ecological momentary assessment design allowed us to collect information on people's affective states throughout the course of their normal, daily life, thereby capturing our measures of coherence in a naturalistic setting (Bolger, Davis, & Rafaeli, 2003). Findings dovetail with prior literature that shows evidence of physiology-experience coherence in lab settings (Brown et al., 2019; Friedman et al., 2014; Sommerfeldt et al., 2019), and extends these findings to daily life.

Importantly, there were substantial between-person differences in coherence captured in daily life, as evidenced by the random slopes in our models. This suggests that, while on average, individuals display coherence between physiology and self-reports of arousal, there remains a great degree of variation in the extent to which individuals exhibit coherence. By adding cross-level interactions into our model, we sought to attribute this variation in the extent to which individuals experience coherence to certain person-level variables which prior literature suggests to be theoretically important. Accordingly, we tested associations of between individual differences in the degree of coherence in daily life and three person-level predictors that have been associated with coherence in previous studies: well-being, negative emotionality, and gender (Brown et al., 2019; Mauss et al., 2011; Hastings et al., 2009; Rattel et al., 2020). It should be noted that given our small sample size, these analyses can be considered as exploratory and should be followed up on in research using larger samples. In our analyses, no evidence of moderation by any of these factors emerged, and as a result, we cannot attribute the variation in the random slopes to these factors in our study. This may relate to the power of the sample to detect between-person differences. The study was designed to maximize power to test within-person coherence in daily life, with $t =$ 168 planned repeated measures per person. However, the small number of participants limits power to detect between person effects ($N = 25$). This is especially the case for gender, as there were only were $n = 8$ men in our sample. In the Bayesian framework, although we are able to estimate the full random effects structure, we still have limited power to detect between-person differences in associations.

It is also possible that our ability to find an association between trait-level well-being and negative emotionality was limited by the chosen measurements of these constructs. For example, prior work has examined coherence in relation to the Ryff well-being scale (Sommerfeldt et al., 2019), life satisfaction (Brown et al., 2019; Mauss et al., 2011), depression (Mauss et al., 2011), and Big-Five neuroticism (Wu et al., 2020). We used a multi-dimensional measure of well-being, namely, the PERMA index, along with the PERMA scale of negative emotionality, which is relatively similar theoretically to other measures of well-being used in prior research on coherence (e.g., Ryff well-being scale;

Sommerfeldt et al., 2019). However, it is possible that the PERMA indices of well-being tap into a different construct than measured in prior research. To examine this idea, the analysis was repeated with two additional measures of well-being: the Satisfaction with Life Scale (Diener, Emmons, Larsen, & Griffin, 1985) and the SF-36 Emotional Well-Being subscale (Ware, 1999). Results (included in supplemental material) were largely consistent with our findings using PERMA. This disagreement with the literature suggests that coherence in the context of daily life may not have immediate implications for well-being, or at least that its impact on well-being is nonlinear; although further research is needed to examine whether these results generalize to larger samples.

Measurement of coherence in the daily-life context captures a much broader picture of emotion coherence than a laboratory-based assessment. Lab-based studies of coherence tend to measure specific emotional states, typically experiences of strong negative affect designed to assess reactivity to more extreme emotional experiences (e.g., anger; fear). The extent to which individuals feel these more extreme emotions in daily life is unclear. By assessing individuals across 28 days, we maximize the probability of capturing a wide range of emotional experiences, but also include experiences of mild emotional intensity. It is possible that coherence across the full gradient of emotional intensity is not related to psychological well-being, but rather only the extent to which individuals experience emotional coherence in the context of more aversive, more intense, or less ambiguous emotional experiences reflects an adaptive emotional process.

It is also possible that the adaptive value of coherence varies situationally. The notion that coherence across emotion channels is inherently adaptive may be incongruent with models of emotion regulation that promote an active decoupling between physiological reactivity and subjective state through cognitive reappraisal (Butler, Gross, & Barnard, 2014), and/or between physiological reactivity and behavior through inhibitory control (Cole, Michel, & Teti, 1994). It may be that daily life contexts require flexibility in emotion coherence such that well-being is promoted when individuals' coherence is situationally appropriate, with the ability to decouple emotion across levels when needed. For instance, in a laboratory setting, emotion induction is frequently achieved through watching a film—a context in which the circumstances are not personally-relevant and require no behavioral response. Coherence in this setting may reflect an adaptive attunement to one's emotional experiences. In daily contexts, individuals are often called upon to behave in ways that are potentially incongruent with their emotional state, such as being nice to a co-worker that has made them angry or smiling through a job interview despite being nervous. It may be adaptive in these situations for one to be less attuned to their physiological arousal in order to regulate their emotional experience. Future EMA studies could collect more contextual information in order to examine the conditions in which greater coherence is or is not beneficial.

It is worth noting that there may additionally be between-person moderators of the extent to which coherence is associated with well-being. Some research indicates that emotion coherence may be moderated by cultural factors that may shape participants' emotional display norms, labeling of physiological states, or willingness to disclose subjective emotional state in ways that lead to discontinuity between physiological responses to emotion conditions and the behavioral and subjective manifestations of emotion (Mauss, Butler, Roberts, & Chu, 2010). These cultural effects suggest that coherence may be associated with well-being only in cultural environments where emotional expression is valued and accepted, whereas less coherence may be more adaptive in cultural contexts where expression is discouraged. Thus, future research could examine the extent to which individuals' identities and beliefs about emotional expression (e.g., belief that "boys shouldn't cry") moderate the extent to which coherence has adaptive implications. Researchers have argued for the need for psychophysiological research to attend to the effects of factors like culture and gender in moderating how physiological processes relate to psychological function rather than presuming that findings generalize to all humans (Gatzke-Kopp, 2016).

Finally, it is possible that daily coherence may be linked to daily measures of well-being, rather than trait-based measures of well-being. In laboratory settings participants typically complete the trait-based questionnaire on the same day that coherence is assessed, whereas in our study, participants completed a baseline measure, and were then followed for 28 days. Although trait-based well-being measures ask participants to provide ratings that capture how they feel "in general", research has found that purportedly stable constructs, such as life satisfaction, can demonstrate considerable short-term variability (Willroth, John, Biesanz, & Mauss, 2020). Thus, the measurement of momentary well-being and negative emotionality would be a fruitful avenue for future research on daily coherence, as well as further consideration of what functional outcomes of adaptation may be most relevant for daily coherence per theoretical accounts.

Taken together, our findings suggest that coherence between physiology and self-reports of arousal can be measured in daily life, and that coherence may be evident in more ecologically valid settings, thereby extending lab-based coherence research to the daily arena. Furthermore, there was some evidence for individual variation in coherence, underscoring the importance of continued research to identify what individual difference factors may account for these differences, and how individual differences in coherence at the daily level may impact functional outcomes.

5.1. Limitations and future directions

Our study presents with several strengths, including high power detect within-person effects, the use of an ecologically valid design, and in-vivo physiological recording to capture coherence in daily life. Nonetheless, several limitations warrant mention. First, although we had a large sample size to test our main hypothesis about coherence within-persons, our between-person sample size was small, limiting our power to detect between-person effects. Thus, it is possible that future studies with larger sample sizes may be able to identify moderation of coherence by well-being, negative emotionality, or gender, as has been found in prior lab studies (e.g., Rattel et al., 2020). Second, although the use of wearable physiology sensors enabled us to test our hypotheses in an ecologically valid manner, levels of physiological activity recorded with wearable devices do differ from activity recorded with standard laboratory equipment (Menghini et al., 2019), and may have accounted for the discrepancies with previous studies. Further, the use of self-reported arousal as our emotion measure limits our ability to test whether findings would generalize to specific affective experiences (e.g., anger; sadness) in daily life. In addition, the use of a one-item measure to assess the subjective experience of arousal via self-reports= can be a double-edged sword—while it has the advantage of increasing participant compliance, it may have limited reliability. Finally, measures of HR and EDA do not by themselves provide insight into emotional processes such as valence, motivational orientation, or mental effort. Accordingly, our conclusions regarding coherence are limited to the arousal dimension of affective responses. Limitations notwithstanding, our study provides a novel contribution to the literature by testing coherence in daily life in an ecologically valid manner.

6. Conclusion

The present study utilized ambulatory physiological measures and ecological momentary assessment conducted over a 4-week period to examine the extent to which emotional experience and physiology covary in daily life, and whether individual differences moderate this relationship. Results revealed that, on average, individuals exhibited coherence between subjective experience of emotional arousal and physiology, but there was significant between-person variation in the extent of this coherence. However, we were not able to credibly link the variation in coherence to individual differences in well-being, negative emotionality, or gender. Findings contribute to the literature by providing a novel methodological approach to measuring coherence in daily life and add credence to theoretical accounts of emotion coherence by demonstrating the generalizability of coherence to the daily context. Future research should continue to build on this work by examining between-person effects in larger samples, corroborating daily measures with lab measures, and measuring specific affective states.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgements

Computations for this research were performed on the Pennsylvania State University's Institute for Computational and Data Sciences' Roar supercomputer.

Funding

The research reported in this paper was sponsored by grant #48192 from The John Templeton Foundation. The first author was supported by the National Institute on Drug Abuse [T32 DA017629, PI: Linda M. Collins]. The NIDA did not have any role in study design, collection, analysis, and interpretation of the data; writing the report; and the decision to submit the report for publication. The second author was supported by the Biomedical Big Data to Knowledge training grant from the National Library of Medicine [T32 LM012415, PI: James R. Broach].

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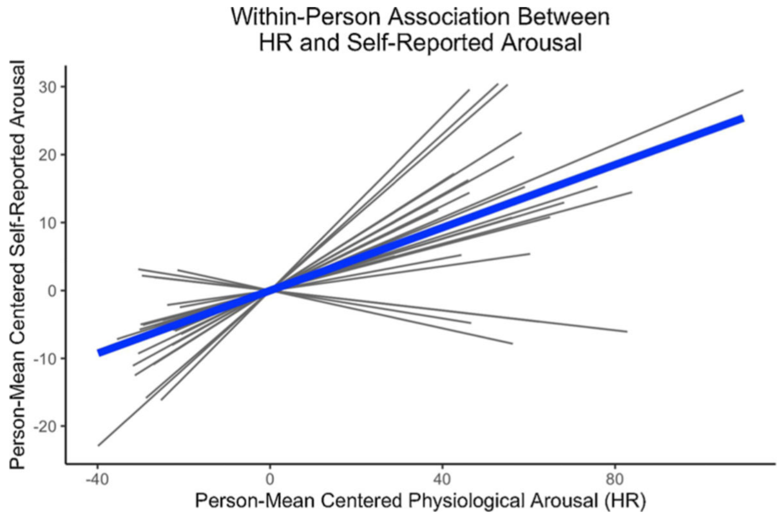

Fig. 1.

Note. Line plot of the within-person association between self-reported arousal (y-axis) and physiological arousal (HR = heart rate; x-axis). Solid line shows the prototypically positive within-person association, indicating coherence between HR and self-reported arousal. Light gray lines show the range of individual differences in the extent of coherence. Values are person-mean centered such that (0,0) represents each individual's mean HR and mean self-reported arousal across all momentary occasions.

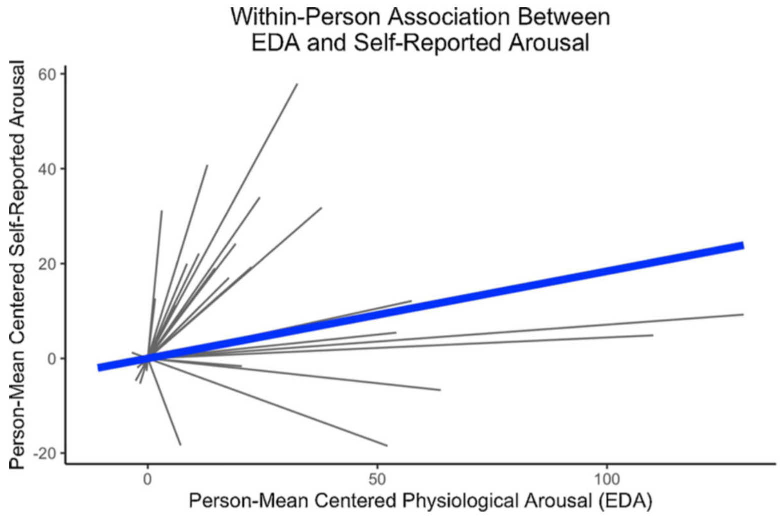

Fig. 2.

Note. Line plot of the within-person association between self-reported arousal (y-axis) and electrodermal activity (EDA; x-axis). Solid line shows the prototypically positive within-person association, indicating coherence between EDA and self-reported arousal. Light gray lines show the range of individual differences in the extent of coherence. Values are person-mean centered such that (0,0) represents each individual's mean EDA and mean self-reported arousal.

Table 1

Bayesian Multilevel Modeling Results for Coherence Between HR and Self-Reported Arousal.

	Estimate	S.E.	CI
Fixed Effects			
Intercept (γ_{00})	70.07	2.93	[64.36, 75.98]
$\mathrm{HR}_{\mathrm{it}}$ (γ_{10})	0.23	0.04	[0.15, 0.31]
Random Effects			
Residual (ε_{it})	18.48	0.24	[18.02, 18.95]
Intercept (u_{0i})	14.90	2.32	[11.11, 20.22]
HR (u_{1i})	0.17	0.04	[0.11, 0.26]

Note. *N* = 25; CI = 95 % Credible Interval. HR = heart rate.

Table 2

Bayesian Multilevel Modeling Results for Predicting HR Coherence from Person-Level Predictors.

	Estimate	S.E.	CI
Fixed Effects			
Intercept (γ_{00})	70.21	2.83	[64.46, 75.72]
HR_{it} (γ_{10})	0.26	0.05	[0.15, 0.36]
$WellBeing_i$ (γ_{01})	7.78	1.99	[3.95, 11.73]
$NegEmotion_i$ (γ_{02})	0.59	1.65	[−2.69, 3.89]
$Gender_i$ (γ_{03})	−0.64	5.08	[−10.48, 9.43]
HR_{it}*$WellBeing_i$ (γ_{20})	−0.05	0.04	[−0.12, 0.02]
HR_{it}*$NegEmotion_i$ (γ_{30})	−0.04	0.03	[−0.10, 0.02]
HR_{it}*$Gender_i$ (γ_{40})	−0.09	0.09	[−0.26, 0.10]
Random Effects			
Residual (e_{it})	18.48	0.24	[18.03, 18.95]
Intercept (u_{0i})	11.28	1.91	[8.25, 15.66]
EDA (u_{1i})	0.17	0.04	[0.09, 0.26]

Note. N = 25; CI = 95 % Credible Interval. HR = heart rate.

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Table 3

Bayesian Multilevel Modeling Results for Coherence Between EDA and Self-Reported Arousal.

	Estimate	S.E.	CI
Fixed Effects			
Intercept (γ_{00})	69.87	2.93	[64.06, 75.62]
EDA_{it} (γ_{10})	0.68	0.23	[0.28, 1.17]
Random Effects			
Residual (ε_{it})	18.73	0.25	[18.26, 19.23]
Intercept (u_{0i})	14.77	2.36	[11.04, 20.17]
EDA (u_{1i})	0.81	0.22	[0.46, 1.32]

Note. $N = 25$; CI = 95 % Credible Interval. EDA = electrodermal activity.

Table 4

Bayesian Multilevel Modeling Results for Predicting EDA Coherence from Person-Level Predictors.

	Estimate	S.E.	CI
Fixed Effects			
Intercept (γ_{00})	70.18	2.80	[64.68, 75.64]
EDA_{it} (γ_{10})	0.81	0.28	[0.28, 1.38]
$WellBeing_i$ (γ_{01})	7.79	2.00	[3.88, 11.81]
$NegEmotion_i$ (γ_{02})	0.64	1.64	[−2.59, 3.90]
$Gender_i$ (γ_{03})	−0.54	5.16	[−10.67, 9.80]
EDA_{it}*$WellBeing_i$ (γ_{10})	−0.33	0.25	[−0.86, 0.12]
EDA_{it}*$NegEmotion_i$ (γ_{20})	−0.29	0.18	[−0.65, 0.06]
EDA_{it}*$Gender_i$ (γ_{30})	−0.09	0.48	[−0.99, 0.90]
Random Effects			
Residual (e_{it})	18.73	0.24	[18.26, 19.21]
Intercept (u_{0i})	11.20	1.94	[8.11, 15.66]
EDA (u_{1i})	0.84	0.23	[0.48, 1.38]

Note. N = 25; CI = 95 % Credible Interval. EDA = electrodermal activity.