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Investigating the relationship between emotional granularity and cardiorespiratory physiological activity in daily life

Katie Hoemann[1] | **Zulqarnain Khan**[2] | **Nada Kamona**[3] | **Jennifer Dy**[2] | **Lisa Feldman Barrett**[3,4,5] | **Karen S. Quigley**[3,6]

[1]Department of Psychology, Katholieke Universiteit Leuven, Leuven, Belgium

[2]Department of Electrical and Computer Engineering, Northeastern University, Boston, MA, USA

[3]Department of Psychology, Northeastern University, Boston, MA, USA

[4]Department of Psychiatry, Massachusetts General Hospital, Harvard Medical School, Boston, MA, USA

[5]Athinoula A. Martinos Center for Biomedical Imaging, Massachusetts General Hospital, Charlestown, MA, USA

[6]Center for Healthcare Organization and Implementation Research, Edith Nourse Rogers Memorial Veterans Hospital, Bedford, MA, USA

Correspondence
Katie Hoemann, Department of Psychology, Katholieke Universiteit Leuven, Leuven, Belgium.
Email: khoemann@gmail.com

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Abstract

Emotional granularity describes the ability to create emotional experiences that are precise and context-specific. Despite growing evidence of a link between emotional granularity and mental health, the physiological correlates of granularity have been under-investigated. This study explored the relationship between granularity and cardiorespiratory physiological activity in everyday life, with particular reference to the role of respiratory sinus arrhythmia (RSA), an estimate of vagal influence on the heart often associated with positive mental and physical health outcomes. Participants completed a physiologically triggered experience-sampling protocol including ambulatory recording of electrocardiogram, impedance cardiogram, movement, and posture. At each prompt, participants generated emotion labels to describe their current experience. In an end-of-day survey, participants elaborated on each prompt by rating the intensity of their experience on a standard set of emotion adjectives. Consistent with our hypotheses, individuals with higher granularity exhibited a larger number of distinct patterns of physiological activity during seated rest, and more situationally precise patterns of activity during emotional events: granularity was positively correlated with the number of clusters of cardiorespiratory physiological activity discovered in seated rest data, as well as with the performance of classifiers trained on event-related changes in physiological activity. Granularity was also positively associated with RSA during seated rest periods, although this relationship did not reach significance in this sample. These findings are consistent with constructionist accounts of emotion that propose concepts as a key mechanism underlying individual differences in emotional experience, physiological regulation, and physical health.

Katie Hoemann and Zulqarnain Khan shared first authorship.

KEYWORDS

ambulatory assessment, ECG, emotion differentiation, experience sampling, heart rate variability, respiratory sinus arrhythmia

1 | INTRODUCTION

Emotional granularity, also known as emotion differentiation, describes an individual's ability to create experiences of emotion that are precise and context-specific (Barrett, 2013, 2017a). Individuals with lower granularity are unable to distinguish rage from frustration, or even anger from sadness (e.g., they just say they feel "bad"). By contrast, individuals with higher granularity are able to make finer distinctions, which they may mark with specific words. Emotional granularity is typically measured using data from experience-sampling studies, in which individuals are prompted to report their experiences multiple times per day, across multiple days, allowing experimenters to examine their pattern of responses over time in natural settings. As reviewed next, there is growing evidence of a link between emotional granularity and mental health in both clinical and non-clinical samples. However, the physiological correlates of granularity have been under-investigated. Incorporating cardiorespiratory physiological measures into the study of granularity can provide insights into the biological underpinnings of individual differences in emotional experience and corresponding ties to physical health. With the present study, we begin to fill this gap.

Recent findings strongly indicate that lower emotional granularity is a transdiagnostic feature of mental disorders (for reviews, see Barrett, 2017a; Kashdan et al., 2015; Smidt & Suvak, 2015) and a likely risk factor for mental illness. Lower granularity occurs across a range of mental disorders, including schizophrenia (Kimhy et al., 2014), depression (Demiralp et al., 2012), social anxiety disorder (Kashdan & Farmer, 2014), eating disorders (Selby et al., 2013), autism spectrum disorders (Erbas et al., 2013), and borderline personality disorder (Suvak et al., 2011). In non-clinical samples, lower granularity is related to more symptoms associated with anxiety (Seah et al., 2020) and depression (Erbas et al., 2014, 2018; Starr et al., 2017; Willroth et al., 2019). Further, lower granularity is linked to poorer behavioral indices of coping. Individuals with lower granularity report greater alcohol consumption during intense negative emotional experiences (Kashdan et al., 2010), more urges to binge eat (Dixon-Gordon et al., 2014), higher incidence of drug relapse (Anand et al., 2017), and increased urges to physically aggress when provoked (Pond et al., 2012). By contrast, higher granularity is associated with more specific action planning and better self-regulation (Barrett et al., 2001; Kalokerinos et al., 2019).

Emotional granularity is one of multiple related constructs for individual differences in the experience of emotion, including emotional awareness (e.g., Lane & Schwartz, 1987) and alexithymia—the latter referring to a "lack of words for feelings" (Nemiah & Sifneos, 1970) and therefore conceptually equivalent to very low granularity. In the present study, we focused on emotional granularity because its measurement using repeated emotion endorsements allowed us to derive a behavioral estimate that theoretically could vary over time. Although granularity is typically discussed as a stable trait, there is evidence to suggest that it may fluctuate on a moment-to-moment basis (e.g., Tomko et al., 2015), and that these fluctuations may be related to stress and negative affect (Erbas et al., 2018). In this respect, emotional granularity is related to constructs for affective dynamics (Trull et al., 2015). These findings are consistent with how the construct of emotional granularity has been elaborated within constructionist theories of emotion—in particular, the theory of constructed emotion (TCE; Barrett, 2006, 2012, 2013, 2017a, 2017b).

The TCE links emotional granularity to mental and physical health by providing biologically principled hypotheses for individual differences in emotional experience. Fundamentally, the TCE proposes that a primary purpose of the brain is to accomplish allostasis: the active adjustment of peripheral bodily systems to expected environmental perturbations in consideration of expected metabolic needs (Sterling, 2012). To do this, the brain constructs an internal model of its body in the world and uses prior experience to predictively regulate the autonomic, immune, and neuroendocrine systems to prepare for situated behavior and anticipate viscerosensory inputs (Barrett, 2006, 2012, 2013, 2017b). It is hypothesized that the brain re-implements past experiences that are similar to the present as a prediction signal. When a prediction is confirmed by incoming sensory inputs from the world and the body, it has explained them (by categorizing sensations) and guided action (by identifying causes and consequences; Barrett & Simmons, 2015; Chanes & Barrett, 2016; Hohwy, 2013). In the context of the TCE, the accrued knowledge and prior experience that the brain uses to issue predictions are understood as *concepts*. As such, concepts are the mechanism by which the brain makes meaning of the current situation (i.e., constructs experience), and proactively tailors the body's responses accordingly (i.e., enacts allostasis; Barrett, 2017b; Hoemann et al., 2017).

Following from the TCE, individual differences in emotional experience are hypothesized to reflect differences in the

emotion concepts that a person's brain can construct. More precise emotional experiences (i.e., higher emotional granularity) come from precise emotion concepts, which the brain uses to create diverse, context-specific predictions to guide physiological regulation and situated action (e.g., Barrett, 2006, 2013, 2017a, 2017b). Accordingly, the TCE hypothesizes that individuals with higher granularity will also demonstrate patterns of physiological activity that are more situationally precise and more diverse. By contrast, individuals with lower granularity—who have fewer emotion concepts, or little diversity in the exemplars that they construct—may be unable to make meaning of their highly variable physiological sensations (effectively remaining experientially blind to them), thereby experiencing general feelings of pleasantness and activation and accomplishing allostasis less efficiently (Barrett, 2017a, 2017b).[1] This hypothesis is largely consistent with neuroimaging studies, which have shown that emotional experiences are constructed by brain networks involved in implementing emotion concepts (Lindquist et al., 2012; Wilson-Mendenhall et al., ,2011, 2015), and these same networks contain the majority of the visceromotor (limbic) circuitry that regulates the periphery of the body (Kleckner et al., 2017). Recently, electroencephalography (EEG) has been used to investigate emotional granularity's relationship to patterns of neural (i.e., central nervous system; CNS) activity. Individuals with lower versus higher emotional granularity were found to differ on event-related patterns of neural activity while viewing affective images, suggesting that higher granularity is associated with more efficient processing of affective stimuli (Lee et al., 2017; see also Wang et al., 2020). However, studies have yet to test hypotheses using measures of peripheral physiological (i.e., autonomic nervous system; ANS) activity.

Among measures of ANS function, respiratory sinus arrhythmia (RSA) is a potential means of examining the efficiency by which the brain accomplishes allostasis, and so may be related to emotional granularity. RSA is an estimate of vagal influence on the heart (Acharya et al., 2006; Berntson et al., 1993; Task Force, 1996) and represents heart rate variability (HRV) occurring within the typical respiratory frequency range (approximately 0.12–0.40 Hz; Beauchaine, 2001). RSA is driven almost exclusively by the parasympathetic nervous system (PNS; Akselrod et al., 1985; Cacioppo et al., 1994; Pomeranz et al., 1985). Some research suggests that resting RSA is related to individual differences in mental and physical health (e.g., Buccelletti et al., 2009; Kemp & Quintana, 2013; Mulcahy et al., 2019; Stein et al., 2007; Togo & Takahashi, 2009; Villareal et al., 2002). Lower resting RSA is associated with more negative affect (Bleil et al., 2008), depression (e.g., Kemp et al., 2010; Koenig et al., 2016), anxiety (e.g., Thayer et al., 1996), and post-traumatic stress and panic disorders (Cohen et al., 2000; for a review, see Beauchaine, 2015). Higher resting RSA, by contrast, is associated with greater affective stability (Koval et al., 2013) and subjective well-being (e.g., Geisler et al., 2010), lower anxiety (Chalmers et al., 2014) and depression (Carnevali et al., 2018), and more effective emotion regulation (for a review, see Balzarotti et al., 2017). However, not all findings favor the interpretation of a global, linear relationship between resting RSA and health (e.g., Hill et al., 2015; Kogan et al., 2013, 2014; Sloan et al., 2017).[2] For example, a nationally representative study found support for RSA's (inverse) relationship with negative affect, but not with positive affect or other measures of psychological well-being (Sloan et al., 2017).

In the present study, we investigated the relationship between emotional granularity and cardiorespiratory physiological activity with data collected using experience sampling with ambulatory monitoring. This approach provided for enhanced ecological validity and allowed us to characterize patterns within individuals, over time, in real-world situations (Quigley & Barrett, 2014; Wilhelm & Grossman, 2010). As part of a larger study on affective experience and decision making in daily life, participants were outfitted with sensors and portable equipment to measure their electrocardiogram (ECG) and impedance cardiogram (ICG) as well as bodily movement and posture (via accelerometers). To enable efficient sampling of psychologically salient moments, we used a novel, physiologically triggered experience-sampling approach, in which a custom smartphone application initiated an experience-sampling prompt any time there was a substantial, sustained change in interbeat interval (IBI; also called heart period) in the absence of movement. In response to each experience-sampling prompt, participants freely labeled their current state with emotion words. At the end of each day, participants elaborated on each prompt by rating the intensity of their experience using a set of 18 emotion adjectives.

Using the emotion intensity ratings from the end-of-day surveys, we computed estimates of emotional granularity for each participant. Using the ambulatory physiological data, we derived three cardiovascular features for analysis (Table 1): IBI, RSA, and pre-ejection period (PEP). We

[1]For example, individuals with alexithymia have impoverished emotion concepts and restricted emotion vocabulary (Lecours et al., 2009; Meganck et al., 2009; Roedema & Simons, 1999), and report physical symptoms and feelings of affect, but do not consistently experience them as emotional (Lane et al., 1997; Lane & Garfield, 2005).

[2]A related concern is how to interpret resting RSA as a between-participants variable, as unmeasured third variables can be the underlying cause of group differences (Berntson et al., 1993). In particular, many studies do not account for respiration (e.g., Grossman et al., 1991) or assess the potential relationship with prevailing heart period (de Geus et al., 2019). We addressed this concern by accounting for both of these variables in our analysis of the relationship between resting RSA and emotional granularity.

TABLE 1 Cardiorespiratory features derived from ambulatory physiological data

Feature	Definition	Interpretation
Interbeat interval (IBI)	Time (in ms) between heartbeats (inverse of heart rate)	IBI describes how fast the heart is beating; greater (i.e., longer) IBI values denote a slower heart rate
Respiratory sinus arrhythmia (RSA)	High frequency variability in IBI which occurs at the respiratory frequency	RSA is an estimate of parasympathetic (PNS) influence on the heart; greater RSA values typically indicate greater PNS activation
Respiration rate (RR)	Number of breaths (in cycles) per unit of time (min)	RR describes how fast the person is breathing; greater RR values indicate faster breathing
Pre-ejection period (PEP)	Time (in ms) between the onset of electrical initiation of the heartbeat and the opening of the aortic valve	PEP is an inverse estimate of cardiac contractility and sympathetic (SNS) control of the heart; greater (i.e., longer) PEP values typically indicate reduced contractility and SNS withdrawal[a]

[a]The use of PEP as an inverse estimate of SNS activity can be negatively impacted by large changes in afterload and preload.

also derived one respiratory feature: respiration rate (RR). These features were chosen because of their importance in prior work on physiological changes associated with motivated performance tasks (Blascovich & Mendes, 2001; Seery, 2011; Tomaka et al., 1993; Wormwood et al., 2019). We derived these features for periods of seated rest when participants did not receive experience-sampling prompts. We also computed change scores for each experience-sampling event, as the difference in physiological activity before and after the IBI change that initiated the experience-sampling prompt (Hoemann et al., 2020). By parsing apart seated resting physiological activity from reactivity in this way, we were able to make more specific inferences from the data than if we had randomly sampled without regard to ongoing context (e.g., posture).

In a set of pre-registered analyses (https://osf.io/5jmfw/), we tested three hypotheses. First, in a set of correlational analyses, we tested the hypothesis that emotional granularity is related to resting RSA because both have ties with health and may be indices of efficient allostasis. We predicted that granularity would be positively associated with resting RSA. Second, in a set of unsupervised clustering analyses, we tested the hypothesis that emotional granularity is related to the number of patterns (i.e., clusters) in cardiorespiratory physiological activity during seated rest, as discovered using person-specific clustering algorithms. By examining ANS activity during seated rest that was unlikely to be associated with an emotional event, we were able to investigate the broader relationship between granularity and resting physiological regulation. The brain constructs concepts to regulate the body even in the absence of psychologically salient experiences (Kleckner et al., 2017; Raichle, 2015). Therefore, we predicted that a greater number of physiological clusters would be discovered for participants with higher granularity due to having more context-specific shifts in ANS activity. Third, in a set of supervised classification analyses, we tested the hypothesis that granularity is related to how distinctly patterns in ANS activity map onto the words used to label emotional events. We predicted that granularity would be positively correlated with classifier performance, such that participants with higher granularity would have patterns of change in cardiorespiratory physiological activity during emotional events that could be more accurately classified.

2 | METHOD

All experimental protocols described below were approved by the Northeastern University Institutional Review Board. These methods were carried out in accordance with the relevant guidelines and regulations for research with human subjects.

2.1 | Participants

Sixty-seven participants ranging in age from 18 to 36 years (55% female; 38.8% White, 3.0% Black, 29.8% Asian, 28.4% other; M_{age} = 22.8 years, SD_{age} = 4.4 years) were recruited from the greater Boston area through posted advertisements, and Northeastern University classrooms and online portals. Eligible participants were non-smoking, fluent English-speakers, and were excluded if they had a history of cardiovascular illness or stroke, chronic medical conditions, mental illness, asthma, skin allergies, or sensitive skin. Eligible participants also confirmed they were not taking medications known to influence autonomic physiology including those for attentional disorders, insomnia, anxiety, hypertension, rheumatoid arthritis, epilepsy/seizures, cold/flu, or fever/allergies. Informed consent was obtained from all participants

before beginning the study. Participants received $490 as compensation for completing all parts of the study, plus up to $55 in task incentives as detailed on page 2 of the Supporting Information.

Of the 67 recruited participants, six withdrew and an additional nine were dismissed due to poor compliance. A total of 50 participants completed the full protocol (54% female; 40% White, 2% Black, 44% Asian, 14% other; $M_{age} = 22.34$ years, $\underline{SD}_{age} = 4.45$ years). A priori power analyses in G*Power 3.1 (Faul et al., 2009) confirmed that this data set was adequately powered to detect bivariate correlations with a moderate to large effect size ($r = .30$–$.50$), as well as multiple regressions with two predictors and a moderate to large size effect ($R^2 = .15$–$.25$). All power analyses assumed $\alpha < .05$ and power ($1\text{-}\beta$) > .80.

2.2 | Procedure

Each participant completed approximately 14 days ($M = 14.4$, $SD = 0.6$) of context-aware experience sampling distributed across a 3–4-week period ($M = 24.9$ days, $SD = 5.5$ days). On each day of experience sampling, participants came into the lab and were instrumented for peripheral physiological recording. Participants were instructed to continue physiological recording for 8 hr each day, after which they were able to remove and recharge all equipment. Upon completing experience sampling each day, participants automatically received an end-of-day survey via SurveyMonkey (San Mateo, CA), which they used to provide additional details about the prompts they completed throughout the day. Before and after the 2-week experience-sampling protocol, participants completed two in-lab sessions. In each session, participants completed tasks and questionnaires that are not reported here (see pages 2 and 4 of Supporting Information for overview).

All ambulatory physiological measures were recorded at 500 Hz on a mobile impedance cardiograph from MindWare Technologies LTD (Model # 50-2303-02, Westerville, OH), which participants wore clipped onto their clothing on the hip. ECG and ICG were obtained using pre-gelled ConMed (Westborough, MA) Cleartrace Ag/AgCl sensors, connected via wires to the cardiograph. ECG was obtained using a modified lead II configuration. The ECG signal was acquired using a low cutoff of 0.50 Hz and a high cutoff of 45 Hz. ICG was obtained using a four-spot electrode configuration (Qu et al., 1986). Basal impedance (Z_0) was acquired using a low frequency cutoff of 10 Hz. The first derivative, dZ/dt, was acquired using a low frequency cutoff of 0.50 Hz and a high cutoff of 45 Hz. The mobile impedance cardiograph collected continuous three-axis accelerometry data that were used to assess movement. Participants also wore two inertial measurement units (IMUs) from LP-Research (Minato-ky, Tokyo, Japan) to derive measures of posture and changes in posture. One IMU was placed medially on the sternum; the other IMU was placed on the front of the thigh.

Physiological and accelerometric data were recorded continuously throughout the 8-hr sampling period and communicated via Bluetooth to a Motorola Moto G[4] smartphone. A custom smartphone application, MESA, processed the continuous ECG and accelerometer data in real time, and initiated an experience-sampling prompt anytime a substantial, sustained change in IBI was detected in the absence of movement or posture change, with a minimum interval of 5 min between prompts. On the first day of sampling, a substantial, sustained change in IBI was operationalized as more than ±167 ms over an 8-s period. On subsequent days, this IBI parameter was manually adjusted up or down to ensure each participant received approximately 20 prompts per day. For more information on threshold adjustment, see page 1 of the Supporting Information. Movement was determined from the continuous accelerometer data from the mobile impedance cardiograph. Minimal movement was operationalized as any time none of the three accelerometry channels (alone or in aggregate) exceeded a threshold of 10 cm/s^2 within the preceding 30 s. Posture (standing, sitting, reclining) was determined by comparing the relative orientation of the two IMUs on a participant's torso and thigh. Absence of posture change was operationalized as any time when the relative orientation of the two IMUs did not change within the preceding 30 s.

Participants also received an average of two "random" prompts per experience-sampling day, which occurred in the absence of movement or posture change, but which were not contingent on a change in IBI. One random prompt would be generated in the first 4 hr and one in the second 4 hr. In total, participants received an average of 21.70 prompts per day ($SD = 6.90$). We observed that prompts were relatively evenly distributed throughout the 8-hr experience-sampling day, which typically began around 9 a.m. On average, participants completed 34% of prompts in the morning (before 12 p.m.), 52% of prompts in the afternoon (12–5 p.m.), and 14% of prompts in the evening (after 5 p.m.). Participants were not required to complete all the prompts they received: rather, they were required to complete at least three prompts each day, and an average of at least six prompts each day. Participants were further incentivized to complete an average of eight prompts per day, as detailed on page 2 of the Supporting Information. Participants ultimately completed an average of 8.80 prompts ($SD = 1.22$) per day, in line with previous experience-sampling studies that have asked participants to complete 10 prompts per day (e.g., Tugade et al., 2004; Widdershoven et al., 2019).

At each sampling prompt, participants were asked to respond to a series of questions presented in the MESA application. Participants first provided a brief free-text description of what was happening at the time they received the prompt. Participants then self-generated words to label their current

affective experience. Participants were able to provide as many words as they felt necessary to describe their affective experience but were required to input at least one word. For each self-generated word, participants were asked to provide an intensity rating on a five-point Likert-style scale from 1 ("not at all") to 5 ("very much"). Participants also responded to additional questions that are not included in the present report (see page 1 of the Supporting Information for details).

At the end of each experience-sampling day, participants received a modified day reconstruction survey (Kahneman et al., 2004; Stone et al., 2006), in which they were presented with the brief description of each prompt they completed during the day. After describing the event in more detail, participants were asked to rate the intensity of their emotional experience on a set of 18 emotion adjectives ("afraid," "amused," "angry," "bored," "calm," "disgusted," "embarrassed," "excited," "frustrated," "grateful," "happy," "neutral," "proud," "relieved," "sad," "serene," "surprised," "worn out") using a seven-point Likert-style scale from 0 ("not at all") to 6 ("very much"). Participants also provided additional details about each experience-sampling event that are not reported here (see pages 2–3 of the Supporting Information).

2.3 | Physiological signal processing and feature extraction

From the physiological data, we identified periods of seated rest according to the following criteria: participant position is seated and not moving (i.e., no forward acceleration); participant maintains this position for at least 60 s; no experience-sampling prompt was generated. We excluded data from the first 30 s of each period of seated rest to allow for signals to stabilize following movement. For each rest period, we derived IBI, RSA, PEP, and RR using 30 s bins and computed the mean and standard deviation of each feature across all bins. As reported in Hoemann et al. (2020), we also computed change scores for each experience-sampling event as the difference in each feature between the 30 s preceding the IBI change that initiated the experience-sampling prompt and the 30 s following (Figure S1). We used change scores, rather than residualized change, because of their enhanced interpretability (Llabre et al., 1991). This decision was supported by previous laboratory studies that have found change scores to be as reliable as residualized change for measuring reactivity in cardiovascular features (e.g., Llabre et al., 1991; Myrtek, 1985). Physiological signals were processed as follows, using an in-house pipeline coded in Python (Forouzanfar et al., 2018; Nabian et al., 2018; see also Hoemann et al., 2020). Specific parameter values are noted in Table S2. Signal processing and feature extraction scripts are available via a repository hosted by the Center for Open Science (https://osf.io/5jmfw/).

Raw ECG signal was passed through an elliptic bandpass filter to remove baseline and high frequency noise. Initial quality checks were then performed for each beat, checking for overall waveform shape, and acceptable minimum, maximum, and minimum-to-maximum values (Table S2). R-peak detection for ECG was performed using established methods (Hamilton, 2002) and implemented using the BioSPPy package (Carreiras et al., 2018). Mean IBI was then derived as the average R-R interval. Additional quality checks (Table S2) were performed on each IBI series to ensure that values were within acceptable ranges (300–2,000 ms), and that expected beat-to-beat differences were consistent with normal beats and unlikely to be artifacts (following established benchmarks; Berntson et al., 1990). ECG data failing any quality check were excluded from analysis. RSA was derived from the IBI series. These calculations were coded to mimic the processing steps of standard HRV analysis software (MindWare Technologies LTD, Westerville, Ohio), including cubic interpolation of beat-to-beat IBI, detrending to minimize nonstationarity, tapering using a Hamming window, and lastly, fast Fourier transformation (FFT). RSA was calculated as the natural log of the area under the power spectrogram from 0.12 to 0.40 Hz.

Raw ICG signal was processed by segmenting dZ/dt into time windows corresponding to 250 ms before the ECG R-peak to 500 ms after; eight such segments (i.e., eight beats) were averaged together to form overlapping ensembles. B points were detected in each ensemble by taking the first and second derivatives of dZ/dt and comparing them with thresholds based on signal frequency (Table S2). Forward and reverse autoregressive modeling was then used to perform detection and correction of B point outliers (Forouzanfar et al., 2018). X points were detected by examining the second derivative of dZ/dt within each ensemble (Nabian et al., 2018). Segments of the ICG signal from which we could not detect B or X points and segments that corresponded with unusable ECG data were excluded from analysis. PEP was calculated as the time (ms) between the ECG R peak and the ICG B point—also referred to as PEP_R (Berntson et al., 2004). Quality checks (Table S2) were performed; only values that occurred within an acceptable range (30–200 ms) and that did not result in changes in the gradient greater than 30 ms from one ensemble to the next were retained.

RR feature detection was performed based on methods described in previous work (Ernst et al., 1999; de Geus et al., 1995). The basal impedance signal, Z_0, was tapered using a Hamming window and an interpolated finite impulse response (IFIR) bandpass filter was applied using the defined RSA frequency band (0.12–0.40 Hz ± 20%) as the low/high cutoffs. The resulting waveform was then detrended and zero-averaged before being subjected to an FFT. The resulting frequency spectrum was used to identify the primary (i.e., highest power) frequency above 0.17 Hz (approximately

10 cycles/min). This lower boundary was introduced to avoid potential influence from the Traub-Hering-Mayer (THM) peak related to baroreceptor activity (Berntson et al., 1993) and to reflect clinical guidelines of a 12 cycle/min minimum (Bleyer et al., 2011). As described on page 2 of the Supporting Information, two 5-min resting baselines were recorded for participants in the lab. During these baselines, RR was recorded using a respiratory belt, such that these values represented criterion measures for participants' ambulatory RR. In-lab RR for each baseline was scored in 30 s bins, with maximum resting RR defined as $M_{RR} + 3{*}SD_{RR}$ and minimum resting RR defined as $M_{RR} - 3{*}SD_{RR}$. Maximum change in in-lab RR was defined as the greatest (absolute value) difference between subsequent 30 s bins. Segments of the ICG signal in which derived RR value(s) exceeded any of these thresholds, and segments that corresponded with unusable ECG data, were excluded from analysis.

2.4 | Behavioral data processing

Estimates of emotional granularity were computed from the intensity ratings for the 18 emotion adjectives in the end-of-day surveys. Following prior literature (e.g., Tugade et al., 2004), granularity was computed as an intraclass correlation (ICC) using agreement with averaged raters ("A–k" method; Shrout & Fleiss, 1979). Higher ICC values reflected lower emotional granularity (i.e., greater shared variance among adjectives' ratings). Negative values are outside the theoretical range for an ICC, and so were recoded as 0 (following e.g., Anand et al., 2017). Separate indices of granularity were computed for pleasant (positive) versus unpleasant (negative) emotions, with this distinction based on normative ratings (Warriner et al., 2013). These indices were averaged to create an overall estimate of granularity (e.g., Edwards & Wupperman, 2017). ICCs were Fisher *r*-to-*z* transformed to fit the variable to a normal probability distribution. These transformed values were multiplied by −1 to yield an estimate of granularity that scaled intuitively, such that lower (more negative) values reflect lower granularity, and higher (less negative) values reflect higher granularity. Data for a given experience-sampling day were excluded from analysis if the participant did not complete at least six prompts or if the participant completed the corresponding end-of-day survey late (i.e., the following day).

2.5 | Analyses

Our first set of analyses examined the relationship between emotional granularity and resting RSA. We entered granularity as a predictor in a multiple regression with resting RSA as the dependent variable, and controlling for resting RR (e.g., Grossman et al., 1991). We also fitted a model in which we adjusted RSA for IBI as $100{*}[\mathrm{RSA}/\ln(\mathrm{IBI}^2)]$ (Van Roon et al., 2016), which allowed us to account for the positive relationship between heart period and RSA (de Geus et al., 2019). Recent studies have shown that RSA is nonlinearly related to indices of mental and physical health (with extreme values of RSA linked to maladaptive psychological and physiological processes; Kogan et al., 2013, 2014; Stein et al., 2005). Accordingly, we examined the nature of the relationship between resting RSA and granularity and, if necessary, fitted regressions using a quadratic term for RSA. In all analyses, we used the R^2 for the granularity term as a measure of variance explained. Because we had a directional prediction, we used a one-tailed test of significance at $\alpha < .05$.

Our second set of analyses used person-specific unsupervised clustering algorithms to examine the relationship between emotional granularity and the number of patterns in cardiorespiratory physiological activity during seated rest. We submitted all periods of seated rest from each participant to a separate Dirichlet Process-Gaussian Mixture Model (DP-GMM) with Variational Inference (Bishop, 2006; Blei & Jordan, 2006). DP-GMM is a specialized variant of Gaussian Mixture Modeling (GMM) that allowed us to discover the number of clusters in the data, as well as each cluster's location (i.e., mean), shape (i.e., covariance), and relative size (i.e., mixture proportion or prior probabilities of a point belonging to that cluster relative to others; see Table S3 for specific parameter values). Data points were four-dimensional vectors of resting period means for RSA, RR, IBI, and PEP, standardized prior to clustering. These features were selected to further investigate the role of RSA (and thereby PNS activity) during seated rest: RR and IBI are directly related to RSA, whereas PEP provides an inverse estimate of sympathetic nervous system (SNS) activity. Three participants were excluded because they had fewer than 35 seated rest periods, the minimum necessary to cluster on four features. An average of 118.30 ($SD = 66.63$; range = 35–298) seated rest periods were submitted to clustering per participant. Because a DP-GMM discovers the number of clusters in each participant's data, in principle a greater number of data points (here, periods of seated rest) allows for the discovery of a greater number of clusters. To account for this, we entered granularity as a predictor in a multiple regression with the number of clusters discovered as the dependent variable and controlling for the number of seated rest periods submitted. We assessed the cross-participant relationship between number of clusters and granularity using a one-tailed test of significance at $\alpha < .05$.

Our third set of analyses used person-specific supervised classification analyses to examine the relationship between emotional granularity and the performance of classifiers trained on event-specific changes in cardiorespiratory physiological activity. Here, we examined accuracy for the events that

corresponded with participants' top three most frequently generated emotion labels. We chose this number of classes because it allowed us to go beyond a simple binary distinction in the patterns of cardiorespiratory activity that co-vary with emotional experience. We also set a standard number of events to sample per class, to ensure that person-specific models were being trained on the same amount of data and were therefore comparable in terms of classification accuracy. We set this number to 10 following the procedure described on page 9 of the Supporting Information. Requiring a minimum of 10 events per class resulted in the exclusion of 20 participants (i.e., $N = 30$), with an average number of 61.93 ($SD = 21.45$; range = 34–108) events used across all three classes. The data point for each event was a three-dimensional vector of the change scores for IBI, RSA, and PEP. RR was not included in this analysis because breathing rates are typically too low in frequency to enable measurement of reliable changes from one 30-s period to the next. For each participant, a linear support vector machine (SVM) was trained and tuned using five-fold cross-validation as follows. First, 30 events (10 per label) were randomly selected from those available. These events were then split into sets for training (24 events; 8 per label) and testing (6 events; 2 per label), with event selection stratified such that each fold had an equal number of events per emotion label. For each fold, accuracy was measured as the proportion of events for which vectors of changes scores were classified as belonging to their respective emotion labels. This process was then repeated 10 times to achieve mean classification accuracy across all folds and repetitions. We assessed the cross-participant relationship between mean classification accuracy and granularity using a two-tailed test of significance at $\alpha < .05$.

For each analysis, we examined the influence of individual data points on the results using Cook's distance (D), which is used to identify multivariate outliers in a set of predictor variables by combining each observation's leverage and residual values (Cook, 1977). Following standard thresholds (e.g., Altman & Krzywinski, 2016), we identified influential points as observations with D values exceeding $4/n$ (where n is the number of observations). These outliers are identified in the figures below. We report regression results and visualize lines of fit with these points removed.

3 | RESULTS

3.1 | Correlational analyses

Consistent with our predictions, a multiple regression across participants revealed a positive relationship between emotional granularity and resting RSA, such that individuals with higher granularity exhibited higher mean resting RSA over the course of experience sampling. However, this relationship had a small effect size and was not significant when controlling for RR and removing multivariate outliers ($n = 1$), $N = 49$, $b = .53$, 95% CI [−0.44, 1.51], $\beta = .15$, $R^2 = .03$, $F(1,46) = 1.19$, $p \leq .14$, one-tailed (Figure 1). Consistent with prior literature (de Geus et al., 2019), we observed a significant positive correlation between mean resting RSA and mean resting IBI ($r = .61$, $p < .001$, two-tailed). However, IBI was not related to emotional granularity ($r = .06$, $p \leq .70$, two-tailed), and the results of the multiple regression did not change when adjusting RSA for IBI, $N = 49$, $b = 3.75$, 95% CI [−2.86, 10.35], $\beta = .16$, $R^2 = .03$, $F(1,46) = 1.30$, $p \leq .13$, one-tailed. An examination of the scatter plots of both raw and residualized variables suggested a linear relationship, so we did not fit regressions using a quadratic term for RSA. See page 10 of the Supporting Information for exploratory within-participants correlational analyses.

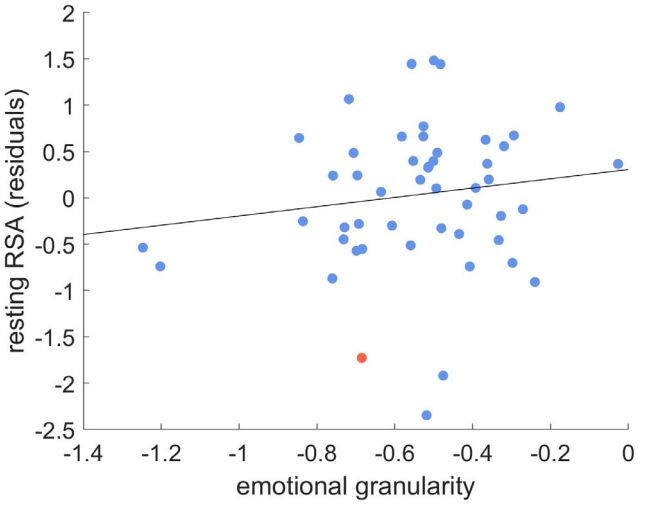

FIGURE 1 Scatter plot of the relationship between emotional granularity (x-axis) and mean RSA measured during periods of seated rest in everyday life (y-axis). Residualized RSA scores are shown (controlling for RR). The line-of-fit does not include the effect of one multivariate outlier, which is identified in red

3.2 | Clustering analyses

Consistent with our predictions, a multiple regression across participants revealed a positive relationship between emotional granularity and the number of clusters discovered when controlling for the number of seated rest periods submitted and removing multivariate outliers ($n = 6$). Individuals with higher granularity exhibited a greater number of patterns of cardiorespiratory physiological activity during seated rest. This relationship had a medium effect size and was significant, $N = 41$, $b = 2.85$, 95% CI [.07, 5.63], $\beta = .25$, $R^2 = .07$, $F(1,38) = 4.30$, $p \leq .02$, one-tailed (Figure 2). The discovered clustering solutions fit the data well, such that the overall probability of seated rest periods' cluster membership was high across participants (grand mean; $GM = .91$; $SD = .04$).

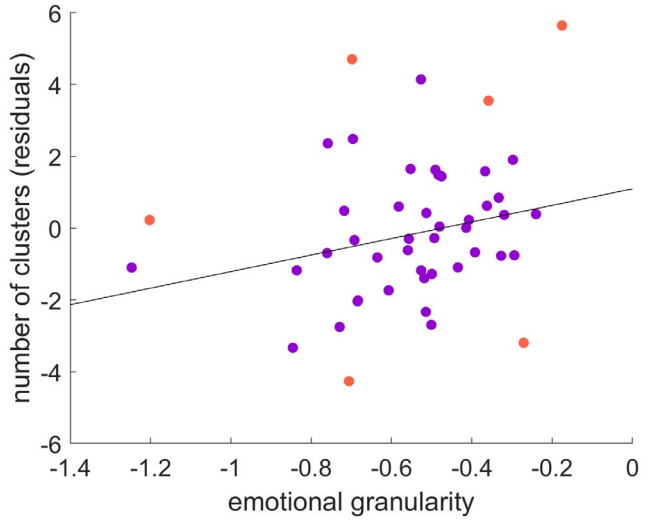

FIGURE 2 Scatter plot of the relationship between emotional granularity (*x*-axis) and number of clusters discovered in cardiorespiratory physiological activity during periods of seated rest in everyday life (*y*-axis). Residualized number of clusters is shown (controlling for number of seated rest periods). The line-of-fit does not include the effects of six multivariate outliers, which are identified in red

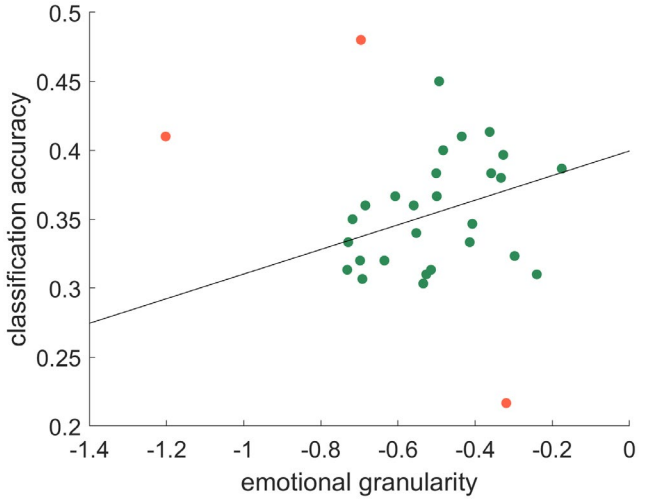

FIGURE 3 Scatter plot of the relationship between emotional granularity (*x*-axis) and classification accuracy for patterns of change in cardiorespiratory physiological activity during emotional events in everyday life (*y*-axis). The line-of-fit does not include the effects of three outliers, identified in red

Additional measures of cluster separation, reported on page 9 of the Supporting Information, provided further evidence of fit. We also performed sensitivity analyses to examine whether these results were robust to different DP-GMM hyperparameter settings and cluster inclusion criteria. These analyses, reported on pages 8–9 of the Supporting Information, demonstrated overall stability in the effect size of the relationship between emotional granularity and number of clusters. See pages 10–15 of the Supporting Information for exploratory between-participants clustering analyses.

3.3 | Classification analyses

Consistent with our predictions, a regression across participants revealed a positive relationship between emotional granularity and mean classifier performance after outliers were removed ($n = 3$). Individuals with higher granularity exhibited patterns of cardiorespiratory physiological activity during emotional events that were more accurately matched to their corresponding emotion label (i.e., based on participants' own ground truth). This relationship had a medium effect size and approached a conventional level of significance despite the reduced sample size, $N = 27$, $b = .09$, 95% CI [−.008, .19], $\beta = .39$, $R^2 = .13$, $F(1,25) = 3.61$, $p \leq .07$, two-tailed (Figure 3).

4 | DISCUSSION

There is strong evidence of a link between emotional granularity and mental health (e.g., Kashdan et al., 2015; Smidt & Suvak, 2015), motivating the search for the physiological mechanisms by which this relationship plays out. To date, the physiological correlates of emotional granularity have been under-investigated, however. In the present study, we used data from an experience-sampling study with ambulatory monitoring to test hypotheses about the relationship between granularity and cardiorespiratory physiological activity in daily life. We found that individuals with higher granularity exhibited a greater number of patterns of physiological activity (as discovered during seated rest), and that these patterns were more distinctive (as assessed during emotional events), consistent with the hypothesis that higher granularity is related to precise emotion concepts, which the brain uses to create diverse, context-specific predictions in the service of allostasis. We also found that individuals with higher granularity tended to exhibit higher RSA during periods of seated rest, consistent with evidence that both are associated with health and may represent efficient allostasis. However, this relationship did not reach statistical significance. These findings join a growing number of studies linking granularity to more specific action planning, as manifested via better self-regulation (e.g., Barrett et al., 2001; Kalokerinos et al., 2019) and adaptive coping strategies (e.g., Kashdan et al., 2010; Starr et al., 2017). By demonstrating an empirical link between granularity and physiological diversity and precision, these findings provide the first evidence of how granular action planning may be manifested in the body and brain (see also Lee et al., 2017).

Understanding emotional granularity's relationship to cardiorespiratory physiological activity in everyday life is especially relevant given evidence of lower emotional granularity in depression (Demiralp et al., 2012), coupled with the

well-established association between depression and cardiovascular disease (CVD; e.g., Carney et al., 2005; Grippo & Johnson, 2002; Sheps & Sheffield, 2001; Stein et al., 2000).[3] Disordered mood is associated with detrimental activity of the two branches of the ANS to visceral functions throughout the body, in particular lower resting PNS activity (Bleil et al., 2008; Hamilton & Alloy, 2017; Kapczinski et al., 2008), which may be a core vulnerability for CVD and other cardiovascular risk factors (e.g., Buccelletti et al., 2009; Thayer et al., 2010; Togo & Takahashi, 2009). Moreover, better self-regulation and adaptive coping strategies are observed in individuals with higher resting RSA (e.g., Appelhans & Luecken, 2006; Geisler et al., 2010), suggesting a potential common mechanism underlying both (dys)regulated psychological and physiological processes. Prior work has also identified a number of emotion-related risk factors for CVD (Krantz & McCeney, 2002; Rozanski, 2014), with protective factors including more effective emotion regulation—in turn associated with higher granularity (Barrett et al., 2001; Kalokerinos et al., 2019). Higher granularity (measured as reduced alexithymia) is further associated with decreased risk for cardiac events in patients with previous myocardial infarction (Beresnevaite, 2000). Indeed, better emotion regulation and coping strategies are directly associated with having fewer cardiovascular risk factors (Kinnunen et al., 2005), even when experienced negative affect is taken into account (Yancura et al., 2006).

In the present study, we have referred to resting RSA as a potential index of efficient allostasis on the basis of prior theoretical and empirical work that suggests it as a proxy outcome for health (e.g., Appelhans & Luecken, 2006; Kemp & Quintana, 2013; Mulcahy et al., 2019; Thayer & Lane, 2000). There are a few potential concerns with this interpretation. First, RSA is not a defended parameter of physiology (e.g., blood pressure), which likely makes it a less reliable index for overall metabolic well-being. Second, there is evidence to suggest that resting heart period (HP; the inverse of heart rate) has stronger links with CVD than other surrogate indicators of vagal influence on the heart (e.g., Aune et al., 2017; Böhm et al., 2015; Fox et al., 2007; Palatini, 2007). Resting HP is more strongly impacted by PNS activity than by SNS activity (Berntson et al., 1994; Cacioppo et al., 1994), especially in young, healthy, seated samples such as ours. In this regard, we would expect resting RSA (as an index of PNS activity) to capture an analogous aspect of cardiorespiratory activity as would resting HP—and, indeed, we found the two variables to be positively and significantly correlated. This observation is consistent with prior literature and occurs, at least in part, because RSA is inextricably and neurophysiologically linked to the HP itself (de Geus et al., 2019). Nevertheless, we also found that resting HP was not related to emotional granularity in our sample.

From the perspective of the TCE, psychological and physiological (dys)regulation are hypothesized to be intrinsically linked through the process of allostasis (Sterling, 2012). This hypothesis provides a mechanistic, brain-based explanation of how a potential vulnerability factor—insufficiently distinct emotion concepts—relates lower granularity to less effective psychological and physiological regulation (Barrett, 2017b; Barrett et al., 2014, 2015; Kashdan et al., 2015). The TCE is broadly consistent with other neurobiological accounts, such as that proposed by Gianaros and Jennings (2018), in which maladaptive patterns of cardiovascular physiological activity are the result of visceral prediction errors (i.e., predictions for metabolic support that are disproportionate or mismatched to actual demands). In turn, afferent neural pathways convey visceral sensory information from the body to the brain, and this information shapes future predictions.[4] In this way, dysregulated psychological and physiological processes are linked through a maladaptive brain–body loop (Gianaros & Jennings, 2018). Similarly, Thayer and Lane (2000) present a dynamical systems approach to neurovisceral integration in their model of emotion (dys)regulation and its relationship to cardiovascular health (see also Lane et al., 2009; Thayer et al., 2012; Thayer & Lane, 2009). The present findings cannot be fully accounted for by these frameworks, however, as they do not postulate a role for both diversity and specificity of predictions (e.g., via emotion concepts) in efficient allostasis. In this regard, the TCE offers unique insight into the relationship between emotional experience, physiological regulation, and physical health.

The hypotheses of the TCE notwithstanding, there are alternative explanations that may account for the present findings. For example, the relationship between emotional granularity and the number of patterns in cardiorespiratory physiological activity during seated rest may be due to individual differences in the proportion of time spent in various situational contexts (e.g., work vs. home) or engaged in various activities (e.g., socializing vs. watching TV). It could be that individuals whose days are distributed across a greater diversity of situations and activities also exhibit a greater diversity of accompanying patterns of physiological activity. This hypothesis remains to be tested in future research. Additionally, it is possible that individual differences in interoceptive ability (e.g., Garfinkel

[3]There is reduced working memory capacity and reduced episodic memory specificity in depression (e.g., Dalgleish et al., 2007), which is also consistent with the link between depression and lower emotional granularity.

[4]Visceral prediction errors may also have psychological consequences, as metabolic burdens (e.g., inflammatory responses) are associated with changes in affect (e.g., unpleasant mood, fatigue) and with depression (Harrison, Brydon, Walker, Gray, Steptoe, & Critchley, 2009; Harrison, Brydon, Walker, Gray, Steptoe, Dolan, et al., 2009).

et al., 2015) may partially account for these findings, as individuals with higher granularity may be better able to differentiate between bodily states underlying emotional experience (Barrett et al., 2004; Herbert et al., 2011). Measures of interoceptive ability (e.g., Schandry, 1981; Whitehead et al., 1977) were not collected in the present study and should be added by future extensions of this work. Finally, it is possible that the present findings can be partially accounted for by factors such as age, sex, ethnicity, and socioeconomic status (SES). In the present sample, participants were rather homogeneous demographically (except for sex), so these factors could have contributed to the observed effects (as suggested for ethnicity by Hill et al., 2015). Future work using more diverse samples will be needed.

There are also several considerations and limitations to keep in mind when interpreting the present findings. We used DP-GMMs in our unsupervised clustering analyses, as this approach allowed us to discover, in a data-driven manner, the number of clusters in each participant's seated rest data, as well as each cluster's location, shape, and relative size. However, there is disagreement about whether or not DP-GMMs, as mixture models, can be considered clustering algorithms (e.g., Bauer, 2007; Bauer & Curran, 2003). The goal of a mixture model is to discover the number of unobserved components necessary to approximate the observed data. As such, it could be that, rather than discovering unique patterns of physiological activity, the DP-GMMs in the present study were capturing distributions of cardiorespiratory features that were increasingly non-normal and thus required more components to approximate. If this were the case, we would expect to see low overall probabilities of cluster membership (e.g., around 0.25 for four-cluster solutions). Instead, we observed a high overall probability of cluster membership, supporting our interpretation of model results as reflecting clusters.

Additionally, this study was the first to use a two-step approach to measure emotional granularity, in which participants received experience-sampling prompts during the day but completed emotion intensity ratings for each prompt in the end-of-day survey. It is possible that participants would have responded differently if they had provided intensity ratings in the moment. However, recent evidence demonstrates moderate to high correlations between affective ratings collected in the moment versus through a day reconstruction method similar to that used in the present study (Schneider et al., 2020). The end-of-day surveys used in the present study also provided participants with some details recorded at the time of the experience-sampling moment, theoretically allowing them to re-instantiate earlier experiences with greater fidelity. Multiple prior studies have assessed granularity using daily diary methods in which participants rate emotional events from earlier in the day (e.g., Barrett et al., 2001; Dasch et al., 2010).

This study was also the first to employ a physiologically triggered experience-sampling paradigm. This approach allowed us to estimate person-specific effects with greater reliability but entailed greater complexity in data collection. The sample size was set accordingly and was not adequately powered to detect smaller between-participants effect sizes, especially once participants were excluded based on data quality and sparsity. Larger sample sizes are necessary to provide a robust test of the individual differences in question. We plan to collect a second sample using these methods, which can serve to replicate and extend the present findings. More broadly, it is reasonable that our observed effect sizes were small given that the measures in question (e.g., emotional granularity, RSA) are indirect estimates of psychological and physiological function and were restricted in the range of values that could be observed in our young healthy sample. Likewise, the use of ambulatory data may have decreased our signal-to-noise ratio, obscuring relationships that we may have been able to discern in the lab. However, we view the use of ambulatory measures as a strength rather than a weakness; ambulatory data can provide a greater assessment of the range of physiological activity across situations and contexts. By providing support for our hypotheses using data collected in daily life, we have established a lower bound on the possible effect size of granularity's relationship with physiological activity and demonstrated the generalizability of these effects to everyday life.

The present study is the first to demonstrate a relationship between emotional granularity and cardiorespiratory physiological measures. Interpreted within the framework of the TCE, these findings raise the possibility that changes in granularity will have corresponding impacts for cardiorespiratory function. It is an open question whether emotional granularity has impacts for physical (i.e., cardiovascular) health, but several promising lines of research identify lower granularity as a target for intervention. For example, simply cueing participants to focus on the subtlety and variety of their experiences can improve their ability to make nuanced distinctions between different emotions, and help them to better understand how emotions impact judgments (Cameron et al., 2013). There is also evidence that mindfulness-based interventions (Van der Gucht et al., 2019)—and even experience sampling itself (Widdershoven et al., 2019)—can lead to improvements in granularity. Moving forward, these techniques can be assessed for their potential to produce changes in the ANS activity associated with emotional experience, including changes in RSA. Future work of this nature ultimately has the potential to extend the current line of research into tests of a causal relationship between granularity and cardiorespiratory physiological activity, with the prospect of deepening the understanding of how the mind and body are integrated.

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AUTHOR CONTRIBUTION

Katie Hoemann: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Project administration; Visualization; Writing-original draft; Writing-review & editing. **Zulqarnain Khan:** Data curation; Formal analysis; Methodology; Software; Writing-review & editing. **Nada Kamona:** Formal analysis; Visualization; Writing-review & editing. **Jennifer Dy:** Funding acquisition; Supervision. **Lisa Feldman Barrett:** Conceptualization; Resources; Supervision; Writing-review & editing. **Karen S. Quigley:** Conceptualization; Funding acquisition; Methodology; Project administration; Resources; Supervision; Writing-review & editing.

DATA AVAILABILITY STATEMENT

All data analyzed in this paper, along with the accompanying analysis code, are available via a repository hosted by the Center for Open Science at https://osf.io/5jmfw/.

ORCID

Katie Hoemann https://orcid.org/0000-0002-9938-7676
Zulqarnain Khan https://orcid.org/0000-0001-6945-5052
Karen S. Quigley https://orcid.org/0000-0001-8844-990X

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SUPPORTING INFORMATION

Additional Supporting Information may be found online in the Supporting Information section.

FIGURE S1 Example interbeat interval (IBI) series taken from ECG signal 30 s preceding and following an event trigger, or the start of the period of heart rate change preceding an experience sampling prompt. All physiological measures are calculated as change scores, in which the mean of the 30 s preceding the trigger is subtracted from the mean of the 30 s following the trigger

TABLE S1 Questionnaire measures for in-lab sessions 1 and 2

TABLE S2 Hyperparameters for physiological signal processing

TABLE S3 Hyperparameters for Dirichlet process-Gaussian mixture modeling (DP-GMM)

FIGURE S2 Marginal likelihood values (*y*-axis) for different values of the alpha hyperparameter (*x*-axis) for a representative participant. This participant had 119 seated rest periods (i.e., $N = 119$), such that the alpha value implemented ($1/N$) in the main analysis was roughly .001 or 10^{-2}. Increasing the value of alpha (i.e., moving right on the *x*-axis) results in a drop in marginal likelihood; decreasing (i.e., moving left on the *x*-axis) improves marginal likelihood but does not change the result in any significant way. The numbers at the bottom of each data point along the plotted line reflect the total number of clusters discovered; the numbers at the bottom reflect the number of small clusters (i.e., clusters with weights $\leq .05$). Increasing alpha results in worse solutions (indicated by lower marginal likelihood values) with many small clusters

FIGURE S3 Marginal likelihood values (*y*-axis) for different values of the prior for the initial number of components hyperparameter (*x*-axis) for a representative participant. This participant had 119 seated rest periods (i.e., $N = 119$). Decreasing the prior (i.e., moving left on the *x*-axis) results in a drop in marginal likelihood. The numbers at the bottom of each data point along the plotted line reflect the total number of clusters discovered; the numbers at the bottom reflect the number of small clusters (i.e., clusters with weights $\leq .05$). Decreasing the prior results in worse solutions (indicated by lower marginal likelihood values) with many small clusters

TABLE S4 Sensitivity analyses for unsupervised clustering results

FIGURE S4 Bar graphs of the mutual information (MI) between each physiological feature and participants' group-level clustering assignments. *Upper left panel:* clustering analysis including mean IBI, PEP, RR, and RSA per

participant. *Upper right panel:* clustering analysis including emotional granularity in addition to mean IBI, PEP, RR, and RSA per participant. *Lower left panel:* clustering analysis including mean and standard deviation IBI, PEP, RR, and RSA per participant. *Lower right panel:* clustering analysis including emotional granularity in addition to mean and standard deviation IBI, PEP, RR, and RSA per participant

FIGURE S5 Feature correlation matrices per cluster discovered in between-participants clustering analysis 1a. A DP-GMM over participant-level means for RSA, RR, IBI, and PEP discovered six clusters of participants. Feature correlation matrices are provided for the five clusters that included more than one participant

FIGURE S6 Feature correlation matrices per cluster discovered in between-participants clustering analysis 1b. A DP-GMM over participant-level means for RSA, IBI, RR, and PEP, and including granularity, discovered 10 clusters of participants. Feature correlation matrices are provided for the seven clusters that included more than one participant

FIGURE S7 Feature correlation matrices per cluster discovered in between-participants clustering analysis 2a. A DP-GMM over participant-level means and standard deviations for RSA, IBI, RR, and PEP discovered six clusters of participants. Feature correlation matrices are provided for the four clusters that included more than one participant

FIGURE S8 Feature correlation matrices per cluster discovered in between-participants clustering analysis 2b. A DP-GMM over participant-level means and standard deviations for RSA, IBI, RR, and PEP, and including granularity, discovered 29 clusters of participants. Feature correlation matrices are provided for the five clusters that included more than one participant

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