Structured variation in daily life experience within and across individuals

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Abstract

Human experience varies across contexts and individuals. Yet, psychological studies typically constrain rather than discover this structured variation. We demonstrate an alternative approach that samples deeply and broadly to discover reliable person-specific, multimodal patterns of daily life experience. Ninety-seven healthy adults wore cardiac monitors for 8 hours/day for 14 days and reported current valence, arousal, primary activity, social context, and emotions (via free report) when prompted following a substantial cardiac interbeat interval change (and twice randomly each day). From each event (10,755 total, *M*=110.9 events/person), we extracted cardiovascular, postural, affective, and contextual features. Integrative clustering of these features identified 313 multimodal patterns (*M*=3.2 patterns/person), which were largely person-specific, with 81.7% of patterns being unique to one person. The pattern-distinguishing features also varied by person. Finally, self-generated emotion labels had many-to-many mappings with multimodal patterns. Our approach has broad utility and provides further evidence that emotions are diverse populations of instances.

Human experience is highly variable. This variation is situated within a context and individual, meaning that it is structured rather than random. Structured variation across contexts and people has been documented in a growing body of literature[1–9] and is central to a variety of domains in psychology, such as personality[10–12], concepts[13–15], attitudes[16], development[17], psychopathology[18–20], stress[21], and emotion[22–24]. Yet, psychological studies are typically designed to constrain rather than discover this structured variation[8,25,26]. Here, we demonstrate an alternative approach designed to discover structured variation in daily life experience using a powerful sampling tool and an analytic innovation. First, we sample individuals deeply across evocative experiences and broadly across biological, mental (e.g., valence, arousal), and contextual features as participants navigate the complex contexts of daily life (a method called biologically-triggered experience sampling[4,25]). Second, we use a novel analytic strategy to characterize experiential variation across contexts and across people and to identify the features that structure this variation. We leverage this approach to address an ongoing debate about the nature of emotion[4,6]: specifically, whether emotions are fixed categories that exist in nature (i.e., the natural kinds view) or rather diverse populations of instances situated in context (i.e., the populations view).

In sampling individuals deeply, our biologically-triggered experience sampling approach overcomes multiple limitations of more typical approaches in psychology[25]. A typical psychological study assesses participants in a laboratory where movement is restricted. This means that physiology is also restricted, as physiological signals such as blood pressure are constrained by body posture and skeletomotor movement[27]. By contrast, our approach – which we pioneered in prior work using one of the two samples in the present study[4] – samples a much greater range of contexts and allow participants free movement. Participants wore cardiac monitors for an average of eight hours per day for an average of 14 days and reported their experience periodically throughout their daily life[4]. Critically, sampling events were triggered by the participant's physiology – when their interbeat interval (IBI; the inverse of heart rate; **Table**

1) changed substantially from baseline in the absence of motion or recent posture change – thus increasing the likelihood of sampling events that were affectively evocative[4,25]. This procedure, employed by a growing number of studies[25,28–31], differs from most experience sampling studies, which sample daily life events randomly or at pre-specified times[32,33]. At each biologically-triggered sampling event, participants described some features of their experience, including their emotional experiences, using self-generated (free) reports[4]. As such, our approach avoided the theory-laden choices common to typical psychological studies, which have the potential to artificially harmonize experiential reports across situations and individuals[8,34].

New analytic innovations to our broad sampling approach are needed to more comprehensively model the structured variation of human experience. In our prior work with an initial cohort, we used data-driven cluster analyses to identify reliable cardiovascular patterns that recurred throughout each participant's daily life, and found that these patterns mapped in a many-to-many fashion to self-reported emotion experience[4]. But daily life experiences all involve a multimodal ensemble of signals from the body's sensory surfaces and from within the brain[8]. In our view, to understand experience – including, but not limited to, the experience of emotion – scientists need to measure as many of these signals as feasible in the dynamically changing contexts of the world. In modeling patterns based on only one domain of features (i.e., cardiovascular features), our prior study left unanswered the question of whether other biological, mental, or contextual features structured the observed variation. We address this question here, identifying recurring patterns of daily life experience formed by an expanded ensemble of cardiovascular, postural, mental (i.e., experienced valence and arousal), and contextual features (i.e., the person's primary activity and social context). To achieve this, we employ novel, multimodal integrative cluster analyses[35] that allow for including in the same model both continuous features (i.e., cardiovascular and affective features rated on a continuous scale) and categorical features (e.g., the social context, dichotomized as alone vs.

not alone). We also develop a new approach, using existing indices grounded in information theory[36–38], to identify, for each person, the features that distinguish one multimodal pattern from another. In this way, our analytic approach overcomes an additional limitation of the typical psychological study, in which data from individual persons and instances are primarily analyzed in aggregate[i]. In sum, our analytic approach searches for variation in daily life experience and the features that structure it in a deeply idiographic way.

In the present study, we analyzed an expanded data set, both in the number of sampled features and the number of participants sampled (*n*=45 from our prior study[4] plus *n*=52 newly sampled participants for a total of *N*=97 participants). Throughout our 14-day biologically-triggered experience sampling protocol, participants wore mobile electrocardiograph, impedance cardiograph, and inertial measurement units, and reported their current valence, arousal, primary activity (e.g., working, relaxing), social context (i.e., alone, not alone), and emotions (via self-generated report) when prompted either due to a substantial cardiac IBI change (relative to baseline) without any gross bodily movements (*M* = 23.8, *SD* = 11.5 prompts/day) or randomly (2 prompts/day). For each event, we extracted six features reflecting cardiac and vascular function (i.e., IBI; respiratory sinus arrhythmia, RSA; pre-ejection period, PEP; left ventricular ejection time, LVET; stroke volume, SV; and cardiac output, CO), one postural feature (i.e., sitting, standing, lying), two affective features, and two contextual features (**Table 1**) and submitted them to multimodal integrative clustering[35]. This approach identified clusters of events with similar underlying patterns of multimodal features, and each event was assigned to exactly one pattern. We determined the features that were most important for distinguishing one pattern from another for each participant using indices of Normalized Mutual Information[37] and Joint Mutual Information[38]. Following our prior work[4], we expected to observe

[i] The aggregate approach is thus steeped in a typological view of the mind, or the idea that mental phenomena (e.g., memory, attention, fear, sadness) are distinct categories (or natural kinds), each with a prototype, defined as an instance whose pattern of features best describes all instances in the category. For further details, see the Discussion and [8].

variation across people in the number and nature of multimodal patterns from daily life. In addition, we expected the distinguishing features to vary by person, and that contextual features, in particular, may play a prominent role in structuring these daily life patterns. Lastly, based on our prior findings[4], we expected a many-to-many mapping between self-generated emotion labels and multimodal patterns within and across participants (such that many emotion labels map to a single pattern, and a single label maps to many patterns).

Table 1. Features used to derive multimodal patterns of experience

Continuous Features		
Feature	**Definition**	**Interpretation**
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 activity
Interbeat interval (IBI)	Time (in ms) between heartbeats (inverse of heart rate)	IBI reflects how fast the heart is beating; greater IBI values denote a slower heart rate
Pre-ejection period (PEP)	Time (in ms) between the beginning of electrical stimulation of the heart and the opening of the aortic valve	PEP is an inverse estimate of cardiac contractility and sympathetic (SNS) control of the heart; greater PEP values typically indicate reduced contractility and less SNS activity
Left ventricular ejection time (LVET)	Time (in ms) between the opening and closing of the aortic valve	LVET describes how long it takes the heart to pump blood from the heart on a given heartbeat; greater LVET values are associated with a longer time to eject blood per heartbeat
Stroke volume (SV)	Volume (in mL) of blood ejected by the heart with each beat	SV describes the volume of blood ejected from the heart during each heartbeat; greater SV values indicate a greater blood volume ejected per heartbeat
Cardiac output (CO)	Volume (in L) of blood circulated in the body per unit of time (min)	CO describes blood flow over time; greater CO values indicate greater overall body-wide blood flow rate (in L/min)
Valence	Subjective experience of pleasantness/unpleasantness	Greater valence values denote a more pleasant subjective experience
Arousal	Subjective experience of wakefulness	Greater arousal values denote a more energized and wakeful subjective experience
Categorical Features		
Feature	**Definition**	**Levels**
Posture	Participant's body posture	standing, sitting, lying
Activity	Participant's primary activity	non-work task, work, leisure, eating, using a computer
Social	Participant's social setting	alone, not alone

Results

Ninety-seven healthy adults were included in the study (ages 18-36 years, M_{age} = 22.6, SD_{age} = 3.6, 57.7% female, 25.8% white, 1.0% black, 62.9% Asian, 10.3% other race). Complete, quality data (i.e., data unaffected by physiological artifacts and with no missing self-reported mental or contextual features) was available for 10,755 total events and the average number of sampled moments for each participant was *M* = 110.9 (*SD* = 28.2, *range* = 69-197). Integrative clustering (using the INTEGRATE approach[35]) was conducted separately on each participant's events, deriving 313 multimodal patterns. The experience sampling events served as the input to INTEGRATE, which returned, for each participant, the number of clusters and the cluster assignments that minimized the cost of coding the events into clusters as measured by the information-theoretic minimum description length[35] (iMDL; i.e., the cost of clustering the data). The number of reliable patterns (i.e., clusters) varied across participants from two to six, with an average of *M* = 3.2 (*SD* = 1.0) patterns per person, and *M* = 34.4 (*SD* = 24.7) events per pattern (**Fig. 1**). One participant had only one pattern, suggesting either that the participant's 77 experience sampling events formed one uniform pattern, or that the participant's events did not cluster together at all (i.e., all events were unique).

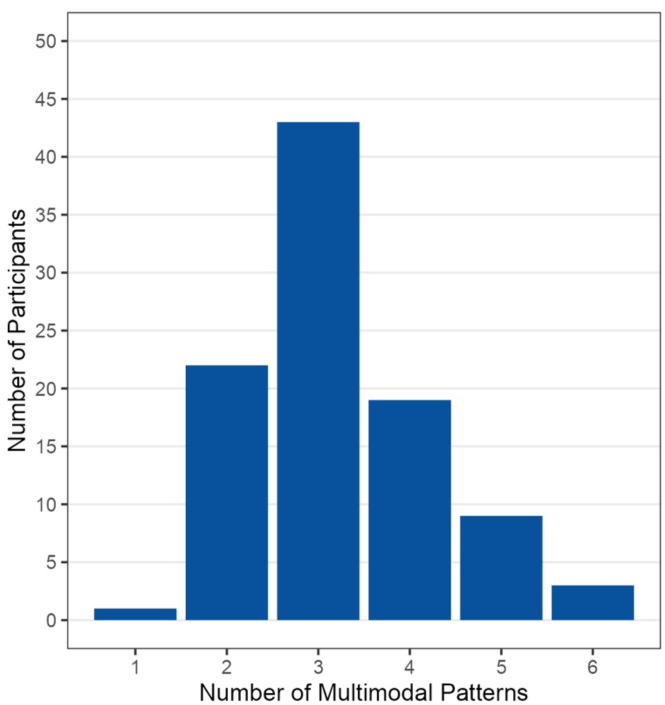

Fig. 1. Between-person variability in the number of multimodal patterns derived from integrative clustering. The average number of patterns per person was *M* = 3.2, *SD* = 1.0. The average number of events per pattern was *M* = 34.4, *SD* = 24.7.

Person-Specific Multimodal Patterns: Few Patterns Recur Across Participants

We examined the nature of all patterns by computing effect sizes for each feature and pattern[4]. For continuous features (i.e., the six cardiovascular and two affective features), effect sizes quantified the extent to which the feature's mean value differed from zero within the pattern (similar to Cohen's *d* for a one-sample *t*-test[39]), thus representing the average magnitude of cardiovascular change from baseline and deviation of affective features from neutral. For categorical features (i.e., posture, primary activity, and social context), effect sizes quantified the frequency of each categorical response within the pattern relative to chance probability, thus capturing the predominance of specific postures (e.g., sitting) and contexts (e.g., leisure, alone). To illustrate an outcome using this method, we present an example participant (Participant #1) in **Fig. 2**. We used the computed effect sizes to determine that one pattern (Pattern A) comprised events that Participant #1 tended to experience as pleasant with moderately high arousal, in a seated position while doing leisure activities in a mixture of social settings, with negligible changes in the cardiovascular features. Another pattern (Pattern B) comprised events that this participant tended to experience as pleasant with moderate arousal, in a seated position while doing leisure activities or using a computer, while alone, and accompanied by an increase in RSA (suggesting increased parasympathetic nervous system activity) and IBI (slower heart rate). A third pattern (Pattern C) comprised events that this participant tended to experience as pleasant with moderate arousal, in a seated position while doing leisure activities in both social and non-social settings, accompanied by an increase in PEP (suggesting reduced sympathetic nervous system activity) along with a decrease in RSA, LVET, SV, and CO on average, but with considerable variation around these mean cardiovascular changes. For additional example participants, see Participant #2 in the lower panel of **Fig. 2** and Participants #3-6 in **Fig. S1.**

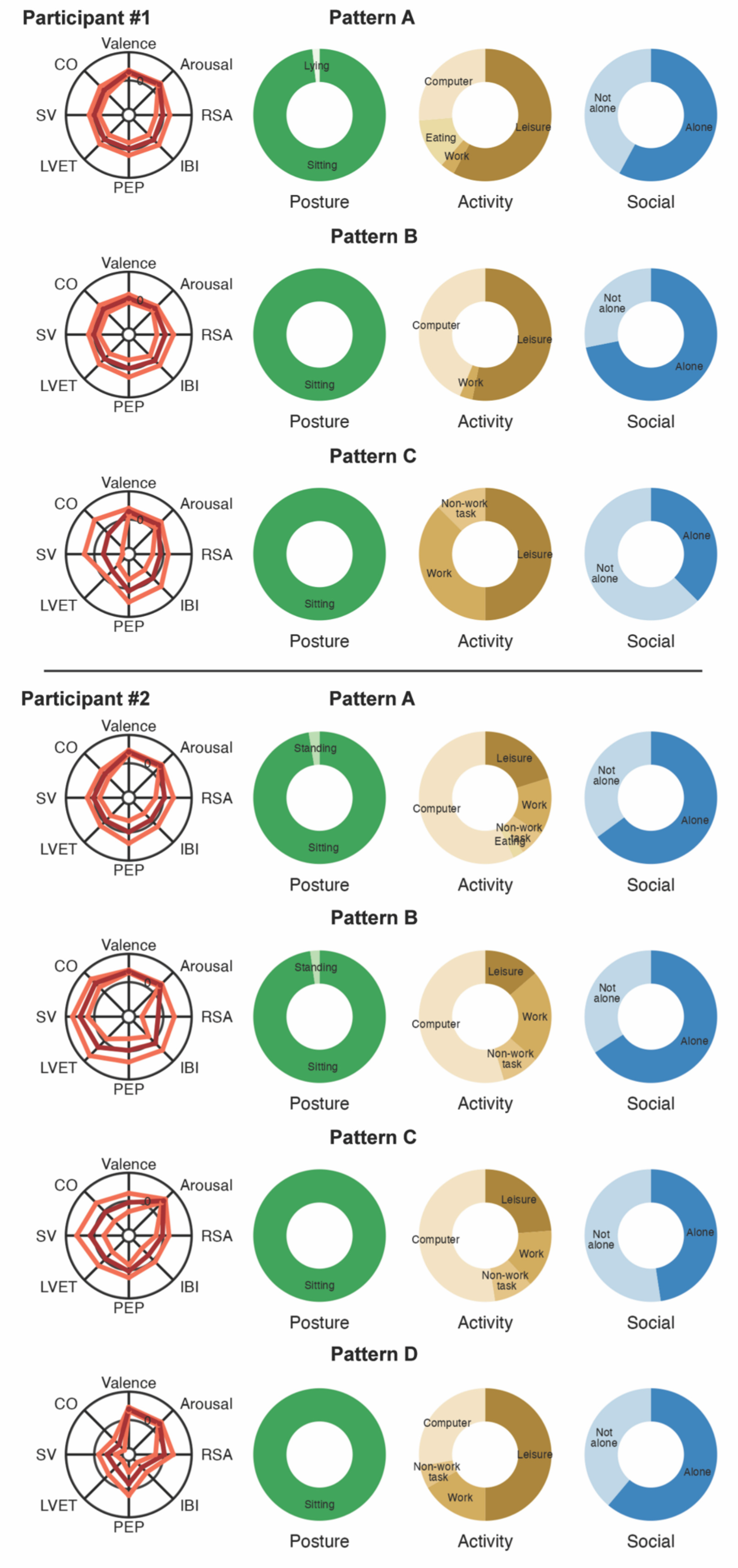
Participant #1
Pattern A
Valence
Arousal
RSA
IBI
PEP
LVET
SV
CO
Lying
Sitting
Posture
Computer
Eating
Work
Leisure
Activity
Not alone
Alone
Social
Pattern B
Sitting
Posture
Computer
Work
Leisure
Activity
Not alone
Alone
Social
Pattern C
Sitting
Posture
Non-work task
Work
Leisure
Activity
Alone
Not alone
Social
Participant #2
Pattern A
Standing
Sitting
Posture
Leisure
Work
Computer
Non-work task
Eating
Activity
Not alone
Alone
Social
Pattern B
Standing
Sitting
Posture
Leisure
Work
Computer
Non-work task
Activity
Not alone
Alone
Social
Pattern C
Sitting
Posture
Leisure
Computer
Work
Non-work task
Activity
Not alone
Alone
Social
Pattern D
Sitting
Posture
Computer
Non-work task
Work
Leisure
Activity
Not alone
Alone
Social

Fig. 2. (previous page) Summaries of multimodal patterns for two example subjects. Cardiovascular and mental features (i.e., valence and arousal), which are continuous, are displayed on radar plots, in which dark red lines represent the within-pattern mean, and light red lines represent the within-pattern standard deviation. The middle (i.e., second largest) ring represent zero. Values toward the center are negative, values toward the outside are positive. The social context, posture, and primary activity, which are categorical, are summarized in donut plots. Section size represents the proportions of within-cluster events.

We compared these characterizations across participants to identify recurrent patterns. The majority of patterns (256 or 81.7% of all patterns) were unique to one participant (i.e., did not recur across multiple participants). Of the patterns that did recur across participants, the most common pattern – pleasant, heightened arousal during seated posture, negligible changes in cardiac activity, during leisure activities, and unrelated to social context – was observed in five participants and accounted for 1.6% of all patterns; **Table 2**). An additional six patterns – also involving some variant of pleasant, heightened arousal during seated posture – were observed in three participants each (together accounting for 5.7% of the observed patterns; see **Table 2** for full descriptions). Seventeen additional patterns were observed in two participants each (together accounting for 10.8% of patterns).

Table 2. Multimodal patterns recurring across more than two participants

RSA	IBI	PEP	LVET	SV	CO	Valence	Arousal	Posture	Activity	Social	Freq.	%
NC	NC	NC	NC	NC	NC	+	+	Sitting	Leisure	Mixed	5	1.6
+	+	+	+	+	+	+	+	Sitting	Mixed	Mixed	3	1.0
NC	+	NC	NC	+	+	+	+	Sitting	Leisure	Not Alone	3	1.0
NC	-	NC	-	-	-	+	+	Sitting	Work	Not Alone	3	1.0
NC	-	-	-	-	-	+	+	Sitting	Leisure	Mixed	3	1.0
NC	NC	NC	NC	NC	NC	+	+	Sitting	Leisure/Work	Mixed	3	1.0
-	-	-	-	-	-	+	+	Sitting	Mixed	Mixed	3	1.0

Note. For valence, arousal, and cardiovascular features, patterns with effect sizes >= .2 are denoted with "+" (i.e., positive valence, high arousal, increase in value of cardiovascular feature), effect sizes <= -.2 with "-" (i.e., negative valence, low arousal, decrease in value of cardiovascular feature), and effect sizes < .2 and > -.2 with "NC" (negligible change). For social, posture, and activity, the proportion of each response (e.g., "not alone") within each pattern was compared to chance probability and z-scored. For each of these categorical features, if a response occurred at a rate significantly greater than chance (p < .05), the pattern is labeled with that response (e.g., "not alone"). If no response occurred at a rate significantly greater than chance, the pattern is labeled "Mixed."

The Features that Distinguish Multimodal Patterns Vary Between People

For each participant, the features that were most important for distinguishing one multimodal pattern from another were identified using Normalized Mutual Information (NMI)[37] and Joint Mutual Information (JMI)[38]. Briefly, NMI quantifies the amount of information the values of a feature (e.g., valence) provide about assignment of events to a pattern when that feature is considered *independently*, while JMI quantifies the information value of a feature when considered *in combination with other features*. For each participant, we considered the distinguishing features to be those with either significant NMI values ($p < .05$, identified via 1,000 permutation tests) or those with the top three ranked JMI values. These distinguishing features varied somewhat across participants, but were most often cardiovascular features (**Table 3**). In particular, CO, SV, LVET, and IBI were distinguishing features for ≥ 81.4% of participants. PEP and activity were distinguishing features for over half of participants (61.9% and 56.7%, respectively), while valence (48.5%), RSA (48.5%), arousal (41.2%), posture (33.0%), and social context (32.0%) were distinguishing features for a smaller proportion of participants.

As predicted, the sets of features that distinguished reliable daily life patterns varied by person (**Table 3**). For example, the set of distinguishing features for Participant #1 (the same as described above) were SV, CO, valence, arousal, and activity, while the important features for Participant #2 (the same as described above) were IBI, LVET, SV, CO, valence, and arousal (**Table 3**). Overall, 47 participants (48.5%) had a unique set of distinguishing features, while 30 (30.9%) shared the same set of distinguishing features with one other person, 12 (12.4%) shared the same set with two other people, and eight (8.2%) shared the same set of distinguishing features with three other people.

Table 3. Between-subject variability in the features that were important for distinguishing multimodal patterns

P	RSA	IBI	PEP	LVET	SV	CO	Valence	Arousal	Posture	Activity	Social	# Patterns
1					NMI**	JMI	NMI**	NMI**		NMI**		3
2		NMI**		NMI**	NMI**	NMI**	NMI**	NMI**				4
3		NMI*		NMI**	NMI**	NMI**					NMI**	2
4	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**		NMI**		NMI**		5
5	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI*			NMI*	NMI**	3
6		NMI**	NMI*	NMI*	NMI**	NMI**	NMI*	NMI**		NMI**		3
7	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**			NMI**	NMI**	NMI*	4
8			NMI**	NMI**	NMI**	NMI**	NMI*		NMI*			3
9		NMI**	JMI	NMI**	NMI**	NMI**				NMI**	NMI*	3
10	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**			NMI**			3

Table 3 (cont'd)

P	RSA	IBI	PEP	LVET	SV	CO	Valence	Arousal	Posture	Activity	Social	# Patterns
11	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI*	NMI**	NMI*	NMI**		5
12	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**						3
13	NMI*		NMI**	NMI*	NMI**	NMI*			NMI**	NMI**		3
14	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**			NMI**		4
15	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**		NMI*	NMI*			3
16	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**		NMI**	NMI**	NMI*	3
17	NMI*	NMI**	NMI*	NMI**	NMI**	NMI**	NMI*		NMI**	NMI**		3
18				JMI	JMI	NMI*	JMI					2
19	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	6
20		NMI**	NMI**	NMI**	NMI**	NMI**		NMI**	NMI**			4
21	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**		NMI**	NMI**		NMI**	5
22	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**			NMI*	NMI*		3
23	NMI*	NMI**		NMI**	NMI**	NMI**	NMI**			NMI*		3
24	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**				NMI**		4
25	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**						2
26	NMI**	NMI**	NMI**	NMI**	JMI	NMI*	NMI*					2
27	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**				NMI*	NMI**	2
28		NMI**	NMI**	NMI**	NMI**	NMI**				NMI**	NMI*	3
29	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	JMI					2
30	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**			NMI**	NMI**	NMI**	4
31						NMI*		NMI**	NMI**	NMI**	NMI**	3
32	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	JMI	NMI*	NMI**			4
33	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**			NMI*	NMI**		5
34	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**		NMI**	NMI**	NMI**	NMI**	6
35	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**				4
36		NMI**	NMI**	NMI**	NMI**	NMI**		NMI**	NMI**	NMI**	NMI**	4
37	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**		4
38			NMI**	NMI**	NMI**	NMI**	NMI**	NMI**		NMI*		3
39		NMI**		NMI**	NMI**	NMI**					NMI*	3
40	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI*	NMI**	NMI**	NMI*		5
41	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**			NMI*	NMI*		3
42	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**			NMI*	NMI**		3
43	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**				4
44	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**		NMI**	NMI**	NMI**		4
45	NMI*		NMI**		NMI**	NMI**	JMI					2
46	NMI**	NMI**		NMI**	NMI**	NMI**			NMI**			4
47	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI*	NMI*	4
48	NMI**		NMI**	NMI**	NMI**			JMI			NMI*	2
49	NMI*	NMI**		NMI*	NMI**	NMI**	NMI*	JMI	NMI*	NMI**		4
50		NMI**	NMI**	NMI**	NMI**	NMI**						3
51	NMI*	NMI**		NMI**	NMI**	NMI**		JMI				2
52		NMI**	NMI*	NMI**	NMI**	NMI**	NMI*					3
53	NMI**	NMI**			NMI**	NMI**	NMI**		NMI**	NMI**	NMI**	4
54		NMI**		NMI**	NMI**	NMI**				NMI**	NMI*	3
55		NMI**		NMI**	NMI**	NMI**	NMI**	NMI**				3
56		NMI**		NMI*	NMI**	NMI**				NMI*		3
57	NMI**		NMI**		NMI*	NMI**	NMI*			NMI*		2
58		NMI**			NMI**	NMI**					NMI*	3
59		NMI**		NMI*	NMI**	NMI**	NMI**	NMI**				3
60		NMI**		NMI**	NMI**	NMI**	NMI**	NMI**		NMI**		4
61	NMI**		NMI**	NMI**	NMI**	NMI*		NMI*	NMI*	NMI**		2
62	NMI**	NMI*		NMI**	NMI**	NMI**			NMI*			2
63		NMI**	NMI**		NMI**	NMI**	NMI*				NMI*	3
64		NMI**	JMI	NMI**	NMI**	NMI**						2

Table 3 (cont'd)

P	RSA	IBI	PEP	LVET	SV	CO	Valence	Arousal	Posture	Activity	Social	# Patterns
65	NMI*		NMI**	NMI**	NMI**	NMI**	NMI**		NMI*	NMI**		4
66	NMI*	NMI**		NMI*	NMI*	NMI**		NMI**				2
67			NMI**	NMI**	NMI**	NMI**				NMI**		2
68		NMI*		NMI**	NMI**	NMI**	NMI*			NMI**	NMI*	4
69		NMI**		NMI**	NMI**	NMI**		JMI				2
70		NMI**	NMI**	NMI**	NMI**	NMI**				NMI**	NMI**	3
71		NMI*	NMI*	NMI**	NMI**	NMI**						2
72		NMI**		NMI**	NMI**	NMI**		NMI**				2
73	NMI**			NMI*	NMI**	NMI**	NMI**					2
74			NMI**	NMI**	NMI**	NMI*	NMI**	NMI**		NMI**		3
75		NMI**		NMI**	NMI**	NMI**	NMI**	NMI**		NMI**	NMI**	5
76		NMI**		NMI**	NMI**	NMI**						3
77		NMI**			NMI**	NMI**	NMI*			NMI*		3
78	JMI	NMI**	NMI**	NMI**	NMI**	NMI**				NMI**		3
79		NMI**		NMI*	NMI**	NMI**	NMI**	NMI**		NMI**		3
80		NMI*		NMI**	NMI**	NMI**	NMI*	NMI*	NMI**			3
81			NMI**	JMI	NMI*	NMI**	NMI*	NMI*				2
82												1
83						NMI*	NMI**	NMI**		NMI**	NMI**	3
84		NMI**	NMI*	NMI**	NMI**	NMI**				NMI**		2
85		NMI**	NMI**	NMI**	NMI**	NMI**			NMI*	NMI**	NMI**	3
86		NMI**	NMI**	NMI**	NMI**	NMI**				NMI**		3
87		NMI**	NMI**	NMI**	NMI**	NMI**						3
88		NMI**		NMI**	NMI**	NMI**				NMI*	NMI*	2
89	NMI*	NMI**		NMI**	NMI**	NMI**				NMI**		4
90		NMI**	NMI**	NMI*	NMI**	NMI**	NMI**	NMI**			NMI**	5
91		NMI**		NMI**	NMI**	NMI**	NMI**	NMI**		NMI*	NMI**	6
92				NMI**	NMI**	NMI**	NMI*			NMI**		3
93		NMI**		NMI**	NMI**	NMI**	NMI**					3
94		NMI**		NMI**	NMI**	NMI**						3
95		NMI**	NMI**	NMI**	NMI**	NMI**	NMI**	NMI**		NMI*	NMI*	5
96	NMI*	NMI**	NMI*	NMI**	NMI**	NMI**	NMI**				NMI*	3
97		NMI**		NMI**	NMI**	NMI**	NMI**	NMI*		NMI*	NMI**	3

*Note. Each row represents an individual participant, with example participants 1-6 corresponding to those displayed in **Figs. 2, 3, S1, and S2**. Features with significant NMI values are indicated (NMI* p < .05; NMI** p < .01), along with any additional features that were among the top three ranked according to JMI. Abbreviations: P = Participant; RSA = respiratory sinus arrhythmia; IBI = interbeat interval; PEP = pre-ejection period; LVET = left ventricular ejection time, SV = stroke volume, CO = cardiac output; NMI = normalized mutual information; JMI = joint mutual information*

Many-to-Many Mappings Between Multimodal Patterns and Emotion Labels

Following our prior work[4], we continued to observe many-to-many mappings between emotion labels and feature patterns both within a participant and across participants. This is illustrated in **Fig. 3**, which displays data from the same two example participants as described above. Participant #1 used 25 different emotion words over the course of the 14-day recording period, and these words mapped to three reliable, multimodal patterns in a many-to-many fashion. For example, Participant #1 used the word “happy” to describe events in each of their three patterns, and they used disparate descriptors such as “happy,” “bored,” “excited,” and “anxious” to describe events in a single pattern (Pattern A). Participant #2 used 38 different emotions words, which similarly mapped to four reliable, multimodal patterns in a many-to-many fashion. Participant #2 used the word “anxious” to describe events in each of their four patterns, and they used disparate words such as “calm,” “excited,” “annoyed,” and “nostalgic” to describe events in a single pattern (Pattern A). This many-to-many mapping was observed across participants (for additional example participants, see Participants #3-6 in **Fig. S2**).

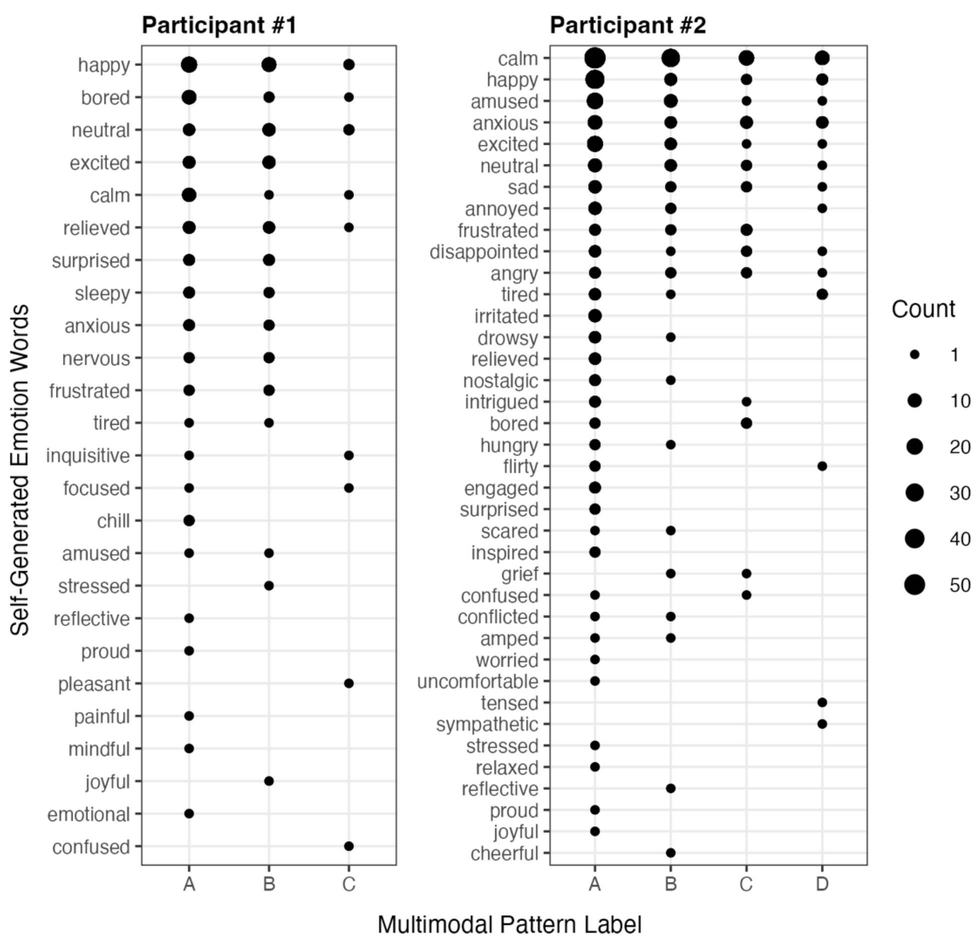

Fig. 3. Within- and between-person variability in the emotion words used to describe each multimodal pattern. Data are presented for two example participants with differing numbers of patterns and emotion words.

Discussion

Here we have demonstrated a comprehensive approach for modeling, rather than constraining, the vast structured variation in human experience. As in prior studies[2–7,40], when we designed our approach to discover structured variation across contexts and individuals, we found it. Our approach fused a powerful sampling tool, called biologically-triggered experience sampling[4,25], with analytic innovations to model person-specific variation in an ensemble of biological, mental, and contextual features as participants navigated the highly variable contexts of daily life. In a large sample of participants (*N*=97), we sampled over 10,000 daily life events and identified, via integrative cluster analyses[35], over 300 multimodal patterns. Results were consistent with three of our four hypotheses: as expected, the number and nature of multimodal patterns of daily life experience varied by person, the features that distinguished these patterns varied by person, and the mapping between self-generated emotion labels and the multimodal patterns was many-to-many. However, contrary to our hypothesis, the contextual features structured the patterns only for some participants. The current study demonstrates the utility of our approach for studying a broad range of psychological phenomena and, within emotion science specifically, provides further evidence that emotions are highly variable across individuals and situated in context[4,6].

In their daily life, each person exhibited relatively unique patterns of biological, mental, and contextual feature ensembles. Patterns also varied within-person, such that each pattern comprised a range of cardiovascular changes, affective experience, social contexts, and activities, with some patterns having greater variation than others. These novel findings align with theories that human experience is highly variable and meaningfully structured at the level of the individual and context[8,9]. Notably, the between-person variation we observed here was greater than in our previous study[4], in which 66% of cardiovascular patterns recurred across two or more people, compared to the 29% of multimodal patterns that recurred in the current study. Between-person variation thus was greater when modeling five additional features (i.e., valence, arousal, posture, social context, and activity) along with the original six cardiovascular features used. Notably, this is a relatively small increase in the number of features that could have been sampled from among a wide array of potentially relevant biological, mental, and contextual features. We propose that between-person variation would continue to increase with further expansion of sampled features, consistent with the hypothesis that, in daily life, each person experiences relatively unique patterns of multimodal signals.

The set of features that distinguished different daily life multimodal patterns also varied by individual. Roughly half of participants had a unique set of features that structured their multimodal patterns (i.e., strongly determined whether an event belonged to one pattern vs. another), while the other half shared their set of important features with one to three other people. Additionally, the cardiovascular features were particularly important in distinguishing most people's multimodal patterns, suggesting that these biological features structured the within-person variation more so than did the mental (i.e., affective) or contextual features. These findings are novel: To our knowledge, no other study has examined the features that structure patterns of daily life experience. These results are consistent with other evidence of the importance of specifying models at the level of the person, which adds explanatory power to models of personality[41,42], of physiological patterns related to experiences such as stress[43–45] and fear[46], and of brain function[47–49]. Person-specific models are critical for the growing movement towards personalized medicine[50,51], precision psychiatry[19], and precision neuroimaging[47,52], premised on the fact that group-aggregate results rarely generalize to the level of the individual[49,53]. In short, empirical approaches that aggregate across people gloss over meaningful variation.

Our comprehensive approach was founded in our philosophical view of the mind[8,54]. In our view, experiences are constructed by a perceiver from a complex ensemble of sensory signals as well as signals that are intrinsic to the brain[8]. These include, for example, sensory signals from the body's visceral organs and musculoskeletal system, as well as signals originating from outside the body and arriving at other sensory surfaces (e.g., light arriving at the retina). The meaning of any one signal is determined by the other signals in the current ensemble[8]. In other words, a perceiver makes meaning of the current signal ensemble in a manner that is *ad hoc* and situated in context. This implies that daily life experience is marked by structured variation in an ensemble of interacting sensory and intrinsic signals. In particular, signals arriving from the visceral organs are likely critical for structuring experience in each moment[8,23], as one of the primary objectives of the brain is to efficiently meet the metabolic needs of the body before they arise, a process called allostasis[55,56].

Applying this theoretical perspective on the mind to the experience of emotion defines emotions as situated and relational concepts that a brain constructs in service of allostasis[8,23,54,57,58]. This contrasts with classical views of emotion, which hold that emotions like fear or joy are *natural kinds*[59,60], or categories of instances that are the same as one another but distinct from instances of other categories[54,61]. Natural kind categories exist in nature regardless of an outside perceiver, for example a human brain[54,61]. The natural kind view of emotion posits that each emotion category has a diagnostic biological fingerprint[4,6]. Real fingerprints (i.e., impressions left on surfaces by the ridges of the pads of the finger) are presumed to be sufficiently unique to distinguish one person from all other people. And although they vary from one instance to the next, real fingerprints are thought to reliably identify a person across instances. Likewise, in the natural kind view, biological fingerprints (e.g., a faster heart rate and sweaty palms) are thought to uniquely and reliably distinguish one emotion category from the next, such that measuring the fingerprint (e.g., via electrocardiography and electrodermal activity) is considered sufficient evidence for the emotion's existence[4,6]. In contrast, in our theoretical view of the mind, emotions like fear or joy are populations of diverse instances constructed by a human perceiver to meet the current moment's allostatic demands[4,6,8,23,58]. Where the natural kinds view assumes variation is trivial, the populations view assumes variation is vast, structured, and meaningful[8].

Results were consistent with the populations view of emotion and with our prior work[4,6]. That is, each person used many emotion labels to describe events in the same multimodal pattern, and used the same emotion label (e.g., happy) to describe events associated with many patterns. This replicated and extended our prior finding of a many-to-many mapping between emotion labels and recurrent patterns of cardiovascular activity[4], and parallels findings from others observing many-to-many mappings between emotion categories and facial muscle movements[62], activity of individual neurons[63], activity of individual brain regions[64,65], activity and connectivity of brain networks[66,67], and distributed patterns of brain activity[68]. Interestingly, here we observed many-to-many relationships despite using the additional affective features of valence and arousal to identify patterns, a new analytic strategy that, in theory, could have increased the specificity and reliability of label-to-pattern mappings. Even in patterns rated in aggregate as pleasant, participants in different instances reported many different emotion labels, including normatively positive (e.g., happy, excited, relieved), neutral (e.g., calm), and negative emotion labels (e.g., anxious, frustrated), accompanied by a spread of valence ratings. Importantly, we observed a many-to-many mapping likely because our approach differed from the typical approach in two key ways. First, the emotion labels were generated by the participant[69] rather than the experimenter. The latter sampling approach, widely used in affective science[62,70,71], is known to artificially constrain variation across individuals including, for example, variation in the emotion labels that individuals ascribe to facial configurations[1,8,34,72,73]. Second, we used unsupervised machine learning (i.e., clustering) algorithms to characterize each person's multimodal patterns in daily life, and then inductively examined the mapping between these patterns and the self-generated emotion labels. This modeling approach placed fewer constraints on emotion label-to-pattern mappings than the typical approach, which employs supervised machine learning (i.e., classification) algorithms to assess these mappings deductively[74–76]. In short, with fewer sampling and modeling constraints, our current approach and prior studies have provided evidence consistent with the view that emotions are populations of instances that vary across individuals and situations.

Our comprehensive approach also has broad utility in multiple psychological domains beyond emotion (e.g., personality[10–12], concepts[13–15], attitudes[16], development[17], psychopathology[18–20], and stress[21]). Indeed, experience sampling (albeit with randomly sampled events) has already proven to be a useful tool for characterizing between- and within-person variation in development (e.g., risk-taking behavior in adolescence[77]), cognition (e.g., attention[78]), and personality (e.g., personality states[42,79]). We will elaborate on the potential utility of our approach in two other domains. First, our approach can help to advance precision psychiatry[19], a movement aimed at overcoming the challenge posed by well-documented and extensive variation between people having the same psychiatric diagnosis (i.e., in terms of symptom profiles[80,81], neurocognitive function[82], and neural correlates[83,84]). Our approach could potentially identify multimodal patterns that predict clinically-relevant events (e.g., substance use relapse) with individual-level precision, a development that could allow clinicians to assess patients and deliver interventions in real-time in the real world (i.e., outside the clinic)[85]. Our approach would extend experience sampling studies of psychiatric samples[86–89,for review, see 90], sampling an expanded ensemble of features and modeling reliable patterns among these features. Second, our approach can help to advance our understanding of how people learn emotion concepts (i.e., learn to differentiate experiences into more granular emotion categories). In fact, in our prior analyses of one cohort from the current study, we observed improvements in predominantly young adults over a three-week span in their emotion granularity (i.e., emotion concept learning)[91]. Future studies might sample children (or adolescents) to probe, for example, how caregivers' use of emotional language scaffolds a child's ability to map multimodal feature ensembles to emotion concepts, and how children learn to abstract away from the details of these feature ensembles to foreground the emotion's goal-oriented function in the current situation[92]. Probing emotion concept learning in this way may also have implications for precision psychiatry, because having more granular emotion concepts facilitates psychological and social well-being[for review, see 93].

The main strength of the current study is its fusing of a powerful sampling tool (biologically-triggered experience sampling) with a novel modeling strategy[25]. Although a growing number of studies have implemented biologically-triggered experience sampling[4,28–31], no study to date has examined the broad ensemble of features measured here or used our comprehensive modeling approach. The modeling approach took advantage of integrative clustering methods[35] to identify multimodal patterns from variables measured either continuously or categorically with equal initial weighting of each feature in determining the clustering outcome. Indeed, both categorical and continuous features determined the clustering outcome for a majority of participants. The modeling approach also took advantage of information-theoretic metrics to identify the features that, either individually or in concert with other features, were most important for delineating the multimodal feature ensembles into reliable patterns. Importantly, modeling was performed at the level of the individual, allowing for comparison within individuals across situations as well as between individuals. Future studies may improve on this method by considering the time series structure of the physiological features - as opposed to (or in addition to) the summary statistics used in the current study. This can allow for capturing patterns in the dynamics of the physiological features during experience sampling. Advances in modern machine learning methods, including the emergence of foundation models (i.e., models that are pretrained through self-supervision to recognize complex and potentially non-linear patterns among features), can enable such a future study[94] - although these models generally require large amount of data and are still in their infancy in their use with physiological data[95].

The current study also had several limitations. First, the integrative clustering approach assigned each event to exactly one pattern, in contrast to our prior work which assigned events to each possible pattern probabilistically[4], a method which better reflects that daily life events share probabilistically similarities. Second, although we sampled a broad ensemble of multimodal features, we did not sample a wide array of other biological, mental, and contextual features that could have been relevant to emotional experience. For example, sampling participants' goals and appraisals[8] or additional biological features (e.g., measures from the lungs or gut) at each daily life event could potentially alter the nature of the recurrent patterns as well as the mapping between these patterns and emotional instances. Third, because participants reported their affective experience and contextual features only at discrete events, our experience sampling data contained "blind spots" between measurements[96]. In future studies, coupling this in-the-moment sampling approach with an approach that enables participants to retrospectively report fluctuations[96] in their affective and contextual features that occur between events would allow experimenters to sample features more continuously throughout the day. We predict that this more continuous sampling approach would reveal additional multimodal patterns of daily life experience for each person and may reveal patterns that recur more frequently across individuals than observed here.

In sum, instantiating the many psychological theories that emphasize the personalized and situated nature of human experience will require new empirical approaches that sample and model this variation. Our approach, broadly applicable and ecologically valid, accomplishes this by sampling experience 'in the wild'. The current study served as a proof-of-concept for this approach and provided further evidence that, when theoretical assumptions that are typically embedded within study design are lifted[8], emotions appear not as natural kinds but as diverse populations.

Methods

Participants

Two cohorts of participants from the greater Boston area were enrolled in the study. Cohort 1 consisted of N=67 participants (ages 18-36 years, M_{age}=22.8 years, SD_{age}=4.4 years, 55% female, 38.8% white, 3.0% black, 46.3% Asian, 11.9% other race) who enrolled and participated in the study between August 2017 and March 2019. This cohort has been described in prior studies[4,69,91,97,98]. Cohort 2 consisted of N=89 participants (ages 18-37 years, M_{age}=23.1 years, SD_{age}=3.1 years, 55% female, 9.0% white, 4.5% black, 77.5% Asian, 9.0% other race) who enrolled and participated in the study between October 2021 and September 2023. Participants in each cohort were recruited through verbal announcements in Northeastern University classrooms, online portals, and fliers distributed on and near the Northeastern University campus. Eligible participants were non-smoking, fluent English speakers without history of cardiovascular illness or stroke, chronic medical conditions, mental illness, asthma, skin allergies, or sensitive skin. Eligible participants were not taking medications known to influence physiological arousal, including medications for ADHD, insomnia, anxiety, hypertension, rheumatoid arthritis, epilepsy/seizures, cold, flu, fever, or allergies. Additionally, participants in Cohort 2 were required to have received at least one vaccine against COVID-19.

All participants provided written informed consent prior to the study. Participants were compensated for their time (see supplementary information for full details). Specifically, participants in Cohort 1 received $490 and participants in Cohort 2 received $495 for completing all portions of the study. Participants in both cohorts could also receive up to $55 in additional compliance and task incentives.

Twenty-two participants in Cohort 1 were excluded from analysis: six withdrew, nine were dismissed from the study due to poor compliance, six were excluded for having usable physiological data for < 68 events, and one was excluded for reporting contextual information for < 68 events. Thirty-seven participants in Cohort 2 were excluded from analysis: twenty withdrew, ten were dismissed from the study due to poor compliance, five were excluded for having usable physiological data for < 68 events, and two were excluded for reporting contextual information for < 68 events. Thus, the final combined sample consisted of N=97 participants (Cohort 1: n=45, ages 18-36 years, M_{age} = 22.4 years, SD_{age} = 4.3 years, 51.1% female, 44.4% white, 0.0% black, 40.0% Asian, 15.6% other race; Cohort 2: n=52, ages 18-29 years, M_{age} = 22.9 years, SD_{age} = 2.9 years, 63.5% female, 9.6% white, 1.9% black, 82.7% Asian, 5.8% other race).

Procedure Overview

Each participant completed approximately 14 days (Cohort 1: *M* = 14.4 days, *SD* = 0.6 days; Cohort 2: *M* = 13.9 days, *SD* = 0.4 days) of biologically-triggered experience sampling across a three- to four-week period (Cohort 1: *M* = 24.9 days, *SD* = 5.5 days; Cohort 2: *M* = 23.9 days, *SD* = 5.4 days). In the morning of each experience sampling day, experimenters in the lab fitted participants with the physiological recording equipment. Experimenters also provided the participant with a Motorola Moto G smartphone with a custom application, MESA (MindWare Technologies LTD, Westerville, OH). The application monitored data from the physiological recording equipment and prompted the participant to answer experience sampling questions after a defined physiological change in interbeat interval (see details below). Participants completed approximately 8 hours of experience sampling each day and responded to at least 68 experience sampling prompts in total to be included in the final dataset (Cohort 1: *M* = 124.9, *SD* = 20.5; Cohort 2: M = 146.8, SD = 40.8). This heuristic threshold of 68 prompts was selected to optimize the ratio of data points to parameters estimated in INTEGRATE while also retaining participants, following our prior work[4].

Physiological measurement. Ambulatory cardiovascular measures – electrocardiography (ECG) and impedance cardiography (ICG) – were recorded at 500 Hz on a mobile impedance cardiograph (MindWare Technologies LTD, model # 50-2,303-02S, Westerville, OH). Pre-gelled ConMed (Westborough, MA) Cleartrace Ag/AgCl electrodes were placed at seven sites and connected via wires to the impedance cardiograph. Electrode sites were cleaned with alcohol and lightly abraded with gauze. ECG electrodes were placed in a modified lead II configuration on the distal right collarbone and an inferior left rib, and a reference electrode was placed on an inferior right rib. The ECG signal was acquired with a bandpass filter of 0.5-45 Hz. ICG electrodes were placed in a four-spot electrode configuration.

Two recording electrodes were placed on the front of the torso, one at the base of the neck at the top of the sternum and one at the bottom of the sternum over the xiphisternal junction. The distance between recording electrodes was measured each day of experience sampling. Two source electrodes were placed on the back of the torso along the midline approximately 4 cm above and below the respective recording electrodes. Source electrodes passed a 4 mA, 100 kHz alternating current across the thorax. Basal impedance (Z_0) was acquired with a high-pass filter of 10 Hz, and its first derivative (dZ/dt) was acquired with a bandpass filter of 0.5-45 Hz.

Changes in posture were measured via inertial measurement units (IMUs). The IMU manufacturer differed between cohorts (Cohort 1: LP-Research, Minato-ky, Tokyo, Japan; Cohort 2: XSENS, Enschede, Netherlands). One IMU was placed on the mid-sternum beneath the top recording ICG electrode, attached to the skin with a double-sided adhesive patch. The second IMU was placed on the front of the thigh, either attached to the skin with a double-sided adhesive patch or in a cloth holder attached to the clothing. Participants wore the IMUs until the end of each experience sampling day unless otherwise instructed by the experimenters (e.g., due to issues synchronizing with the MESA smartphone application).

Biologically-triggered experience sampling. Cardiovascular and accelerometric data were recorded continuously for 8 hours per day and relayed via Bluetooth to the MESA app. In real time, MESA processed the ECG and accelerometer data and triggered an experience sampling prompt when a substantial and sustained (i.e., over an 8 s period) change in heart rate was detected in the absence of motion and at least 30 s had passed since a change in posture. A minimum interval of five minutes was imposed between prompts. Experimenters set a threshold to operationalize ‘substantial changes in heart rate’ on the first experience sampling day and adjusted this threshold on subsequent days to ensure participants received approximately 20 prompts per day. The process for selecting initial thresholds differed by cohort. In Cohort 1, the initial threshold was determined from pilot data and was the same for each participant, such that MESA triggered an experience sampling prompt when the interbeat interval (IBI) changed by more than ± 167 ms for an 8 s period. In Cohort 2, we used data from Cohort 1 to develop a regression model predicting an individualized threshold from the participant's height, weight, and mean baseline IBI. Thus, in Cohort 2 we submitted each participant's information to the regression model to derive initial thresholds that were person-specific (*M* = ± 132.1 ms, *SD* = 13.6 ms). Smaller threshold adjustments were made in Cohort 2 (Cohort 1: *M* = 26.2 ms, *SD* = 25.9 ms; Cohort 2: *M* = 10.9 ms, *SD* = 7.9 ms), and the two cohorts had similar ranges of final thresholds (Cohort 1: ± 65 ms to ± 266 ms; Cohort 2: ± 66 ms to ± 200 ms). The absence of motion was determined from the continuous accelerometer data from the mobile impedance cardiograph (i.e., when none of the three accelerometry channels exceeded 10 cm/s^2 in the preceding 30 s). Posture change was detected from the two IMUs (i.e., when the relative orientation of the two IMUs did not change in the preceding 30 s). To minimize the extent to which participants attended to their heart activity, MESA also generated two random prompts per day that occurred in the absence of motion but were unrelated to heart activity, though participants were told that random prompts would account for half. Random prompts were spread throughout the day, one in the first four hours and one in the second four hours of experience sampling.

As intended, participants received approximately 20 prompts per day (Cohort 1: *M* = 21.7, *SD* = 10.5; Cohort 2: *M* = 25.6, *SD* = 12.3). Participants were incentivized to respond to prompts throughout the two-week period, earning $10 extra for responding to ≥ 40 total prompts in days 1-5, $10 for ≥ 40 prompts in days 6-10, and $10 for ≥ 32 prompts in days 11-14. To remain in the study, participants were required to respond to at least 3 prompts each day. The participants included in the present analyses completed approximately 9 prompts per day (Cohort 1: *M* = 8.7, *SD* = 3.2; Cohort 2: *M* = 10.6, *SD* = 4.8). Prompts were relatively evenly distributed throughout the day, with participants completing prompts in the morning (before 12 pm; Cohort 1: 34% of prompts; Cohort 2: 27% of prompts), afternoon (12-5 pm; Cohort 1: 52%; Cohort 2: 58%), and evening (after 5 pm; Cohort 1: 14%; Cohort 2: 15%).

For each experience sampling event, participants were prompted to respond to a series of questions in the MESA application (see full details in supplementary materials). First, participants rated their current valence and arousal on sliding scales with three anchor points (valence: “very unpleasant,” “neither,” “very pleasant;” arousal: “very deactivated,” “neither,” “very activated”). The sliding scales were quantified as 100-point scales from -50 to 50, and the numerical value of the slider’s position was displayed onscreen. Participants also indicated in an open-ended response who was currently around them, including remotely via phone, text, or video call. Participants were instructed to indicate whether they were alone or in a group, along with the initials of their current companions. Then, participants indicated their current, primary activity from a dropdown menu of provided items (**Table S1**) or selected “other” and provided an open-ended response. Lastly, participants reported in an open-ended response the emotions they were feeling at the time of the prompt ($M = 1.4$, $SD = 0.7$ emotion words provided per event).

Electrocardiogram (ECG) Signal Processing

The ECG signal was processed following our previous study[4] using our published software[99]. The raw ECG signal was passed through an elliptic bandpass filter to remove baseline and high frequency noise. Next, an automated tool inspected the quality of the waveform shape and the minimum, maximum, and minimum-to-maximum values at each heartbeat. R-peak detection was performed in the BioSPPy software package[100] using established methods[101]. We then derived IBI from the average R-R interval in 30 s windows. An automated procedure checked the IBI time series to ensure that values were within acceptable ranges (300-2000ms) and that beat-to-beat differences were unlikely to be artifacts according to published work[102]. From the IBI time series we derived respiratory sinus arrhythmia (RSA), which reflects high-frequency variability in IBI and is often used to estimate parasympathetic nervous system activity[103]. To calculate RSA, the IBI time series underwent cubic interpolation, detrending to minimize non-stationarity, tapering using a Hamming window, and finally fast

Fourier transform. RSA was calculated as the natural log under the 0.12-0.4 Hz range of the power spectrogram. We excluded ECG data that failed any quality check from analysis.

Impedance Cardiogram (ICG) Signal Processing

The ICG signal was also processed following our previous work[4,99,104]. The first derivative of the basal impedance (i.e., dZ/dt) was segmented into time windows from 250 ms before the R-peak to 500 ms after. Overlapping ensembles were formed by averaging eight segments (corresponding to eight beats) together[99]. In each 8-beat ensemble, the B point was detected by comparing the first and second derivatives of the dZ/dt signal to thresholds based on signal frequency (**Table S2**)[104]. All B points were subjected to forward and reverse autoregressive modeling for outlier detection and correction. In each ensemble, the X point was detected from the second derivative of the dZ/dt signal[99]. Segments with undetectable B or X points were excluded from analyses.

We derived four additional cardiovascular features from the ECG and ICG signals. Two features were systolic time intervals: pre-ejection period (PEP) and left ventricular ejection time (LVET). PEP represents the interval from the electrical event that initiates ventricular contraction to the opening of the aortic valve, and serves as an estimate of sympathetic control of the heart[105,106]. We calculated PEP as the time in ms between the ECG R-peak and the ICG B point (also known as PEP_R)[107]. LVET is the interval between the opening and closing of the aortic valve[108]. We calculated LVET as the time in ms between the ICG B and X point. We performed quality checks and retained values within acceptable ranges (PEP: 30-200 ms; LVET: 100-500 ms) and that did not produce gradient changes > 30 ms from one ensemble to the next. The remaining two cardiovascular features were hemodynamic measures: stroke volume (SV) and cardiac output (CO). Stroke volume is the blood volume in mL ejected by the heart with each beat, which we calculated using Kubicek's equation[109]. CO is the systemic blood volume circulated in L/min[108], and calculated as SV times heart rate (in beats/min).

Cardiovascular and Postural Feature Extraction

For each of the six cardiovascular features (IBI, RSA, PEP, LVET, SV and CO), a single change score was extracted from each experience sampling event. Change scores were computed as the difference in cardiovascular activity between the 30 s before the IBI change that triggered the experience sampling prompt and the 30 s following. The resulting change scores were standardized and submitted as features to the integrative clustering analyses. Outlier CO values were detected for three participants (10 total events, 3.3 events/person) based on Cook's Distance[110], and these events were excluded from analysis. Distributions of mean within-subject cardiovascular change scores are displayed in **Fig. S3**. In addition, posture was extracted from each experience sampling event by comparing the orientation of the two IMUs before the prompt. Posture was submitted as a feature to the integrative clustering analyses as a variable with three categories (standing, sitting, lying). The distributions of within-subject percent of events recorded in each posture category are displayed in **Fig. S4**.

Coding Self-Report Affective and Contextual Features and Emotion Labels

Ratings of valence and arousal for each experience sampling event were standardized and submitted as continuous features to the integrative clustering analyses. Distributions of mean within-subject valence and arousal ratings are displayed in **Fig. S5**.

Participants' responses about their current, predominant activity were coded into five categories: non-work tasks, work, leisure, eating, and using computer. 'Non-work tasks' were necessary, obligatory, or directed tasks that were unlikely to be paid or primary work; 'work' activities were tasks related to paid or school work; 'leisure' included activities that were extracurricular, not obligated, or low energy; 'eating' activities involved eating or drinking but not preparing or waiting for food; and 'using computer' was coded for events with specific reference to using a computer. Activity labels from the dropdown menu were coded into one of the five categories (**Table S1**). Additionally, the open-ended "other" activity responses were coded by one pair of independent raters per cohort (mean Cohen's Kappa = .75). Discrepancies between raters were resolved by a third rater or through discussion between the authors. Activity was submitted as a feature with 5 categories to the integrative clustering analyses. Distributions of within-subject percent of events reported for each activity category are displayed in **Fig. S6**.

Current social context was coded from participants' open-ended responses as a dichotomous variable (alone, not alone). Responses were coded as 'alone' if the participant indicated they were alone, or specifically indicated they were not interacting with another person. In contrast, responses were coded as 'not alone' if the participant indicated they were in a group, gave the initials of one or more persons, or specifically stated they were interacting with another person. Two independent raters coded responses other than 'group' or 'alone' into the two categories (Cohen's Kappa = .70). Discrepancies were resolved by a third rater. Social context was submitted as a binary feature to the integrative clustering analyses. Distributions of within-subject percent of events reported for each social context category are displayed in **Fig. S7**.

Self-generated (free report) emotion labels were cleaned by two authors under the supervision of four authors. Cleaning involved changing all responses to lower case, standardizing punctuation, separating multiple entries into individual emotion labels, correcting clear spelling errors, harmonizing words in different tenses to fit the statement "I am feeling" (e.g., changing "stressing" to "stressed"), and removing intensity descriptors (e.g., changing "little tired" to "tired"), extraneous words (e.g., changing "feeling impatient" to "impatient"), and modifiers (e.g., changing "happy-ish" to "happy"). Additionally, unintelligible words (e.g., "X" or non-words), responses that referenced other events (e.g., "happier than before"), and responses with spelling errors that compromised their intelligibility were excluded from analysis.

Data Analysis

Integrative clustering. Eight continuous and three categorical features of individual experience sampling events were submitted to integrative clustering for each participant separately. In this way, we identified patterns of experience for each participant. We derived multimodal patterns using INTEGRATE, a clustering method that can handle mixed data sets including both continuous and categorical features[35]. INTEGRATE aims to code the data into *k* clusters, where each cluster is represented by (1) a normal Gaussian probability density function in *n* dimensions (*n* = number of continuous variables) and (2) a probability for each level of each categorical variable. The mean of the Gaussian function for the continuous variables and the probability vectors for each categorical variable together are the representative pattern for that cluster. INTEGRATE determines an optimal clustering solution in which each data point (i.e., each experience sampling event) belongs to exactly one cluster by minimizing the cost of coding data into clusters, where the cost function is the iMDL. This approach chooses the optimal clustering solution that results in the least number of bits required to represent the data for a given value of k. iMDL consists of a sum of three terms: coding cost (i.e., measuring how well the clusters fit the data), parameter costs (i.e., the cost of storing all parameters for each cluster), and identification costs (i.e., the cost of specifying cluster memberships). The first term can be viewed as a model fit term, while the other two terms are penalty terms that discourage complex models with too many clusters. Therefore, INTEGRATE selects the optimal 'k'. For this purpose, the method is repeated over a range of 'k' values, and the value that results in the minimum coding cost is considered optimal[35]. Here, we performed the clustering for k=1 to k=10 and chose the k that resulted in the minimum cost. Values beyond k=10 were not needed, as in each participant's case the iMDL cost at k=10 was significantly higher than the minimum already and any higher values of k would result in an even higher cost (i.e., as k increases, the models become more complex and thus incur higher penalties that are not offset by the model fit; **Fig. S8**).

Estimation of feature importance. For each participant, we assessed the importance of each feature in determining the participant's clustering solution using a combination of Normalized Mutual Information (NMI)[37] and Joint Mutual Information (JMI)[38]. NMI quantifies the amount of information that the values of each feature provide about the cluster assignments when the feature is considered *independently* of the other features. We used permutation testing to determine significant NMI values. We randomly shuffled cluster labels 1,000 times and calculated the NMI between the features and the randomly shuffled labels for each repetition. For each feature, we then calculated the proportion of times the NMI value with the optimally derived cluster labels was greater than the NMI value with randomly shuffled labels. A proportion greater than 95% corresponded to $p < .05$, and a proportion greater than 99% corresponded to $p < .01$ for each feature.

We supplemented this analysis using JMI. In contrast to NMI, JMI quantifies the amount of information that each feature provides about the cluster to which an event belongs when the feature is considered *in combination with other features*. Thus, we used JMI to identify features that did not significantly explain cluster membership on their own but interacted with other features to explain cluster membership. Specifically, we ranked the features by JMI value and identified the three most important features. In **Table 3**, the top three ranked JMI features are labeled JMI if the feature's NMI values were non-significant. We examined the importance of individual features, as well as the frequency with which participants displayed the same set of important features (e.g., the number of participants whose important features were exactly CO, SV, and valence) as determined by either NMI or JMI.

Effect size estimates. We sought to characterize the nature of each pattern and to identify recurrent patterns of features across people. To this end, we computed cluster-wise effect sizes for each feature[4]. For the continuous features, we computed effect sizes (similar to Cohen's *d*[39]) by dividing the mean change score by the standard deviation, following our prior work[4]. We classified effect sizes of continuous features based on published recommendations[111]. Cardiovascular feature effect sizes were classified as "negligible change" ($|d| < 0.2$; i.e., values near zero), "decrease" ($d \leq -0.2$), or "increase" ($d \geq 0.2$). Valence was classified as "neutral" ($|d| < 0.2$), "negative" ($d \leq -0.2$), or "positive" ($d \geq 0.2$), and arousal was classified as "neutral" ($|d| < 0.2$), "deactivated" ($d \leq -0.2$), or "activated" ($d \geq 0.2$).

Effect sizes for the categorical features were computed by comparing the proportion of each categorical level (e.g., leisure) within each cluster to chance probability, then transforming to z-score. For each feature (e.g., activity), clusters with one category occurring at a rate significantly greater than chance ($p < .05$) were assigned the categorical label (e.g., leisure), while clusters with more than one significant category were assigned multiple categorical labels (e.g., leisure/work). If no category of a feature occurred at a rate significantly greater than chance, the cluster was labeled “mixed.”

Preregistration

Preregistration was published for Cohort 1 on April 19, 2018 (https://doi.org/10.17605/OSF.IO/E7QNX) and for Cohort 2 on August 16th, 2023 (https://doi.org/10.17605/OSF.IO/HZ5R9).

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