A Network Analytic Approach to Measuring Emotional Granularity

Katie Hoemann¹, Miaolin Fan¹, Haakon Engen², Chun-An Chou¹, Karen S. Quigley^{1,3}, Maria Gendron^{4*}, & Lisa Feldman Barrett^{1,5*}

1. Northeastern University
2. University of Oslo
3. Edith Nourse Rogers Memorial Hospital
4. Yale University
5. Massachusetts General Hospital/Martinos Center for Biomedical Imaging

* Indicates shared senior authorship

Abstract

Emotional granularity describes an individual's ability to create instances of emotion that are diverse and context-specific. Considerable evidence suggests that higher emotional granularity is a protective factor for mental and physical well-being. In the present study, we examined emotional granularity using a network analytic approach that produced multi-dimensional, time-varying measures. Individuals with higher granularity exhibited person-specific emotion networks that were less dense, comprised of a greater number of communities of emotions, and organized by a greater diversity of connections. Individuals with higher granularity also exhibited greater network change over time. Network measures of emotional granularity predicted self-reported anxiety and depression, even when controlling for other variables known to be associated with mood symptoms, such as self-reported alexithymia and emotional reactivity. Taken together, these findings serve as a proof-of-concept demonstration of the efficiency of network analysis for describing the dynamic structure of emotional experience.

Keywords: emotion differentiation, graph theory, network analysis, individual differences

Emotional granularity describes an individual's ability to create instances of emotion that are diverse and context-specific (Barrett, 2017a; Tugade et al., 2004). In the scientific literature, the phenomenon of emotional granularity is also referred to as "emotion differentiation" (e.g., Barrett et al., 2001; Erbas et al., 2013; Kashdan et al., 2015). As a psychological construct, emotional granularity has been hypothesized to refer to the number of emotion categories an individual's brain can create, as well as greater situated variation in the instances belonging to those categories (Barrett, 2017a; Hoemann & Barrett, 2018). For example, for individuals whose emotional experiences are characterized as lower in granularity, instances of anger may share many features in common and therefore may be less distinct from instances of sadness, such that the words "angry" and "sad" function as synonyms for 'unpleasant'. Individuals whose emotional experiences are characterized as higher in granularity construct more precise categories that are tailored to specific situations, such that "angry" and "sad" refer to distinct emotion categories whose instances may not share as many features, and the instances within an emotion category also vary in their features in a way that is more tailored to the situation (e.g., the person may experience pleasant and unpleasant instances of anger or sadness).

Considerable evidence suggests that higher emotional granularity is a protective factor for mental and physical well-being (evidence reviewed in Barrett, 2017a; Kashdan et al., 2015). For example, when compared to individuals with lower emotional granularity, those with higher emotional granularity report less frequent and intense symptoms of anxiety (Mennin et al., 2005; Seah et al., 2020) and depression (Erbas et al., 2014, 2018; Starr et al., 2017; Willroth et al., 2019). They have better self-regulation (Barrett et al., 2001; Kalokerinos et al., 2019) and more effective coping behaviors (e.g., they report less alcohol consumption (Kashdan et al., 2010), fewer urges to binge eat (Dixon-Gordon et al., 2014) or physically aggress (Pond et al., 2012), and lower incidence of drug relapse (Anand et al., 2017)). Individuals with higher granularity also report increased mindfulness (Van der Gucht et al., 2019) and better self-esteem (Erbas et al., 2018), and have fewer cancer-related follow-up medical visits (e.g., Stanton et al., 2002).

Emotional granularity is most commonly measured using data from experience sampling studies, in which participants rate the intensity of their momentary experiences using experimenter-provided terms (e.g., "angry", "sad", "calm", "excited"). Participants are prompted to report their experiences multiple time per day, across multiple days, and emotional granularity is assessed as the extent of shared information across ratings of emotion terms using within-person correlations – the most common being the intraclass correlation (ICC; Tugade et al., 2004). ICCs represent the degree to which different emotion terms such as "anger" and "sadness" were rated consistently across sampling instances. Higher consistency or agreement (ICC value near 1) indicates that the ratings had little unique variance, and is interpreted as reflecting lower emotional granularity (e.g., if "anger" and "sadness" were used as synonyms when rating emotional experience). Lower consistency or agreement (ICC value near 0) indicated that the ratings had more unique variance and was interpreted as evidence of higher emotional granularity (e.g., if "anger" and "sadness" were used distinctly when rating emotional experience). Often, separate ICCs are computed for pleasant versus unpleasant emotion categories, producing aggregate estimates that represented how often each individual co-endorsed emotion terms that are stereotypically similar in valence. By using momentary ratings to create implicit, behavioral measures of how individuals report experiencing their emotions, this approach overcomes issues associated with the fidelity of explicit, trait-level and retrospective self-report measures (Barrett, 2004; Robinson & Clore, 2002), and in principle

allows for changes in emotional granularity to be tracked more accurately over time (e.g., Erbas et al., 2018).

Conceptually, emotional granularity reflects the precision and complexity with which the brain creates instances of emotion, with the understanding that these qualities vary based on situation-specific needs and relevant features of emotion categories (Barrett, 2017b). However, assessing emotional granularity via within-person correlational (i.e., ICC-based) approaches produces only a single estimate for each individual and therefore does not make it possible to capture intra-individual fluctuations nor different dimensions of emotional granularity such as the information shared between different pairs or groups of emotion terms (but see Erbas et al., 2019; Willroth et al., 2020).

In the present investigation, we addressed these needs by estimating emotional granularity using measures provided by network analysis (Boccaletti et al., 2006). A network is a graph that consists of nodes (i.e., connection points), which represent the objects of analysis (e.g., emotion terms), and edges (i.e., links), which represent pairwise relations between these objects (Barrat et al., 2004). Networks are well-suited to measuring emotional granularity because they are high-dimensional and can be characterized using multiple measures. Data can also be modeled dynamically, evidencing changes in network structure over time. Visualization provides further insight into network structure, as nodes with stronger connections can be plotted closer together, evidencing group-level relationships. Using experience sampling data to generate person-specific (i.e., idiographic) networks, we estimated the number of distinct emotion categories, the complex relationships between these categories, and changes in these over time that captured each participant's momentary ratings of emotional experience. We also visualized and descriptively analyzed a subset of networks. Our approach builds on recent work using networks to derive insights into the semantic lexicon for emotion (Toivonen et al., 2012), experience of emotion in everyday life (e.g., Moeller et al., 2018; Trampe et al., 2015), and features of psychological phenomena (e.g., Bringmann et al., 2013; Epskamp et al., 2017; Lange et al., 2020).

We constructed networks for participants in two experience sampling studies, using the experimenter-provided emotion terms as nodes. We estimated the relationships between rated emotion terms using pairwise Pearson correlations (e.g., Barrett, 1998; Demiralp et al., 2012). Networks constructed in this manner (e.g., Trampe et al., 2015) reveal general trends in the co-occurrence of emotions. For example, if an individual routinely experienced instances of emotion that they described equivalently as “anger” and “sadness” (and correspondingly they described the absence of “anger” as the absence of “sadness” and vice versa), then the nodes for these emotion terms would have a strong, positive, close connection in the network. Conversely, if an individual almost never experienced instances of emotion that they described equivalently as “anger” and “calm”, then the nodes for these emotion terms would have a weaker, negative, distanced connection in the network. In this way, the structure of the network reflected the number and content of emotion categories evidenced by each individual's ratings.

We examined emotion networks in two ways. First, we examined individuals' *overall* emotion networks, constructed using data from all experience sampling instances. In Figure 2, we present example networks to demonstrate the variety in structures of emotional experience. Second, we examined individuals' *time-varying* networks, constructed using data from a subset of experience sampling instances selected using three-day overlapping sliding windows, such that window 1 represented time points for days 1, 2, and 3, window 2 included time points for days 2, 3, and 4, window 3 included days 3, 4, and 5, and so on. These time-varying networks

described dynamic relationships between emotion categories by modeling changes in network structure over time. For example, an individual may exhibit a network consistent with higher emotional granularity in window 1, moderate granularity in window 2, and lower granularity in window 3. Emotion networks can be quantified using a variety of network measures (see Table 1). Because time-varying analyses generated multiple, window-level networks per individual, we were able to estimate the average network structure over time (i.e., the means of specific network measures) as well as the variation or change in network structure over time (i.e., the standard deviations of network measures).

Table 1. Network Measures for Emotional Granularity

Measure	Definition
Clustering coefficient	The mean fraction of nodes' neighbors (i.e., connected nodes) that are neighbors of each other (Onnela et al., 2005)
Density	The mean connection weight across the network (Barrat et al., 2004)
Number of communities	The number of non-overlapping groups of nodes (i.e., communities), such that nodes are more strongly connected to each other than to nodes in other groups (Rubinov & Sporns, 2011)
Diversity coefficients (positive and negative)	The mean diversity of nodes' connections across communities; measured separately for positively- vs. negatively-weighted connections (Rubinov & Sporns, 2011)
Community radius	The mean radius of a network's communities, computed based on the Euclidean distances between nodes (Lohse et al., 2014) according to their normative valence and arousal ratings (Warriner et al., 2013)
Valence focus	The fit of a two-community structure based on normative valence ratings (i.e., nodes are assigned to either a 'pleasant' or 'unpleasant' community)

To examine the interdependencies between variables as a way of reducing the number available for hypothesis testing, we subjected each set of emotion network measures (mean estimates and standard deviation estimates) to a separate exploratory factor analysis (EFA; Osborne & Costello, 2005), also including the typical measure of emotional granularity, the ICC. The resulting 'granularity factors' were then entered into multiple regressions with self-reported mood (i.e., anxiety, depression) symptoms as dependent variables, allowing us to test the additive utility of each set of network-derived measures for predicting mental health outcomes. By repeating this process across samples from two independent experience sampling studies, we were able to assess the replicability of our findings, as well as any potential changes due to differences in network size (i.e., number of nodes) or constituency (i.e., sampled emotion terms). A meta-analysis of the results of both studies was used to further confirm our findings.

Methods

Participants

Sample 1. Participants were 67 adults ranging in age from 18-36 years ($M = 22.8$ years, $SD = 4.4$ years; 55% female) who participated in a larger study examining affective experience, decision-making, and peripheral physiological activity in daily life. The study was approved by the Northeastern University Institutional Review Board (protocol #16-01-13); participants were recruited from the greater Boston area through posted advertisements, as well as Northeastern University classrooms and online portals. Eligibility criteria predominantly concerned the peripheral physiological monitoring that accompanied experience sampling, and are reviewed on page 1 of the supplemental materials. Informed consent was obtained from participants before beginning the study. Participants were compensated \$490 for completing all parts of the study, plus up to an additional \$55 in compliance and task incentives (as detailed on page 1 of the supplemental materials). Of the 67 recruited participants, six withdrew and an additional nine were dismissed due to poor compliance. Fifty-two participants completed the full protocol, with two participants excluded due to excessive missing data, for a final sample size of 50 ($M = 22.5$ years, $SD = 4.4$ years; 54% female).

Sample 2. Participants were 82 adults ranging in age from 18-28 years ($M = 19.3$ years, $SD = 1.58$ years; 46% female). The study was approved by the Northeastern University Institutional Review Board (protocol #11-04-07); participants were recruited from Northeastern University classrooms and online portals. Eligible participants were native English speakers enrolled in years 1-3 of their undergraduate course of study; full eligibility criteria are reviewed on page 4 of the supplemental materials. Informed consent was obtained from participants before beginning the study. Participants were compensated \$200 for completing all parts of the study, and a pro-rated amount for partial completion (for details, see page 4 of the supplemental materials). Participants with a response rate over 90% were entered into a gift card raffle. Seven participants were excluded from data analysis due to compliance issues, resulting in a final sample size of 75 ($M = 19.31$ years, $SD = 1.28$ years; 46% female).

Sample size considerations. Previous research has demonstrated that a sample size of 50, equivalent to sample 1, is large enough to observe sufficient variability and examine individual difference relationships (VanVoorhis & Morgan, 2007). Similar sample sizes have been used to develop and validate other measures of emotional granularity (Barrett, 1998, 2004; Barrett et al., 2001; Feldman, 1995). *A priori* power analyses in G*Power 3.1 (Faul et al., 2009) confirmed that both samples are adequately powered to conduct multiple regression analyses with moderate size effects (Cohen's $f^2 = .15 - .20$) at $\alpha < .05$ and power $(1-\beta) > .80$ (Cohen, 1988).

Data Collection

Sample 1. Each participant completed approximately 14 days ($M = 14.42$, $SD = 0.57$) of context-aware experience sampling distributed across a three- to four-week period. On each day of experience sampling, participants came into the lab and were instrumented for peripheral physiological recordings, including electrocardiogram (ECG). A custom-built smartphone application (MESA; MindWare Technologies LTD, Westerville, OH) linked with the recordings initiated an experience sampling prompt any time the interbeat interval (IBI; also called heart period) changed by more than ± 167 ms over an eight-second period, with these thresholds adjusted per participant to ensure they received a comparable number of prompts per day ($M = 21.22$, $SD = 10.40$). Prompts were not generated if participants had moved substantially or

changed posture within the preceding 30 seconds. Included in this total were an average of two ‘random’ prompts per day, which were not contingent on changes in IBI. Participants were instructed to continue physiological recordings for eight hours each day, after which they could remove and recharge all equipment. Additional details are available on pages 1-2 of the supplemental materials.

At each experience sampling instance, participants were asked to respond to a series of questions, including a brief, free-text description of what was happening at the time they received the prompt. 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. Participants were presented with some of the information they had provided at each of the prompts, including the brief description. After describing the event in more detail, participants were asked to rate the intensity of their emotional experience on a set of 18 emotion terms (“afraid”, “amused”, “angry”, “bored”, “calm”, “disgusted”, “embarrassed”, “excited”, “frustrated”, “grateful”, “happy”, “neutral”, “proud”, “relieved”, “sad”, “serene”, “surprised”, “worn out”) using a 7-point Likert-style scale rating from 0 (“not at all”) to 6 (“very much”). These terms were selected to sample high-, mid-, and low-arousal octants of the affective circumplex (e.g., Barrett, 1998) using frequently-used emotion words in English. Participants also provided additional details about each experience sampling event that are not reported here; see page 2 of the supplemental materials for details. Data for a given experience sampling day were excluded from analysis if the participant did not receive or complete at least six prompts or if the participant completed the end-of-day survey the following day, resulting in a final sample in which participants completed an average of 9.21 prompts per day ($SD = 2.98$) over an average of 13.20 days ($SD = 1.40$).

Before and after the experience sampling period, participants completed in-lab sessions. In each session, participants completed self-report questionnaires related to mental and emotional health. Measures relevant to the present analyses are reviewed below. The full list of tasks and questionnaires from the in-lab sessions is reported on pages 2-4 of supplemental materials.

Sample 2. Participants completed between 4 and 16 days of experience sampling distributed across a two- to three-week period: 20 participants completed between 11 and 16 days, 45 participants completed between 8 and 10 days, and 10 participants completed seven days or fewer. Participants received a palm pilot programmed for experience sampling, on which they received ten randomly-generated prompts per day, between the hours of 8 am and 11 pm. Participants were dismissed from the study if they did not respond to at least 75% of prompts. Altogether, participants completed an average of 8.02 prompts per day ($SD = 2.45$) over an average of 9.47 days ($SD = 3.21$).

At each experience sampling instance, participants were asked to rate the intensity of their emotional experience on a set of 39 emotion terms (“admiring”, “amazed”, “amused”, “angry”, “appreciative”, “bored”, “calm”, “contemptuous”, “content”, “depressed”, “disgusted”, “dislike”, “down”, “elated”, “enthusiastic”, “excited”, “fearful”, “furious”, “grateful”, “guilty”, “happy”, “hateful”, “irritated”, “joyous”, “nervous”, “peaceful”, “prideful”, “relaxed”, “remorseful”, “repulsed”, “restful”, “sad”, “scornful”, “shocked”, “sorry”, “successful”, “superior”, “surprised”, “terrified”) using a 5-point Likert-style scale rating from 1 (“not at all”) to 5 (“very much”). Compared to sample 1, these terms more robustly sampled high-, mid-, and low-arousal octants of the affective circumplex. Ratings were subsequently transformed to a 0-to-4 rating scale for consistency with sample 1.

During experience sampling, participants completed end-of-day diaries and questionnaire measures about emotional experience and health. Participants also completed three in-lab sessions (before, during, and after the experience sampling period). Self-report measures relevant to the present analyses are reviewed below. For a full list of tasks and questionnaires from the in-lab sessions, see pages 5-6 of supplemental materials.

Measures

Derived from emotion networks. We used the experience sampling data from each participant to construct an emotion network, in which nodes were emotion terms and pairwise Pearson correlation coefficients were edge weights. As such, these networks were undirected, weighted, and signed (i.e., edge weights could be positive or negative). For each network, we derived the seven measures presented in Table 1; descriptions and equations for these measures are provided in Table 2, with histograms and scatter plots on pages 7-9 and 13-15 of the supplemental materials. Data were processed using custom scripts and functions from the Brain Connectivity Toolbox (BCT; Rubinov & Sporns, 2010) and Network Community Toolbox (NCT; Bassett et al., 2020) in MATLAB (The MathWorks, Inc., Natick, MA). Although these toolboxes were developed for use with neuroimaging data, they are agnostic to the type of data analyzed and are particularly well-suited to our needs: brain connectivity networks are often based on pairwise correlations and, as such, are undirected, weighted, and signed.

Derived from experience sampling data. We derived four measures of emotional experience directly from the experience sampling data to serve as comparison and control variables for the network-derived measures. See Table 2 for equations; histograms are provided on pages 10-11 and 16-17 of the supplemental materials. Data were processed using custom scripts in MATLAB. Measures were computed for each set of network measures, resulting in separate estimates corresponding to time-varying mean and standard deviation network measures.

Emotional granularity. As outlined previously, emotional granularity was computed as an intraclass correlation (ICC) using agreement with averaged raters (“A-k” method; Shrout & Fleiss, 1979). Higher ICC values reflect lower emotional granularity. We computed separate indices of emotional granularity over pleasant (positive) versus unpleasant (negative) emotion categories, with valence determined based on normative ratings (Warriner et al., 2013). Negative values are outside of the theoretical range for the ICC and so were recoded as 0 (following e.g., Anand et al., 2017). We then averaged these indices to create a single estimate of emotional granularity per participant (following e.g., Edwards & Wupperman, 2017). This two-step procedure avoided interpretation issues that arise from including ratings for all emotion terms in a single ICC; because ratings for pleasant and unpleasant emotion terms are typically negatively correlated, including all emotion terms in the same analysis can result in negative ICC values. Before use in further analyses, ICCs were Fisher r -to- z transformed to fit the variable to a normal probability distribution.

Negative affect (mean and standard deviation). Recent research indicates that measures of overall affect – particularly negative affect – are predictive of mental health outcomes above and beyond other individual difference measures (Dejonckheere et al., 2019). To test the incremental validity of our network-derived measures in comparison to measures of negative affect, we computed the mean and standard deviation of the intensity of all negative emotions. Valence was again determined based on normative ratings (Warriner et al., 2013).

Emotional instability. Research on affective dynamics (e.g., Trull et al., 2015) seeks to characterize emotional experience in terms of its moment-to-moment changes. For example, emotional instability captures the average change in emotional intensity between successive measurement occasions (Dejonckheere et al., 2019), with greater emotional instability associated with depression (e.g., Thompson et al., 2012) and anxiety (e.g., Pfaltz et al., 2010). We computed emotional instability for each participant as the grand mean of successive squared differences (MSSD) of intensity across all emotion terms, with higher MSSD reflecting greater instability (e.g., Jahng et al., 2008). Entered as a control variable for time-varying standard deviation estimates, emotional instability allowed us to adjudicate whether network changes over time reflected detrimental (i.e., unstable) patterns of emotional experience or adaptive (i.e., flexible) patterns.

Self-report questionnaires. As part of the above-described experience sampling protocols, participants completed the following self-report questionnaires. These questionnaires serve as dependent (anxiety, depression) or control (alexithymia, emotional reactivity) variables for testing the incremental validity of the network-derived measures. We focus on predicting mood (i.e., anxiety, depression) symptoms as mental health outcomes of interest, as these variables were collected in both samples and are widely used in the emotional granularity literature (e.g., Seah et al., 2020; Willroth et al., 2019). Histograms for all questionnaire measures are provided on pages 12 and 18 of the supplemental materials.

Mood symptoms. Participants in sample 1 completed the Generalized Anxiety Disorder scale (GAD-7; Spitzer et al., 2006) and the Patient Health Questionnaire depression scale (PHQ-8; Kroenke et al., 2009) at in-lab sessions before and after the experience sampling period. Scores were averaged across time points. We observed a strong positive inter-correlation between the GAD-7 and PHQ-8 scores ($r = .77$), consistent with prior studies that have demonstrated robust associations between self-reported depression and anxiety symptoms (e.g., Clark & Watson, 1991; Feldman, 1993). For this reason, we standardized and then averaged GAD-7 and PHQ-8 scores to achieve a single estimate of mood symptoms per participant.

Participants in sample 2 completed the Beck Anxiety Inventory (BAI; Beck et al., 1988) and the Beck Depression Inventory (BDI-I; Beck et al., 1961) during a single lab visit. Data from the BDI-I were excluded from the present analyses because it is an earlier version of the currently-used measure (i.e., the BDI-II; Beck et al., 1996). This decision was also supported by a greater restriction of range on BDI-I scores (Figure S20) and lower inter-correlation between BDI-I and BAI scores ($r = .42$). Scores on the BAI were standardized prior to analysis for consistency with sample 1.

Alexithymia. Participants in both samples completed the Toronto Alexithymia Scale, 20-item version (TAS-20; Bagby et al., 1994). Participants in sample 1 completed the TAS-20 at in-lab sessions before and after the experience sampling period; scores were again averaged across time points. The TAS-20 includes subscales for Difficulty Identifying Feelings (DIF), Difficulty Describing Feelings (DDF), and Externally-Oriented Thinking (EOT). For the present analyses, we used only the average of the DIF and DDF subscales, as these dimensions show greatest theoretical and empirical overlap with emotional granularity (e.g., Erbas et al., 2014).

Emotional reactivity. Participants in sample 1 completed the Emotion Reactivity Scale (ERS; Nock et al., 2008) at the in-lab session before the experience sampling period. The ERS measures affective dynamics in terms of emotion sensitivity, intensity, and persistence. Participants in sample 2 did not complete an equivalent measure.

Table 2. Network Analyses and Resulting Network and Non-Network Measures

Notation and Basic Measures		
Nodes	N is the set of all nodes in the network, and n is the number of nodes.	
Links	L is the set of all links (i.e., edges) in the network, and l is number of links ¹ . (i,j) is a link between nodes i and j ($i,j \in N$). a_{ij} is the connection status between i and j , such that $a_{ij} = 1$ when link (i,j) exists. Links (i,j) are associated with connection weights w_{ij} . l^w is the sum of all weights in the network, computed as $l^w = \sum_{i,j \in N} w_{ij}$.	
Degree	The degree of a node is the number of links connected to it. The degree of a node i is computed as $k_i = \sum_{j \in N} a_{ij}$; the weighted degree of node i is computed as $k_i^w = \sum_{j \in N} w_{ij}$.	
Number of triangles	The number of triangles around a node is the number of interconnected triads a node belongs to, and is used as a basis for measuring segregation. The weighted, geometric mean of triangles around a node i is computed as $t_i^w = \frac{1}{2} \sum_{j,h \in N} (w_{ij} w_{ih} w_{jh})^{\frac{1}{3}}$.	
Superscripts	^{w} denotes a measure computed for a weighted network $^\pm$ denotes a measure computed separately for positively- versus negatively-weighted link	
Network Measures		
Measure	Equation	Reference
Clustering coefficient	Weighted clustering coefficient for network N : $C^w = \frac{1}{n} \sum_{i \in N} \frac{2t_i^w}{k_i(k_i - 1)}$	Onnela et al. (2005)
Density	Weighted density for network N : $D^w = \frac{1}{l} \sum_{i,j \in N} w_{ij}$	Barrat et al. (2004)
Number of communities	Algorithm maximizes modularity (Q^w) to create a set of non-overlapping modules (i.e., communities) of nodes. Structural resolution parameter γ governs how large modules are, such that $\gamma > 1$ detects smaller modules and $\gamma < 1$ detects larger modules. We implemented classic modularity with default $\gamma = 1$.	Blondel et al. (2008); Rubinov & Sporns (2011)
Modularity (valence focus)	Weighted modularity of network N partitioned into a set of communities or modules M : $Q^w = \frac{1}{l^w} \sum_{i,j \in N} \left[w_{ij} - \gamma \frac{k_i^w k_j^w}{l^w} \right] \delta_{u_i u_j}$ Where u_i is the module containing node i , and $\delta_{u_i, u_j} = 1$ if $u_i = u_j$ and 0 otherwise.	Newman (2004)

¹ Without any thresholding or edge-pruning procedure applied, the network is fully connected: each node is connected to every other node, such that $l = n(n-1)/2$.

	In the present analyses, we computed valence focus as the modularity for a two-community structure in which each node is assigned to either a ‘pleasant’ or ‘unpleasant’ community (Q_{VB}^w). When these assignments are passed into the community detection function along with the original edge weights, Q_{VB}^w reflects the fit of the two-community structure.	
Diversity coefficients (positive and negative)	Weighted, signed diversity coefficient for node i: $H_i^{\pm} = -\frac{1}{\log m} \sum_{u \in M} p_i^{\pm}(u) \log p_i^{\pm}(u)$ Where $p_i^{\pm}(u) = \frac{s_i^{\pm}(u)}{s_i^{\pm}}$, $s_i^{\pm}(u)$ is the strength of node i within module u (i.e., the total weight of connections of i to all nodes in u), and m is the number of modules in partition M. Weighted, signed diversity coefficient for network N: $H_N^{\pm} = \frac{1}{n} \sum_{i \in N} H_i^{\pm}$	Rubinov & Sporns (2011); Shannon (1948)
Community radius	Each node i has a position in affective space delineated by valence (x) and arousal (y) coordinates (i.e., that node’s position vector r_i, as determined using normative ratings; Warriner et al., 2013). The radius for module u: $R_u = \frac{1}{n_u} \left(\sum_{i \in u} r_i^2 - \sum_{i \in u} r_i^2 \right)^{\frac{1}{2}}$ Community radius for network N: $R_N = \frac{1}{n} \sum_m n_u \frac{R_u}{\rho_N}$ ρ_N is a normalization constant equal to the radius of N: $\rho_N = \frac{1}{n} \sqrt{\left(\sum_{i=1}^n \ r_i\ ^2 - \left\ \sum_{i=1}^n r_i \right\ ^2 \right)}$	Lohse et al. (2014)
Non-Network Measures		
<i>Measure</i>	<i>Equation</i>	<i>Reference</i>
Negative affect (M)	Mean negative affect across time points T: $M_{NA} = \frac{1}{T} \sum_{t=1}^T NA_t$ Where NA is the intensity ratings for all emotion terms considered ‘unpleasant’ based on normative ratings (Warriner et al., 2013).	Dejonckheere et al. (2019); Watson et al. (1988)
Negative affect (SD)	Standard deviation negative affect across time points T :	Dejonckheere et al. (2019);

	$SD_{NA} = \sqrt{\frac{\sum_{t=1}^T (NA_t - M_{NA})^2}{T-1}}$	Eid & Diener (1999)
Emotional granularity	Granularity for unpleasant (negative) emotions E_{NA}: $NA_{te} = \sum_{t=1}^T NA_e + NA_t - M_{NA} + \varepsilon_{te}$ $MSE_{E_{NA}} = \frac{\sum_t \sum_e^{E_{NA}} \varepsilon_{te}^2}{(T-1)(E_{NA}-1)}$ $MSR_{E_{NA}} = \frac{\sum_t \sum_e^{E_{NA}} (NA_t - M_{NA})^2}{(T-1)}$ $ICC_{E_{NA}} = \frac{MSR_{E_{NA}} - MSE_{E_{NA}}}{MSR_{E_{NA}}}$ Where e is a specific emotion and ε represents residuals. In the present analyses, we calculated granularity separately for unpleasant and pleasant emotions, and averaged them to create a single composite index (ICC_E).	Dejonckheere et al. (2019); Shrout & Fleis (1979); Tugade et al. (2004)
Emotional instability	Emotional instability for emotion e: $MSSD_e = \sqrt{\frac{\sum_{t=2}^T (e_t - e_{t-1})^2}{T-1}}$ Emotional instability for set of emotions E: $MSSD_E = \frac{1}{E} \sum_{e \in E} MSSD_e$	Dejonckheere et al. (2019); Jahng et al. (2008)

Analyses

Network construction. For both samples, person-specific networks were constructed for each participant using custom MATLAB scripts. Initially, all available emotion terms (18 in sample 1, 39 in sample 2) were included as nodes. Edge weights were computed as Pearson correlation coefficients (r) between the intensity ratings of all possible pairs of nodes, and thus ranged between -1 and 1. For the overall networks used to visualize and describe participants' emotion categories, edge weights were based on all time points (i.e., experience sampling instances) for a given participant. In sample 1, overall networks were constructed from an average of 124.56 time points per participant ($SD = 18.25$). In sample 2, overall networks were constructed from an average of 74.84 time points per participant ($SD = 28.75$). Correlation coefficients could not be computed for emotion terms with zero variance (e.g., all '0' ratings); the removal of these nodes from the network resulted in person-specific networks of slightly variable sizes (remaining nodes for sample 1: $M = 17.64$, $SD = 0.83$; for sample 2: $M = 37.89$, $SD = 2.34$).

For the time-varying networks used to test relationships with mood symptoms, edge weights were based on time points within three-day overlapping sliding windows (Figure 1). As both samples provided up to 14 days of experience sampling, we chose a window length of three days to maximize the number of window-level networks that could be estimated, while ensuring

stability of these networks by including more than a single day (which might have been excluded from analysis due to missing data). We used overlapping windows as this would again maximize the number of window-level networks that could be estimated, while also reducing the influence of atypical time points (i.e., outliers) on these networks. In sample 1, an average of 11.12 window-level networks ($SD = 1.41$) were constructed from an average of 24.75 time points per window ($SD = 3.68$). In sample 2, an average of 7.41 window-level networks ($SD = 3.23$) were constructed from an average of 25.29 time points per window ($SD = 2.82$). Emotion terms with zero variance within a given window were removed from the corresponding network (remaining nodes for sample 1: $M = 15.22$, $SD = 2.25$; for sample 2: $M = 34.64$, $SD = 4.48$).

Figure 1. Schematic diagram of three-day overlapping sliding windows used to construct time-varying emotion networks.

Measure derivation. For each network, we computed seven network measures (Tables 1 and 2) using custom MATLAB scripts. Because community structure is non-deterministic (Newman, 2006), values for measures that are dependent upon community structure (number of communities [m ; numCom], diversity coefficients [$H_N^\pm$; pDiv, nDiv], and community radius [R_N ; comR]) may fluctuate slightly each time they are computed. To account for this, we iterated community detection 1000 times, selecting the structure that maximized modularity (Q^w) across all runs (as maximal modularity indicates better community structure fit; Blondel et al., 2008). If multiple highest values were achieved, we selected the first corresponding community structure. This discovered community structure was subsequently used to compute the average positive and negative diversity coefficients across all nodes, as well as the average community radius across all communities.

As given in Tables 1 and 2, we computed the modularity of a valence-based partition of each participant's network, which reflects the fit of a stipulated two-community structure in which nodes are assigned to either a 'pleasant' or 'unpleasant' community. To make these assignments, we identified the normative valence ratings (Warriner et al., 2013) for all emotion terms in a given network. These ratings are provided on a scale from 1 (most unpleasant) to 9 (most pleasant), such that the scale midpoint (5) represents neutral valence. An examination of the distributions across the entire database ($M = 5.06$, $SD = 1.27$) as well as the terms in samples 1 ($M = 5.11$, $SD = 2.34$) and 2 ($M = 5.03$, $SD = 2.26$) confirmed that valence ratings were not skewed. Accordingly, we split valence ratings at the scale midpoint, such that terms rated above

5 were considered ‘pleasant’ and terms rated below 5 were considered ‘unpleasant’. No emotion term was rated exactly 5 (“neutral” [sample 1] was rated 5.5 and thus treated as ‘pleasant’).

For each participant, we computed three sets of network measures: one set estimated from an overall emotion network, a second set estimated by taking the mean across all window-level estimates (i.e., time-varying means), and a third set estimated by taking the standard deviation across all window-level estimates (i.e., time-varying standard deviations). Only the time-varying means and standard deviations were used to subsequently test the relationship between network measures and mood symptoms, as described next. For each set of network measures, we computed four corresponding non-network measures (Table 2) directly from participants’ experience sampling data. All measures were inspected to verify their ranges were suitable for use as individual difference measures. All data and analysis code are available via a repository hosted by the Center for Open Science at <https://osf.io/nmja4/>.

Factor analysis. For each sample, we conducted two exploratory factor analyses (EFAs): one for the time-varying means, and another for the standard deviations. We conducted separate EFAs to maintain the highest possible subject-to-item ratio (Osborne & Costello, 2005). To each EFA, we submitted eight measures that, we hypothesize, reflect aspects of emotional granularity: the typical ICC and the seven network measures (clustering coefficient [C^w ; cluster], density [D^w ; density], number of communities [m ; numCom], positive diversity coefficient [H_N^+ ; pDiv], negative diversity coefficient [H_N^- ; nDiv], community radius [R_N ; comR], and valence focus [Q_{VB}^w ; vFocus]). Any measure that was non-normally distributed (as indicated by a significant Kolmogorov-Smirnov test) was normalized prior to analysis using an inverse normal transformation (Blom, 1958).

Multiple regression. To test whether time-varying network measures for emotional granularity were predictive of mental health outcomes, we entered the factor scores resulting from each EFA (henceforth referred to as ‘granularity factors’) into a multiple regression with mood symptoms as the dependent variable. This regression included all emotional granularity factors, along with several control variables, as predictors. For both types of network estimates (time-varying means and standard deviations), we compared the contributions of granularity factors to those from the mean and standard deviation of negative affect (M_{NA} and SD_{NA} , respectively)². For the standard deviation estimates, we further compared the contribution of granularity factors to those from emotional instability ($MSSD_E$). Lastly, we compared the contributions of granularity factors to those from self-report measures of emotional health. Mean estimates were compared to self-reported alexithymia, using the mean of the DIF and DDF subscales from the TAS-20 (DIF/DDF). Standard deviation estimates for sample 1 were compared to emotional reactivity, as reported using the ERS (this variable was included only for sample 1, as no comparable measure was collected as part of sample 2). When we had a priori predictions about the relationship between granularity factors and mood symptoms, we used one-tailed tests of significance ($\alpha = .05$). Otherwise, we used two-tailed tests of significance.

Meta-analysis. We quantified the regression results across samples 1 and 2 by conducting a meta-analysis of the significant granularity factors (following Goh et al., 2016). We represented the unique variance captured by each granularity factor using the t value resulting

---

² Granularity factors for time-varying mean and standard deviation estimates were tested against negative affect mean and standard deviation measures computed on data included in the three-day, overlapping sliding windows.

from the regression, and converted these t values to standard effect sizes (r) following established formulae (Borenstein et al., 2011). We then meta-analyzed these r values using a fixed effects model, in which the mean effect size was weighted by sample size.

Results

Overview and Example Networks

Across both samples, we observed that both sets of time-varying network measures predicted self-reported mental health. In three of four analyses, a granularity factor explained unique variance in mood symptoms when compared to other derived measures of emotional experience (mean and standard deviation negative affect and emotional instability) and when compared to other self-report measures of emotional health (alexithymia, emotional reactivity). A summary of the results from these analyses is presented in Table 3.

Table 3. Summary of Results from Exploratory Factor Analyses and Multiple Regressions

Network Measures	Sample 1	Sample 2
<i>Means</i>		
Significant granularity factor	community radius _R , positive diversity _R	number of communities _R , negative diversity _R , ICC
Relationship with mood symptoms	positive**	positive†
<i>Standard Deviations</i>		
Significant granularity factor	clustering, density, negative diversity, ICC, positive diversity, valence focus	(factor not significant)
Relationship with mood symptoms	negative*	

Note: All regressions controlled for mean negative affect (M_{NA}) and standard deviation of negative affect (SD_{NA}). Regressions for mean estimates additionally controlled for self-reported alexithymia (DIF/DDF subscales of the TAS-20; Bagby et al., 1994). Regressions for standard deviation estimates additionally controlled for self-reported emotion reactivity (ERS; Nock et al., 2008). **granularity factor significant addition to model at $p \leq .01$; *granularity factor significant addition to model at $p \leq .05$; †granularity factor approaching significant addition to model at $p \leq .10$; _R measure transformed ($\cdot -1$) to achieve a positive correlation with the ICC.

Using the overall emotion networks, we visualized networks for example participants from each sample in Gephi (Bastian et al., 2009). We selected participants based on their ICC values, to contrast the networks of individuals with higher emotional granularity (lower ICC values) with individuals with lower emotional granularity (higher ICC values). Overall emotion networks for example participants in sample 1 are presented in Figure 2 below; window-level network snapshots from the corresponding time-varying networks are presented in Figures S21 and S22. Overall and time-varying network visualizations for example participants in sample 2 are presented in Figures S23, S24, and S25³.

³ Videos of dynamic time-varying networks for ten representative participants (five higher granularity, five lower granularity) are available at: <https://tinyurl.com/TimeVaryingEmotionNetworks>. Networks were created in Gephi (Bastian et

As can be seen in Figure 2, individuals with lower ICCs (e.g., Figure 2, left panel) have less tightly-clustered or dense networks, in which more communities of nodes (i.e., emotion categories) can be identified. These communities are more complex in their constituency: the pattern of interaction between nodes does more than recapitulate the valence-based distinction between ‘pleasant’ and ‘unpleasant’ experiences. Likewise, there is a greater diversity of both positive and negative edges between communities. In contrast, individuals with higher ICCs (e.g., Figure 2, right panel) tend to have denser networks with two communities: one for pleasant emotion categories, and one for unpleasant emotion categories. These communities have strong positive intra-connections (illustrated by thick, dark gray lines) and, often, strong negative inter-connections (illustrated by light gray lines).

---

al., 2009) by loading a list of edges along with the three-day window(s) in which they existed. For purposes of visualization, edges were binarized (0,1) and only positively-weighted edges were retained. Networks were generated using the ForceAtlas layout (Jacomy, 2007; see also Jacomy et al., 2014) which dynamically updates as edges (dis)appear over time. Screen recording software was used to capture the networks as they played through.

Figure 2. Overall emotion networks for example participants in sample 1 with higher emotional granularity (i.e., a lower ICC; left panel) and lower emotional granularity (i.e., a higher ICC; right panel). Node color represents community assignment; node size represents degree (i.e., number of edges). Edge thickness represents the absolute value of the Pearson correlation coefficient between two nodes. Edge color represents the sign of the correlation: dark gray edges are positive connections; light gray edges are negative connections. The network for the participant with higher granularity has four communities of nodes, and these communities have a complex and overlapping relationship. The network for the participant with lower granularity has only two communities, which have a more bipolar (pleasant-unpleasant) relationship. Data were pre-processed in MATLAB (The MathWorks, Inc., Natick, MA) before network visualization in Gephi (Bastian et al., 2009), with nodes assigned to communities using the Louvain detection algorithm (Rubinov & Sporns, 2011). For purposes of visualization, edges were pruned using a backbone detection algorithm (Hagmann et al., 2008; Hidalgo et al., 2007) that identified the dominant connections while maintaining an average degree one half that of the fully-connected network (i.e., $k_N^w = \frac{1}{2n} \sum_{i,j \in N} w_{ij}$). Networks were generated using the Yifan Hu Proportional layout (Hu, 2005).

Time-Varying Emotion Networks: Mean Estimates

Sample 1. An exploratory factor analysis (EFA) using maximum likelihood extraction indicated the data met acceptable levels of sampling adequacy (Kaiser-Meyer-Olkin [KMO] test $> .60$), and all measures demonstrated sufficiently high initial communalities ($h^2 > .4$). Examination of the scree plot and interpretability of factor loadings led us to retain three factors. Oblique rotation (direct oblimin, delta = 0) confirmed these factors were not strongly correlated ($r_s \leq .3$); orthogonal rotation (varimax) was used to establish the final solution (Table 4; see also Table S4).

Factor scores were created as the composite (i.e., simple mean) of each factor's highest-loading measures. Measures loading with equivalent strength onto multiple factors were excluded from further analysis. All measures were standardized prior to combination. Measures exhibiting strong negative correlations with the ICC were multiplied by -1, so that more positive values reflected lower emotional granularity.

A multiple regression revealed that participants whose networks had shorter affective distances between community members (comR [reversed]) and exhibited lower diversity of positive edges between communities (pDiv [reversed]) reported more mood symptoms (Figure 3, left panel). This was true even when controlling for measures of negative affect and mean DIF/DDF alexithymia score (Table 5).

Sample 2. Data met acceptable levels of sampling adequacy and all measures demonstrated sufficiently high communalities. We retained three factors; these factors were strongly inter-correlated, so the oblique pattern matrix was used to establish the final solution (Table 4). This solution is broadly similar to that identified for sample 1.

A multiple regression revealed that participants with higher ICCs, whose networks had fewer communities (numCom [reversed]) and lower diversity of negative edges (nDiv [reversed]) between those communities, reported more mood symptoms (Figure 3, right panel). Although this granularity factor's contribution to the model did not reach conventional levels of significance, it was a better predictor of mood symptoms than measures of negative affect and mean DIF/DDF alexithymia score (Table 5).

Table 4. Factor Loadings for Time-Varying Mean Estimates

Measure	Sample 1			Sample 2		
	Factor #1	Factor #2	Factor #3	Factor #1	Factor #2	Factor #3
ICC	.67		.53		.79	
cluster	.73		.54	-.51		.68
density	.60			.39		.73
numCom	-.75				-.96	
pDiv		.52		1.00		
nDiv	-.96				-.83	
comR		.99		.60		
vFocus			.97	-.75		-.44

Note: Factor loadings of absolute value $< .3$ are suppressed for ease of viewing. The stronger of the two factor loadings for each measure is boldfaced.

Figure 3. Scatter plots of zero-order correlations between significant granularity factors for time-varying network mean estimates, and self-reported mood symptoms, for sample 1 (left panel) and sample 2 (right panel). Mood symptom measures were standardized prior to analysis and so are presented in z -score units.

Table 5. Regression Coefficients for Factors from Time-Varying Mean Estimates

Sample	Predictor	<i>b</i>	<i>SE</i>	β	<i>t</i>	<i>p</i>	95% CI
1	Factor #1	-.11	.13	-.10	-.87	.20	-.36, .14
	Factor #2	.41	.11	.38	3.75	<.001	.19, .62
	Factor #3	-.13	.10	-.14	-1.27	.11	-.34, .08
	M_{NA}	.27	.15	.29	1.81	.04	-.03, .57
	SD_{NA}	-.03	.15	-.03	-.19	.43	-.33, .27
	DIF/DDF	.66	.11	.61	5.79	<.001	.43, .89
2	Factor #1	.04	.20	.03	.18	.43	-.37, .44
	Factor #2	.19	.18	.17	1.07	.15	-.16, .54
	Factor #3	.36	.24	.33	1.45	.08	-.14, .85
	M_{NA}	.28	.32	.28	.89	.19	-.35, .91
	SD_{NA}	-.31	.32	-.31	-.98	.17	-.35, .91
	DIF/DDF	.18	.14	.16	1.37	.09	-.08, .45

Note: In both regressions, we entered self-reported mood symptoms as the dependent variable and used a one-tailed test of significance for all predictors. Significant p -values ($p \leq .05$) are boldfaced; trending p -values ($p \leq .10$) are italicized.

Meta-analysis. A meta-analysis of the results from both samples confirmed that granularity factors for mean network measures significantly and positively predicted mood symptoms: $M_r = .30$, $SE_r = .09$, $Z = 3.33$, $p \leq .001$, one-tailed, 95% CI [.12, .45].

Time-Varying Emotion Networks: Standard Deviation Estimates

Sample 1. Data met acceptable levels of sampling adequacy, with community radius (comR) excluded due to low initial communalities. We retained two orthogonally-rotated factors (Table 6).

A multiple regression revealed that participants whose networks exhibited less overall change in network structure (cluster, density, nDiv, ICC, pDiv, vFocus) over time reported more mood symptoms (Figure 4, left panel). This was true even when controlling for measures of negative affect, as well as emotional instability ($MSSD_E$) and self-reported emotional reactivity (ERS; Table 7).

Sample 2. Data met acceptable levels of sampling adequacy, with community radius (comR) and number of communities (numCom) excluded due to low initial communalities. Examination of the scree plot limited us to a one-factor solution identical to the first factor in sample 1 (Table 6). However, this granularity factor did not predict mood symptoms (Table 7; Figure 4, right panel).

Table 6. Factor Loadings for Time-Varying Standard Deviation Estimates

Measure	Sample 1		Sample 2
	Factor #1	Factor #2	Factor #1
ICC	.60		.75
cluster	.72		.70
density	.70		.76
numCom		.99	--
pDiv	.59		.82
nDiv	.62	.43	.71
comR	--	--	--
vFocus	.55		.88

Note: Factor loadings of absolute value $< .3$ are suppressed for ease of viewing. The stronger of the two factor loadings for each measure is boldfaced. In both samples, community radius (comR) was excluded from the factor analysis due to low communality. In sample 2, number of communities (numCom) was also excluded.

Figure 4. Scatter plots of zero-order correlations between granularity factor for time-varying network standard deviation estimates, and self-reported mood symptoms, for sample 1 (left

panel) and sample 2 (right panel). Mood symptom measures were standardized prior to analysis and so are presented in z -score units.

Table 7. Regression Coefficients for Factors from Time-Varying Standard Deviation Estimates

Sample	Predictor	<i>b</i>	<i>SE</i>	β	<i>t</i>	<i>p</i>	95% CI
1	Factor #1	-.36	.16	-.27	-2.26	.03	-.68, -.04
	Factor #2	-.15	.12	-.16	-1.33	.19	-.39, .08
	M_{NA}	.01	.15	.01	.09	.93	-.28, .31
	SD_{NA}	-.22	.15	-.23	-1.45	.15	-.52, .08
	$MSSD_E$	.22	.13	.23	1.68	<i>.10</i>	-.04, .48
	ERS	.43	.12	.45	3.55	.001	.18, .67
2	Factor #1	.08	.18	.07	.44	.66	-.28, .44
	M_{NA}	.29	.14	.29	2.09	.04	.03, .57
	SD_{NA}	-.08	.16	-.08	-.47	.64	-.41, .25
	$MSSD_E$	-.04	.15	-.04	-.23	.82	-.34, .27

Note: In both regressions, we entered self-reported mood symptoms as the dependent variable and used a two-tailed test of significance for all predictors. Significant p -values ($p \leq .05$) are boldfaced; trending p -values ($p \leq .10$) are italicized.

Discussion

Using a network analytic approach to study emotional granularity, we created person-specific emotion networks for participants in two experience sampling studies. We examined these networks without consideration for the dimension of time, allowing us to describe the overall characteristics of individuals' emotional experiences. We also analyzed these networks over time, allowing us to capture how they changed throughout the course of experience sampling. We characterized emotion networks according to the typical measure of emotional granularity (ICC) as well as a set of seven network measures (Table 1), and estimated both the mean and standard deviation for these measures across time. Separate exploratory factor analyses of each set of estimates allowed us to identify groups of measures that represented the same aspect of emotional granularity. Multiple regressions revealed that these granularity factors were predictive of mood symptoms – even when controlling for other variables identified by prior research, including measures of negative affect and self-reported alexithymia or emotional reactivity. Individuals with higher emotional granularity were found to have less dense networks that were comprised of a greater number of communities of emotion categories and connected by a greater diversity of connections. Their networks also exhibited greater change over time. These findings broadly held across both experience sampling studies, suggesting they are replicable and robust to differences in network size and constituency.

The present findings serve as a proof-of-concept demonstration of the efficiency of network analysis for describing emotional granularity. As we observed, there are several network measures that may be useful in this endeavor, each with its own implications for the study of emotional granularity. The community radius measure we employed led to a particularly interesting observation: in sample 1, individuals with fewer mood symptoms evidenced networks whose communities included more affectively diverse emotion categories (i.e., they had larger, not smaller, radii). This relationship suggests that mental health is associated with the ability to go beyond simple distinctions of pleasantness or activation in the experience of emotion. As such, the present findings are in line with prior work on emotional and affective complexity (e.g.,

Carstensen et al., 2000; Tobacyk, 1980), especially that which has established a strong relationship between valence-focused or bipolar affect, lower emotional granularity (Barrett, 1998, 2004; Feldman, 1995), and coping and health (Zautra et al., 2000, 2001, 2005). Similarly, these findings echo work on the diversity of emotional experience, or ‘emodiversity’ (Quoidbach et al., 2014), which has been linked to positive mental and physical health outcomes (Grossmann et al., 2019; Ong et al., 2018; Quoidbach et al., 2014; Werner-Seidler et al., 2018). Emodiversity is conceptually based on the Shannon (1948) diversity index, H (although see Benson et al., 2018; Brown & Coyne, 2017), which also forms the basis for the positive and negative diversity coefficients computed in the present study (Rubinov & Sporns, 2011). Indeed, we observed that greater diversity of both positive and negative connections between communities was robustly associated with higher emotional granularity and fewer mood symptoms.

The present findings further expand upon research on the dynamics of emotional experience. In particular, prior work has used vector auto-regression (VAR; Brandt & Williams, 2007) to estimate relationships between instances of self-reported emotion. Networks based on VAR models are referred to as ‘temporal networks’ because they illustrate time-based interdependencies between nodes (e.g., Bringmann et al., 2013, 2015, 2016; Fisher et al., 2017). Studies using temporal networks have found, for example, that stronger average interdependencies – referred to as ‘emotion-network density’ – are associated with major depressive disorder (Pe et al., 2015) and greater self-reported neuroticism (Bringmann et al., 2016). Emotion-network density has been interpreted as an indicator of the resistance of the emotion system to change (Pe et al., 2015), such that individuals with greater density are more constricted and less flexible. In our analyses, network measures were not calculated with respect to temporal interdependencies. Nevertheless, we found in sample 1 that the standard deviations of several time-varying network measures were negatively correlated with mood symptoms, and that they predicted mood symptoms above and beyond emotional instability. Previous research on measures of affect dynamics has likewise observed a close relationship between instability (measured as *MSSD*) and variability (measured as variance or *SD*), suggesting that temporal interdependencies may not be a critical aspect of describing system change over time (Dejonckheere et al., 2019). Taken together, then, the present work supports the hypothesis that individuals with higher granularity have experiences of emotion that are flexible to context-specific needs.

As a proof-of-concept demonstration, the present work also illustrates some challenges for interpretation. Our pattern of findings broadly replicated across both samples, as confirmed by a meta-analysis of granularity factors for the mean network estimates. Nonetheless, effects were strongest (and only reached conventional levels of significance) in sample 1. This may be due to particular features of sample 2, or to differences between the samples. Whereas all participants in sample 1 completed approximately 14 days of experience sampling, participants in sample 2 completed a variable number – some completed approximately 14, while the rest completed approximately 7. This impacted the amount of data available for the time-varying emotion networks, and may be the reason why our findings with the standard deviation estimates in sample 1 were not replicated in sample 2. Further, we observed a restriction of range on all self-report mental health measures (see Figures S10 and S20), consistent with the fact that both samples were non-clinical, excluding participants with a current psychiatric diagnosis. We also found that, despite similar factor solutions, different network measures were predictive in each sample: results in sample 1 were driven by positive diversity (pDiv) and community radius (comR); results in sample 2 were driven by negative diversity (nDiv) and number of

communities (numCom). This divergence may be a function of network size: whereas sample 1 sampled experiences of 18 emotions, sample 2 was gathered using 39 emotion terms. It is rare for a study to include such a large number of terms (cf. Barrett, 2004), and some include far fewer (e.g., Anand et al., 2017). Therefore, an important task for future research is to investigate the generalizability of a network analytic approach for estimating emotional granularity.

One potential cause of differences in emotion categories, and thereby in emotional granularity, is the nature of individuals' conceptual systems for emotion. Constructionist accounts of emotion hypothesize that individuals' use of emotion words reflects their conceptual understanding (Barrett, 2004), and that higher emotional granularity is associated with emotion concepts that are rich, complex, and highly differentiated (e.g., Barrett, 2017a; Kashdan et al., 2015; Lindquist & Barrett, 2008). This account implies that emotion network structure reflects underlying conceptual structure, and that network dynamics reflect emotion concepts' changing relationships over time. Future work could directly compare these 'conceptual' interdependencies against the temporal interdependencies assessed via VAR-based networks (e.g., Bringmann et al., 2016; Epskamp et al., 2017). In doing so, this work can expand network measures for emotional granularity by examining aspects of network connectivity. For example, the *degree distribution* (Barabási & Albert, 1999) represents how evenly nodes are interconnected, and in a time-varying network may be positively associated with emotional granularity, such that transitions between emotions have more similar likelihoods. Inversely, network *coherence* (Bamieh et al., 2012) reflects the degree of stability in patterns of connectivity over time, and may be negatively associated with emotional granularity, such that time-varying networks are more dynamic (i.e., have lower coherence). These time-based measures of emotional granularity can be used to predict dependent variables, such as (self-reported) decision-making behaviors, that are also measured in-the-moment using experience sampling (as in Tomko et al., 2015), allowing for a more precise and context-specific understanding of emotional and mental health in everyday life.

Another opportunity for future work is to connect the methods used in the present study with network analyses used to model individual differences and intra-individual dynamics (i.e., network psychometrics; e.g., Borsboom & Cramer, 2013; Costantini et al., 2019; Schmittmann et al., 2013). This approach has been enthusiastically adopted in clinical psychology and psychiatry, where researchers construct symptom networks to model the dynamics of psychopathology (e.g., Borsboom, 2017; for a recent review, see Fried et al., 2017), but has also been proposed as a method of modeling emotions (Lange et al., 2020). In these models, psychological phenomena are conceptualized as networks of interacting observable features, with covariance between observables understood as a pattern of causal relations (Borsboom, 2017; Cramer et al., 2010; van der Maas et al., 2006). Accordingly, a key focus of many analyses is identifying which nodes play a more central (i.e., causal) role in network dynamics: psychological networks are commonly estimated as regularized partial correlation networks, in which edge weights (partial correlations) represent conditional interdependencies between nodes (Lauritzen, 1996), and spurious (i.e., uninformative) edges are removed (for a review of methods, see Costantini et al., 2019; Epskamp & Fried, 2018). There is undoubtedly value in modeling psychological networks in this manner. In the present study, however, we were interested in broader characteristics of individuals' categories for emotion, rather than relationships between specific features or questions of causality. As such, we intentionally modeled all of the variance available (without using partial correlations to control for other variables), and focused on network measures beyond centrality. Ultimately, we suggest that the

conceptual interdependencies examined in the present work represent a complementary approach to understanding psychological phenomena, which should in future work be integrated with conditional or causal interdependencies (examined using regularized partial correlation networks) as well as temporal interdependencies (examined using VAR-based networks).

All considered, the present work carries profound implications for assessing mental health outcomes and improving emotional granularity over time. We found a number of network measures for emotional granularity to be uniquely predictive of anxiety and depression symptoms. These findings are consistent with research that identifies low emotional granularity as a transdiagnostic feature of mental disorders (Kashdan et al., 2015) and a likely risk factor for mental illness. Lower emotional 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). Nevertheless, the typical within-person correlational methods used to date produce single, static estimates that may be limited in their ability to detect risk factors. Recently, interventions targeting mindfulness have been shown to increase emotional granularity (Van der Gucht et al., 2019), as has the process of experience sampling itself (Widdershoven et al., 2019). To fully capture changes in emotional granularity over time – and better understand the underlying mechanisms – longer-term, multi-method investigations are needed, and must incorporate measures able to account for dynamics in emotional experience. The present findings suggest that network analysis can provide just such a set of sensitive and time-varying measures, facilitating the utilization of emotional granularity for the treatment and prevention of illness.

Author Notes

This work was performed at Northeastern University in partial fulfillment of a Doctor of Philosophy Degree in Psychology awarded to Katie Hoemann. Portions of this work were presented at the 2018 annual meeting of the Society for Affective Science. K.H. was supported by the National Heart, Lung, and Blood Institute (grant number 1F31HL140943-01) and a P.E.O. International Scholar Award. This work was further supported by the U.S. Army Research Institute for the Behavioral and Social Sciences (grant number W911NF-16-1-0191 to K.S.Q. and Dr. Jolie Wormwood, Co-PIs).

All authors designed the analytical approach. K.H. assisted with the collection of sample 1; M.G. collected sample 2. K.H., M.F., and M.G. analyzed the data. K.H. wrote the manuscript. All authors reviewed and revised the manuscript.

The authors are grateful to Dr. Teague Henry and Dr. Sebastian Ruf, as well as Christiana Westlin and Yu Yin, for their advice on and assistance with network analysis methods. The authors are additionally grateful to the team of researchers who collected sample 1: Mallory Feldman, Madeleine Devlin, Catherine Nielson, Zulqarnain Khan, and collaborators Dr. Jennifer Dy, and Dr. Jolie Wormwood.

References

- Anand, D., Chen, Y., Lindquist, K. A., & Daughters, S. B. (2017). Emotion differentiation predicts likelihood of initial lapse following substance use treatment. *Drug and Alcohol Dependence*, 180, 439–444. <https://doi.org/10.1016/j.drugalcdep.2017.09.007>
- Bagby, R. M., Parker, J. D. A., & Taylor, G. J. (1994). The twenty-item Toronto Alexithymia Scale—I. Item selection and cross-validation of the factor structure. *Journal of Psychosomatic Research*, 38(1), 23–32.
- Bamieh, B., Jovanovic, M. R., Mitra, P., & Patterson, S. (2012). Coherence in large-scale networks: Dimension-dependent limitations of local feedback. *IEEE Transactions on Automatic Control*, 57(9), 2235–2249.
- Barabási, A.-L., & Albert, R. (1999). Emergence of scaling in random networks. *Science*, 286(5439), 509–512.
- Barrat, A., Barthélemy, M., Pastor-Satorras, R., & Vespignani, A. (2004). The architecture of complex weighted networks. *Proceedings of the National Academy of Sciences*, 101(11), 3747–3752. <https://doi.org/10.1073/pnas.0400087101>
- Barrett, L. F. (1998). Discrete emotions or dimensions? The role of valence focus and arousal focus. *Cognition and Emotion*, 12(4), 579–599. <https://doi.org/10.1080/026999398379574>
- Barrett, L. F. (2004). Feelings or words? Understanding the content in self-report ratings of experienced emotion. *Journal of Personality and Social Psychology*, 87(2), 266–281. <https://doi.org/10.1037/0022-3514.87.2.266>
- Barrett, L. F. (2017a). *How emotions are made: The secret life of the brain*. Houghton Mifflin Harcourt.
- Barrett, L. F. (2017b). The theory of constructed emotion: An active inference account of interoception and categorization. *Social Cognitive and Affective Neuroscience*, 1–23. <https://doi.org/10.1093/scan/nsw154>
- Barrett, L. F., Gross, J., Christensen, T. C., & Benvenuto, M. (2001). Knowing what you're feeling and knowing what to do about it: Mapping the relation between emotion differentiation and emotion regulation. *Cognition and Emotion*, 15(6), 713–724. <https://doi.org/10.1080/02699930143000239>
- Bassett, D. S., Mattar, M., Muldoon, S. F., Gu, S., & Yang, M. (2020). *Network Community Toolbox*. <http://commdetect.weebly.com/>
- Bastian, M., Heymann, S., & Jacomy, M. (2009). Gephi: An open source software for exploring and manipulating networks. *Third International AAAI Conference on Weblogs and Social Media*.
- Beck, A. T., Epstein, N., Brown, G., & Steer, R. A. (1988). An inventory for measuring clinical anxiety: Psychometric properties. *Journal of Consulting and Clinical Psychology*, 56(6), 893–897.
- Beck, A. T., Steer, R. A., & Brown, G. K. (1996). *Manual for the Beck Depression Inventory-II*. Psychological Corporation.
- Beck, A. T., Ward, C., Mendelson, M., Mock, J., & Erbaugh, J. (1961). Beck Depression Inventory (BDI). *Archives of General Psychiatry*, 4(6), 561–571.
- Benson, L., Ram, N., Almeida, D. M., Zautra, A. J., & Ong, A. D. (2018). Fusing biodiversity metrics into investigations of daily life: Illustrations and recommendations with emodiversity. *The Journals of Gerontology: Series B*, 73(1), 75–86. <https://doi.org/10.1093/geronb/gbx025>

- Blom, G. (1958). *Statistical estimates and transformed beta-variables*. Wiley.
- Blondel, V. D., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, 2008(10), P10008.
- Boccaletti, S., Latora, V., Moreno, Y., Chavez, M., & Hwang, D.-U. (2006). Complex networks: Structure and dynamics. *Physics Reports*, 424(4–5), 175–308.
- Borenstein, M., Hedges, L. V., Higgins, J. P., & Rothstein, H. R. (2011). *Introduction to meta-analysis*. John Wiley & Sons.
- Borsboom, D. (2017). A network theory of mental disorders. *World Psychiatry*, 16(1), 5–13.
- Borsboom, D., & Cramer, A. O. J. (2013). Network analysis: An integrative approach to the structure of psychopathology. *Annual Review of Clinical Psychology*, 9(1), 91–121. <https://doi.org/10.1146/annurev-clinpsy-050212-185608>
- Brandt, P. T., & Williams, J. T. (2007). *Multiple time series models*. Sage Publications.
- Bringmann, L. F., Lemmens, L. H. J. M., Huibers, M. J. H., Borsboom, D., & Tuerlinckx, F. (2015). Revealing the dynamic network structure of the Beck Depression Inventory-II. *Psychological Medicine*, 45(4), 747–757. <https://doi.org/10.1017/S0033291714001809>
- Bringmann, L. F., Pe, M. L., Vissers, N., Ceulemans, E., Borsboom, D., Vanpaemel, W., Tuerlinckx, F., & Kuppens, P. (2016). Assessing temporal emotion dynamics using networks. *Assessment*, 23(4), 425–435. <https://doi.org/10.1177/1073191116645909>
- Bringmann, L. F., Vissers, N., Wichers, M., Geschwind, N., Kuppens, P., Peeters, F., Borsboom, D., & Tuerlinckx, F. (2013). A network approach to psychopathology: New insights into clinical longitudinal data. *PLoS ONE*, 8(4), e60188. <https://doi.org/10.1371/journal.pone.0060188>
- Brown, N. J. L., & Coyne, J. C. (2017). Emodiversity: Robust predictor of outcomes or statistical artifact? *Journal of Experimental Psychology: General*, 146(9), 1372–1377. <https://doi.org/10.1037/xge0000330>
- Carstensen, L. L., Pasupathi, M., Mayr, U., & Nesselroade, J. R. (2000). Emotional experience in everyday life across the adult life span. *Journal of Personality and Social Psychology*, 79(4), 644–655. <https://doi.org/10.1037/0022-3514.79.4.644>
- Clark, L. A., & Watson, D. (1991). Tripartite model of anxiety and depression: Psychometric evidence and taxonomic implications. *Journal of Abnormal Psychology*, 100(3), 316–336.
- Cohen, J. (1988). The effect size index: D. In *Statistical Power Analysis for the Behavioral Sciences* (pp. 284–288). Routledge Academic.
- Costantini, G., Richetin, J., Preti, E., Casini, E., Epskamp, S., & Perugini, M. (2019). Stability and variability of personality networks. A tutorial on recent developments in network psychometrics. *Personality and Individual Differences*, 136, 68–78. <https://doi.org/10.1016/j.paid.2017.06.011>
- Cramer, A. O., Waldorp, L. J., Van Der Maas, H. L., & Borsboom, D. (2010). Comorbidity: A network perspective. *Behavioral and Brain Sciences*, 33(2–3), 137–150.
- Dejonckheere, E., Mestdagh, M., Houben, M., Rutten, I., Sels, L., Kuppens, P., & Tuerlinckx, F. (2019). Complex affect dynamics add limited information to the prediction of psychological well-being. *Nature Human Behaviour*, 3(5), 478–491. <https://doi.org/10.1038/s41562-019-0555-0>
- Demiralp, E., Thompson, R. J., Mata, J., Jaeggi, S. M., Buschkuhl, M., Barrett, L. F., Ellsworth, P. C., Demiralp, M., Hernandez-Garcia, L., Deldin, P. J., Gotlib, I. H., & Jonides, J.

- (2012). Feeling blue or turquoise? Emotional differentiation in major depressive disorder. *Psychological Science*, 23(11), 1410–1416. <https://doi.org/10.1177/0956797612444903>
- Dixon-Gordon, K. L., Chapman, A. L., Weiss, N. H., & Rosenthal, M. Z. (2014). A preliminary examination of the role of emotion differentiation in the relationship between borderline personality and urges for maladaptive behaviors. *Journal of Psychopathology and Behavioral Assessment*, 36(4), 616–625.
- Edwards, E. R., & Wupperman, P. (2017). Emotion regulation mediates effects of alexithymia and emotion differentiation on impulsive aggressive behavior. *Deviant Behavior*, 38(10), 1160–1171.
- Eid, M., & Diener, E. (1999). Intraindividual variability in affect: Reliability, validity, and personality correlates. *Journal of Personality and Social Psychology*, 76(4), 662–676.
- Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological Methods*, 23(4), 617–634. <https://doi.org/10.1037/met0000167>
- Epskamp, S., Rhemtulla, M., & Borsboom, D. (2017). Generalized network psychometrics: Combining network and latent variable models. *Psychometrika*, 82(4), 904–927. <https://doi.org/10.1007/s11336-017-9557-x>
- Erbas, Y., Ceulemans, E., Blanke, E. S., Sels, L., Fischer, A., & Kuppens, P. (2019). Emotion differentiation dissected: Between-category, within-category, and integral emotion differentiation, and their relation to well-being. *Cognition and Emotion*, 33(2), 258–271. <https://doi.org/10.1080/02699931.2018.1465894>
- Erbas, Y., Ceulemans, E., Boonen, J., Noens, I., & Kuppens, P. (2013). Emotion differentiation in autism spectrum disorder. *Research in Autism Spectrum Disorders*, 7(10), 1221–1227. <https://doi.org/10.1016/j.rasd.2013.07.007>
- Erbas, Y., Ceulemans, E., Kalokerinos, E. K., Houben, M., Koval, P., Pe, M. L., & Kuppens, P. (2018). Why I don't always know what I'm feeling: The role of stress in within-person fluctuations in emotion differentiation. *Journal of Personality and Social Psychology*, 115(2), 179–191. <https://doi.org/10.1037/pspa0000126>
- Erbas, Y., Ceulemans, E., Lee Pe, M., Koval, P., & Kuppens, P. (2014). Negative emotion differentiation: Its personality and well-being correlates and a comparison of different assessment methods. *Cognition and Emotion*, 28(7), 1196–1213. <https://doi.org/10.1080/02699931.2013.875890>
- Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G* Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, 41(4), 1149–1160. <https://doi.org/10.3758/BRM.41.4.1149>
- Feldman, L. A. (1993). Distinguishing depression and anxiety in self-report: Evidence from confirmatory factor analysis on nonclinical and clinical samples. *Journal of Consulting and Clinical Psychology*, 61(4), 631–638.
- Feldman, L. A. (1995). Valence focus and arousal focus: Individual difference in the structure of affective experiences. *Journal of Personality and Social Psychology*, 69(1), 153–166.
- Fisher, A. J., Reeves, J. W., Lawyer, G., Medaglia, J. D., & Rubel, J. A. (2017). Exploring the idiographic dynamics of mood and anxiety via network analysis. *Journal of Abnormal Psychology*, 126(8), 1044–1056.
- Fried, E. I., van Borkulo, C. D., Cramer, A. O., Boschloo, L., Schoevers, R. A., & Borsboom, D. (2017). Mental disorders as networks of problems: A review of recent insights. *Social Psychiatry and Psychiatric Epidemiology*, 52(1), 1–10.

- Goh, J. X., Hall, J. A., & Rosenthal, R. (2016). Mini meta-analysis of your own studies: Some arguments on why and a primer on how. *Social and Personality Psychology Compass*, 10(10), 535–549. <https://doi.org/10.1111/spc3.12267>
- Grossmann, I., Oakes, H., & Santos, H. C. (2019). Wise reasoning benefits from emodiversity, irrespective of emotional intensity. *Journal of Experimental Psychology: General*, 148(5), 805–823. <https://doi.org/10.1037/xge0000543>
- Hagmann, P., Cammoun, L., Gigandet, X., Meuli, R., & Honey, C. J. (2008). Mapping the structural core of human cerebral cortex. *PloS Biology*, 6(7), e159.
- Hidalgo, C. A., Klinger, B., Barabási, A.-L., & Hausmann, R. (2007). The product space conditions the development of nations. *Science*, 317(5837), 482–487.
- Hoemann, K., & Barrett, L. F. (2018). Concepts dissolve artificial boundaries in the study of emotion and cognition, uniting body, brain, and mind. *Cognition and Emotion*. <https://doi.org/10.1080/02699931.2018.1535428>
- Hu, Y. (2005). Efficient, high-quality force-directed graph drawing. *Mathematica Journal*, 10(1), 37–71.
- Jacomy, M. (2007). *ForceAtlas layout for Gephi*.
- Jacomy, M., Venturini, T., Heymann, S., & Bastian, M. (2014). ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the Gephi software. *PloS One*, 9(6), e98679.
- Jahng, S., Wood, P. K., & Trull, T. J. (2008). Analysis of affective instability in ecological momentary assessment: Indices using successive difference and group comparison via multilevel modeling. *Psychological Methods*, 13(4), 354–375.
- Kalokerinos, E. K., Erbas, Y., Ceulemans, E., & Kuppens, P. (2019). Differentiate to regulate: Low negative emotion differentiation is associated with ineffective use but not selection of emotion-regulation strategies. *Psychological Science*, 30(6), 863–879. <https://doi.org/10.1177/0956797619838763>
- Kashdan, T. B., Barrett, L. F., & McKnight, P. E. (2015). Unpacking emotion differentiation: Transforming unpleasant experience by perceiving distinctions in negativity. *Current Directions in Psychological Science*, 24(1), 10–16. <https://doi.org/10.1177/0963721414550708>
- Kashdan, T. B., & Farmer, A. S. (2014). Differentiating emotions across contexts: Comparing adults with and without social anxiety disorder using random, social interaction, and daily experience sampling. *Emotion*, 14(3), 629–638.
- Kashdan, T. B., Ferrisizidis, P., Collins, R. L., & Muraven, M. (2010). Emotion differentiation as resilience against excessive alcohol use: An ecological momentary assessment in underage social drinkers. *Psychological Science*, 21(9), 1341–1347. <https://doi.org/10.1177/0956797610379863>
- Kimhy, D., Vakhrusheva, J., Khan, S., Chang, R. W., Hansen, M. C., Ballon, J. S., Malaspina, D., & Gross, J. J. (2014). Emotional granularity and social functioning in individuals with schizophrenia: An experience sampling study. *Journal of Psychiatric Research*, 53, 141–148.
- Kroenke, K., Strine, T. W., Spitzer, R. L., Williams, J. B., Berry, J. T., & Mokdad, A. H. (2009). The PHQ-8 as a measure of current depression in the general population. *Journal of Affective Disorders*, 114(1–3), 163–173.

- Lange, J., Dalege, J., Borsboom, D., van Kleef, G. A., & Fischer, A. H. (2020). Toward an integrative psychometric model of emotions. *Perspectives on Psychological Science*, 15(2), 444–468.
- Lauritzen, S. L. (1996). *Graphical models*. Oxford University Press.
- Lindquist, K. A., & Barrett, L. F. (2008). Emotional complexity. In M. Lewis, J. M. Haviland-Jones, & L. F. Barrett (Eds.), *Handbook of Emotions* (3rd ed., pp. 513–530). Guilford Press.
- Lohse, C., Bassett, D. S., Lim, K. O., & Carlson, J. M. (2014). Resolving anatomical and functional structure in human brain organization: Identifying mesoscale organization in weighted network representations. *PLoS Computational Biology*, 10(10), e1003712. <https://doi.org/10.1371/journal.pcbi.1003712>
- Mennin, D. S., Heimberg, R. G., Turk, C. L., & Fresco, D. M. (2005). Preliminary evidence for an emotion dysregulation model of generalized anxiety disorder. *Behaviour Research and Therapy*, 43(10), 1281–1310.
- Moeller, J., Ivcevic, Z., Brackett, M. A., & White, A. E. (2018). Mixed emotions: Network analyses of intra-individual co-occurrences within and across situations. *Emotion*, 18(8), 1106–1121.
- Newman, M. E. J. (2004). Analysis of weighted networks. *Physical Review E*, 70(5), 056131. <https://doi.org/10.1103/PhysRevE.70.056131>
- Newman, M. E. J. (2006). Modularity and community structure in networks. *Proceedings of the National Academy of Sciences*, 103(23), 8577–8582. <https://doi.org/10.1073/pnas.0601602103>
- Nock, M. K., Wedig, M. M., Holmberg, E. B., & Hooley, J. M. (2008). The Emotion Reactivity Scale: Development, evaluation, and relation to self-injurious thoughts and behaviors. *Behavior Therapy*, 39(2), 107–116.
- Ong, A. D., Benson, L., Zautra, A. J., & Ram, N. (2018). Emodiversity and biomarkers of inflammation. *Emotion*, 18(1), 3–14. <https://doi.org/10.1037/emo0000343>
- Onnela, J.-P., Saramäki, J., Kertész, J., & Kaski, K. (2005). Intensity and coherence of motifs in weighted complex networks. *Physical Review E*, 71(6), 065103. <https://doi.org/10.1103/PhysRevE.71.065103>
- Osborne, J., & Costello, A. B. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research, and Evaluation*, 10(1), 7.
- Pe, M. L., Kircanski, K., Thompson, R. J., Bringmann, L. F., Tuerlinckx, F., Mestdagh, M., Mata, J., Jaeggi, S. M., Buschkuhl, M., Jonides, J., Kuppens, P., & Gotlib, I. H. (2015). Emotion-network density in major depressive disorder. *Clinical Psychological Science*, 3(2), 292–300. <https://doi.org/10.1177/2167702614540645>
- Pfaltz, M. C., Michael, T., Grossman, P., Margraf, J., & Wilhelm, F. H. (2010). Instability of physical anxiety symptoms in daily life of patients with panic disorder and patients with posttraumatic stress disorder. *Journal of Anxiety Disorders*, 24(7), 792–798.
- Pond, R. S., Jr., Kashdan, T. B., DeWall, C. N., Savostyanova, A., Lambert, N. M., & Fincham, F. D. (2012). Emotion differentiation moderates aggressive tendencies in angry people: A daily diary analysis. *Emotion*, 12(2), 326–337.
- Quoidbach, J., Gruber, J., Mikolajczak, M., Kogan, A., Kotsou, I., & Norton, M. I. (2014). Emodiversity and the emotional ecosystem. *Journal of Experimental Psychology: General*, 143(6), 2057–2066. <https://doi.org/10.1037/a0038025>

- Robinson, M. D., & Clore, G. L. (2002). *Belief and feeling: Evidence for an accessibility model of emotional self-report*. 128(6), 934–960. <https://doi.org/10.1037//0033-2909.128.6.934>
- Rubinov, M., & Sporns, O. (2010). Complex network measures of brain connectivity: Uses and interpretations. *NeuroImage*, 52(3), 1059–1069.
- Rubinov, M., & Sporns, O. (2011). Weight-conserving characterization of complex functional brain networks. *NeuroImage*, 56(4), 2068–2079. <https://doi.org/10.1016/j.neuroimage.2011.03.069>
- Schmittmann, V. D., Cramer, A. O. J., Waldorp, L. J., Epskamp, S., Kievit, R. A., & Borsboom, D. (2013). Deconstructing the construct: A network perspective on psychological phenomena. *New Ideas in Psychology*, 31(1), 43–53. <https://doi.org/10.1016/j.newideapsych.2011.02.007>
- Seah, T. H. S., Aurora, P., & Coifman, K. G. (2020). Emotion differentiation as a protective factor against the behavioral consequences of rumination: A conceptual replication and extension in the context of social anxiety. *Behavior Therapy*, 51(1), 135–148. <https://doi.org/10.1016/j.beth.2019.05.011>
- Selby, E. A., Wonderlich, S. A., Crosby, R. D., Engel, S. G., Panza, E., Mitchell, J. E., Crow, S. J., Peterson, C. B., & Le Grange, D. (2013). Nothing tastes as good as thin feels: Low positive emotion differentiation and weight-loss activities in anorexia nervosa. *Clinical Psychological Science*, 2(4), 514–531.
- Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Technical Journal*, 27(3), 379–423.
- Shrout, P. E., & Fleiss, J. L. (1979). Intraclass correlations: Uses in assessing rater reliability. *Psychological Bulletin*, 86(2), 420–428.
- Spitzer, R. L., Kroenke, K., Williams, J. B., & Löwe, B. (2006). A brief measure for assessing generalized anxiety disorder: The GAD-7. *Archives of Internal Medicine*, 166(10), 1092–1097.
- Stanton, A. L., Danoff-Burg, S., & Huggins, M. E. (2002). The first year after breast cancer diagnosis: Hope and coping strategies as predictors of adjustment. *Psycho-Oncology*, 11(2), 93–102.
- Starr, L. R., Hershenberg, R., Li, Y. I., & Shaw, Z. A. (2017). When feelings lack precision: Low positive and negative emotion differentiation and depressive symptoms in daily life. *Clinical Psychological Science*, 5(4), 613–631. <https://doi.org/10.1177/2167702617694657>
- Suvak, M. K., Litz, B. T., Sloan, D. M., Zanarini, M. C., Barrett, L. F., & Hofmann, S. G. (2011). Emotional granularity and borderline personality disorder. *Journal of Abnormal Psychology*, 120(2), 414–426.
- Thompson, R. J., Mata, J., Jaeggi, S. M., Buschkuhl, M., Jonides, J., & Gotlib, I. H. (2012). The everyday emotional experience of adults with major depressive disorder: Examining emotional instability, inertia, and reactivity. *Journal of Abnormal Psychology*, 121(4), 819–829. <https://doi.org/10.1037/a0027978>
- Tobacyk, J. J. (1980). Comparison of five measures of affective complexity derived from P-technique factor analysis. *Perceptual and Motor Skills*, 50(3, Pt 2), 1259–1262.
- Toivonen, R., Kivelä, M., Saramäki, J., Viinikainen, M., Vanhatalo, M., & Sams, M. (2012). Networks of emotion concepts. *PLoS ONE*, 7(1), e28883. <https://doi.org/10.1371/journal.pone.0028883>

- Tomko, R. L., Lane, S. P., Pronove, L. M., Treloar, H. R., Brown, W. C., Solhan, M. B., Wood, P. K., & Trull, T. J. (2015). Undifferentiated negative affect and impulsivity in borderline personality and depressive disorders: A momentary perspective. *Journal of Abnormal Psychology*, 124(3), 740–753. <https://doi.org/10.1037/abn0000064>
- Trampe, D., Quoidbach, J., & Taquet, M. (2015). Emotions in everyday life. *PLoS One*, 10(12), e0145450. <https://doi.org/10.1371/journal.pone.0145450>
- Trull, T. J., Lane, S. P., Koval, P., & Ebner-Priemer, U. W. (2015). Affective dynamics in psychopathology. *Emotion Review*, 7(4), 355–361.
- Tugade, M. M., Fredrickson, B. L., & Barrett, L. F. (2004). Psychological resilience and positive emotional granularity: Examining the benefits of positive emotions on coping and health. *Journal of Personality*, 72(6), 1161–1190. <https://doi.org/10.1111/j.1467-6494.2004.00294.x>
- Van der Gucht, K., Dejonckheere, E., Erbas, Y., Takano, K., Vandemoortele, M., Maex, E., Raes, F., & Kuppens, P. (2019). An experience sampling study examining the potential impact of a mindfulness-based intervention on emotion differentiation. *Emotion*, 19(1), 123–131. <https://doi.org/10.1037/emo0000406>
- van der Maas, H. L., Dolan, C. V., Grasman, R. P., Wicherts, J. M., Huizenga, H. M., & Raijmakers, M. E. (2006). A dynamical model of general intelligence: The positive manifold of intelligence by mutualism. *Psychological Review*, 113(4), 842–861.
- VanVoorhis, C. W., & Morgan, B. L. (2007). Understanding power and rules of thumb for determining sample sizes. *Tutorials in Quantitative Methods for Psychology*, 3(2), 43–50.
- Warriner, A. B., Kuperman, V., & Brysbaert, M. (2013). Norms of valence, arousal, and dominance for 13,915 English lemmas. *Behavior Research Methods*, 45(4), 1191–1207. <https://doi.org/10.3758/s13428-012-0314-x>
- Watson, D., Anna, L., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology*, 54(6), 1063–1070.
- Werner-Seidler, A., Hitchcock, C., Hammond, E., Travers-Hill, E., Golden, A.-M., Breakwell, L., Ramana, R., & Dalgleish, T. (2018). *Emotional complexity across the life story: Diminished positive emodiversity and elevated negative emodiversity in sufferers of chronic depression* [Preprint]. PsyArXiv. <https://doi.org/10.31234/osf.io/kg23q>
- Widdershoven, R. L. A., Wichers, M., Kuppens, P., Hartmann, J. A., Menne-Lothmann, C., Simons, C. J. P., & Bastiaansen, J. A. (2019). Effect of self-monitoring through experience sampling on emotion differentiation in depression. *Journal of Affective Disorders*, 244, 71–77.
- Willroth, E. C., Flett, J. A. M., & Mauss, I. B. (2019). Depressive symptoms and deficits in stress-reactive negative, positive, and within-emotion-category differentiation: A daily diary study. *Journal of Personality*, jopy.12475. <https://doi.org/10.1111/jopy.12475>
- Willroth, E. C., Flett, J. A., & Mauss, I. B. (2020). Depressive symptoms and deficits in stress-reactive negative, positive, and within-emotion-category differentiation: A daily diary study. *Journal of Personality*, 88(2), 174–184.
- Zautra, A. J., Affleck, G. G., Tennen, H., Reich, J. W., & Davis, M. C. (2005). Dynamic approaches to emotions and stress in everyday life: Bolger and Zuckerman reloaded with positive as well as negative affects. *Journal of Personality*, 73(6), 1511–1538.

- Zautra, A. J., Reich, J. W., Davis, M. C., Potter, P. T., & Nicolson, N. A. (2000). The role of stressful events in the relationship between positive and negative affects: Evidence from field and experimental studies. *Journal of Personality*, 68(5), 927–951.
- Zautra, A. J., Smith, B., Affleck, G., & Tennen, H. (2001). Examinations of chronic pain and affect relationships: Applications of a dynamic model of affect. *Journal of Consulting and Clinical Psychology*, 69(5), 786.

Supplemental Materials

Sample 1

The data for sample 1 come from a large study examining affective experience, decision-making, and peripheral physiological activity in daily life. This dataset was first reported by Hoemann et al. (in press). However, the present analyses use a different subset of the data than previously examined. As outlined in the main text, we used the repeated emotion intensity ratings provided during end-of-day diaries to construct emotion networks and estimate emotional granularity. We compared these estimates of granularity to other measures derived from the intensity ratings, as well as other self-report (i.e., questionnaire) measures. Neither the emotion intensity ratings nor the questionnaire measures were analyzed by Hoemann et al. (in press), who also did not examine emotional granularity.

Participants. Eligible participants were non-smoking, fluent English speakers, and excluded if they had a history of cardiovascular illness or stroke, chronic medical conditions, mental illness, asthma, skin allergies, or very sensitive skin. Eligible participants also confirmed they were not taking any medications known to influence physiological arousal including medications for ADHD, insomnia, anxiety, hypertension, rheumatoid arthritis, epilepsy/seizures, cold/flu, or fever/allergies.

Participants received \$30 for their first in-lab session, \$20 per day for the first five days of experience sampling, \$30 per day for the second five days of experience sampling, and \$40 per day for the final four days of experience sampling. Participants were incentivized to respond to an average of eight prompts per day during experience sampling, and received a \$10 bonus for every pay period in which they made this target (i.e., up to three times total). Lastly, participants received \$50 for their second and final in-lab session. Participants also received a \$25 bonus for completion of an in-lab temporal discounting task.

Experience sampling. On each day of experience sampling, participants came into the lab and 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 and inertial measurement units [IMUs]). Peripheral physiological data and accelerometric data were recorded continuously throughout the 8-hour sampling period and communicated via Bluetooth to a Motorola Moto G⁴ smartphone provided to participants. A smartphone application, MESA (MindWare Technologies LTD, Westerville, OH), processed the continuous ECG and accelerometer data in real time, and initiated an experience sampling prompt anytime a substantial, sustained change in heart period was detected in the absence of movement or posture change, with an imposed minimum interval of five minutes between prompts. A substantial, sustained change in heart period was operationalized on the first day of sampling as occurring when the interbeat interval (IBI) changed by more than ± 167 ms over an eight-second period (at a typical resting heart rate of 60 bpm or IBI of 1000 ms, this is equivalent to a decrease of about 9 bpm or an increase of about 12 bpm). On subsequent days, this IBI parameter was manually adjusted up or down to ensure each participant received approximately 20 prompts per day. 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/s² within the preceding 30 seconds. Posture (standing, sitting, reclining) was determined by comparing the relative orientation of the two IMUs on a participant's torso and thigh using their continuous accelerometry data. Absence of posture change was operationalized as any time when the relative orientation of the two IMUs did not change within the preceding 30 seconds.

Participants also received on average 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. Random prompts were spread throughout the experience sampling day. Participants were informed that some experience sampling prompts would be generated randomly while others would be generated based on changes in their cardiac activity. By conveying this information, we were able to instruct participants to avoid responding to prompts following specific physiological events (e.g., coughing, sneezing) and minimize the extent to which they paid special attention to their cardiac activity. Participants 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 above.

Experience sampling questions. At each sampling event, participants were prompted to respond to a series of questions presented in the MESA application. First, participants provided a brief free-text description of what was going on at the time they received the prompt. Second, participants rated their current valence and arousal, each on a 100-point continuous slider scale ranging from -50 (very unpleasant or deactivated) to +50 (very pleasant or activated). Third, participants provided another brief free-text description of their social context by: writing “alone”, listing the initials of direct interaction partners, and/or writing “group” (to indicate the presence of a large number of other people). Fourth, participants selected an activity from a drop-down list consisting of: “socializing”, “eating”, “exercising”, “watching TV”, “working”, “commuting”, “using computer/email/internet”, “preparing food”, “on the phone”, “praying/meditating/worship”, “napping”, “taking care of children”, “housework”, or “other”. Fifth, participants self-generated words to label their current affective experience. Specifically, participants were asked to “list any emotion(s) you were feeling when you received the prompt”. 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 scale: “not at all” (1), “a little” (2), “moderately” (3), “a lot” (4), “very much” (5). Finally, participants received one of two possible single-item decision tasks: either a temporal discounting problem or a scrambled anagram problem.

End-of-day survey. At the end of each experience sampling day, participants automatically received a modified day reconstruction survey (Kahneman et al., 2004; Stone et al., 2006) to an email account they provided upon study enrollment. Participants were requested to complete the survey as soon as possible after finishing their day of experience sampling, and to avoid distractions while doing so.

In the survey, participants were presented with some of the information they provided for each of the prompts they completed during the day: the event time, label, social context, and major activity. Using this information as a guide, participants were asked to provide additional details about each experience sampling event. First, participants were asked to detail the social context of the event, including a brief description of any initials provided (e.g., “SB is a coworker”) and how well they knew their interaction partner(s). Second, participants were asked to provide a brief description of what was happening as they received the prompt, including their thoughts and feelings. Participants were requested to selectively detail three sampling events with a longer, more detailed description (>200 words). Next, participants were asked to recall their affective experience at the time of the prompt in two ways: (1) using slider scales to rate their valence and arousal, and (2) using 7-point Likert-style scales to rate their experienced intensity on a standard set of 18 emotions (“afraid”, “amused”, “angry”, “bored”, “calm”,

“disgusted”, “embarrassed”, “excited”, “frustrated”, “grateful”, “happy”, “neutral”, “proud”, “relieved”, “sad”, “serene”, “surprised”, “worn out”). Lastly, participants were asked to respond to a series of seven questions developed based on the Geneva Appraisal Questionnaire (Geneva Emotion Research Group, 2002) that related to appraisal dimensions (e.g., goal relevance, power, control, coping, predictability; Scherer, 2001).

In-lab tasks and questionnaires. Participants completed in-lab sessions before and after experience sampling, each 2-3 hours in length. During these sessions, participants completed a battery of questionnaires, as well as tasks related to cognitive functioning, decision making, and affective experience. Electrocardiogram (ECG), impedance cardiogram (ICG), electrodermal activity (EDA; recorded from the palm, as well as the back of the neck to correspond with ambulatory measurement), and respiration were captured throughout both sessions. As described below, continuous noninvasive arterial pressure (CNAP) and finger photoplethysmography (PPG) were also captured during select segments.

In-lab session 1. Participants provided informed consent and were provided with an overview of the study. Participants were then instrumented for physiological monitoring and asked to complete health and demographics forms. Participants were then instrumented with blood pressure cuffs (on the arm and finger) and finger PPG after which they sat quietly for a 5-minute resting baseline. The finger PPG was then removed, and participants completed a running letter span (RLS; Broadway & Engle, 2010) task. Both blood pressure cuffs were then removed, and participants completed temporal discounting (DeSteno et al., 2014; Kirby et al., 1999), anagrams (Beversdorf et al., 1999, 2002), and attentional network (ANT; Fan et al., 2002) tasks. Next, participants completed a scenario immersion task (Wilson-Mendenhall et al., 2013, 2015), in which they listened to a series of brief emotional scenarios and rated their felt affect on the dimensions of valence and arousal (Russell, 1980). Lastly, participants completed the Session 1 questionnaires listed in Table S1. Upon completion of the session, participants were disconnected from the physiological equipment, instructed about the scheduling of their experience sampling days, and paid.

In-lab session 2. Participants were instrumented for physiological monitoring and then asked to complete the Session 2 questionnaires listed in Table S1. Participants were then instrumented with blood pressure cuffs and finger PPG and sat quietly for a 5-minute resting baseline. Immediately following the baseline, participants followed a sequence of stressor tasks. Specifically, participants completed mental math problems from the Trier Social Stress Test (Kirschbaum et al., 1993) with the understanding that these would be used to assess personality and would be compared against other participants. Over three trials, participants received increasingly difficult mental math problems from a stern experimenter. After the first two trials, the finger PPG was removed and participants again completed the temporal discounting task (DeSteno et al., 2014; Kirby et al., 1999). After the third trial, blood pressure cuffs were removed and participants again completed another version of the anagrams task (Beversdorf et al., 1999, 2002). Participants were led to believe there would be a fourth mental math trial to maintain stress during the anagrams task; however, this additional trial was never administered. Following the stress sequence, participants again completed the attentional network task (ANT; Fan et al., 2002) and a spatial arrangement task (SpAM; Hout et al., 2013) in which they were asked to arrange emotion words according to their semantic similarity. Upon completion of the session, participants were disconnected from the physiological equipment, debriefed, and paid.

Sample 2

Participants. Eligible participants were native English speakers currently enrolled in years 1-3 of the undergraduate course of study at Northeastern University. Eligible participants were excluded if they reported colorblindness, poor hearing, history of learning/emotional/neurological disorder, previous electroconvulsive therapy (ECT), major head trauma in the last two years, any major surgeries in the last year, history of heart disease or open heart surgery, history of vascular disease, any prior stroke (including a ‘TIA’ or ‘mini-stroke’), any seizures, any alcohol or drug abuse, untreated diabetes, or untreated hypertension.

Participants received \$200 for completing the full study. Compensation was prorated for partial completion as follows: \$5 for each half-hour of an in-lab session; \$70/week for experience sampling, self-reports and end-of-day diaries. In addition, participants with a completion rate over 90% were entered into a gift card raffle.

Experience sampling. Participants were assigned a palm pilot and received instructions for completing experience sampling during an initial in-lab session (detailed below), before completing either a one- or two-week experience sampling period. Initially, all participants completed a two-week protocol. Due to equipment failure, subsequent participants completed one week of experience sampling, along with one week of the Emotional Patterns Questionnaire (EPQ; De Leersnyder et al., 2011). For these participants, the weeks of experience sampling and EPQ were counterbalanced.

During experience sampling, participants received ten random prompts per day, between the hours of 8 am and 11 pm. Sampling data were uploaded from the palm pilot after each week of sampling (at in-lab sessions 2 and 3), at which time participants’ response rate was computed. Participants were required to maintain a 75% response rate to remain in the study. Participants were further incentivized to maintain a 90% response rate, as detailed above.

Experience sampling questions. At each sampling prompt, participants were asked to use 5-point Likert-style scales to rate their experienced intensity on a standard set of 39 emotions (“admiring”, “amazed”, “amused”, “angry”, “appreciative”, “bored”, “calm”, “contemptuous”, “content”, “depressed”, “disgusted”, “dislike”, “down”, “elated”, “enthusiastic”, “excited”, “fearful”, “furious”, “grateful”, “guilty”, “happy”, “hateful”, “irritated”, “joyous”, “nervous”, “peaceful”, “prideful”, “relaxed”, “remorseful”, “repulsed”, “restful”, “sad”, “scornful”, “shocked”, “sorry”, “successful”, “superior”, “surprised”, “terrified”).

Emotional Patterns Questionnaire. As part of experience sampling, participants completed a survey based on the Emotional Patterns Questionnaire (EPQ; De Leersnyder et al., 2011). In the modified EPQ, participants were given general prompts to recall certain types of emotional events (e.g., a time when you were in a social context and felt pleasant), and asked to write a brief description of their experience. For each event, participants were also asked to rate their experienced intensity on the set of 39 emotion adjectives used in experience sampling. The modified EPQ included a total of 80 emotional events; participants were able to complete the measure in multiple sittings over the course of a week.

End-of-day diaries. Participants were also asked to complete end-of-day diaries following a modified day reconstruction survey (Kahneman et al., 2004; Stone et al., 2006). Participants were first asked to ‘map out’ their day into a series of episodes, lasting between 15 minutes and 2 hours, and to provide a brief name (e.g., “at lunch with friend”) as well as the approximate start and end time. Then, participants were asked to select three events (one pleasant, one unpleasant, and one neutral) and provide a more detailed account of each one. Finally, participants were asked, for each event, to indicate whether it was resolved or still ongoing and whether they had enough time to produce a complete account, and to rate the completeness of their account on a

Likert-style scale of 1 (“lacks sufficient detail”) to 5 (“contains all the detail necessary to understand the event in full”). Participants were asked to complete a total of three sets of diaries over the course of experience sampling; see Table S2 for an example experience sampling calendar.

Online questionnaires. Participants were asked to complete a number of online questionnaires over the course of experience sampling. Participants completed the online questionnaires listed in Table S3, according to the schedule noted on their experience sampling calendar (see Table S2 for an example).

In-lab tasks and questionnaires. Participants completed three in-lab sessions over the course of the study, scheduled to take place before, during, and after experience sampling. During these sessions, participants completed a series of tasks designed to examine individual differences in verbal fluency, emotion knowledge, working memory capacity, and emotion perception. Participants also completed questionnaires assessing socioeconomic status, life satisfaction, anxiety, depression, crystallized intelligence, and how they view emotions.

In-lab session 1. Participants provided informed consent and were provided with an overview of the study. Participants were then asked to freely sort a set of emotional faces as a measure of emotion perception (e.g., Lindquist et al., 2014), and to freely label descriptions of emotional situations as a measure of emotion knowledge (e.g., based on Lane et al., 1990). Participants also completed the Session 1 questionnaires listed in Table S3. Lastly, participants received the palm pilot and instructions for experience sampling.

In-lab session 2. As a second measure of emotion knowledge, participants were asked to complete a content generation task. In this task, they were prompted with a subset of negative, high-arousal emotion adjectives used during experience sampling; for each adjective, they were asked to produce situations that could have led to the corresponding experience, and to indicate what they would have done in such a situation. For each emotion adjective, participants were also asked to indicate, using a body outline, where they experience it most, and to associated it with a color chip. As a second measure of emotion perception, participants were presented with a separate set of emotional faces, and asked to rate each one for how intensely the individual in the photo is feeling the 39 emotion adjectives used in experience sampling. Participants then completed semantic fluency tasks for emotions and for personality adjectives, the Controlled Oral Word Association Test (COWAT; Benton et al., 1983) for verbal fluency, and the Automated OSPAN test of working memory (Unsworth & Engle, 2005). Finally, participants completed the Session 2 questionnaires listed in Table S3.

In-lab session 3. Participants first completed a two-part memory task. In the encoding phase, they were presented with either emotional or neutral visual scenes, with either an emotional or neutral face embedded, and asked to make a judgement about the face that was either emotional (e.g., “is this face angry?”) or neutral (“is this face female?”). After a distractor task, participants were presented with the previously-seen stimuli along with new, previously-unseen stimuli, and asked to indicate which are new and old (faces and scenes were tested separately). Participants were then asked to complete the Shipley Vocabulary Test (Zachary, 1986) and an autobiographical recall task of the life events they reported earlier in the study. Upon completion of the session, participants were debriefed and paid.

Table S1. Sample 1: Questionnaire Measures for In-Lab Sessions 1 and 2

Questionnaire Name	Acronym	Reference	In-lab 1	In-lab 2
Anxiety Sensitivity Index	ASI-3	Taylor et al. (2007)	x	
Emotion Reactivity Scale	ERS	Nock et al. (2008)	x	
Need for Arousal Scale	NAS	Figner et al. (2009)	x	
Generalized Anxiety Disorder	GAD7	Spitzer et al. (2006)	x	x
Toronto Alexithymia Scale, 20-item version	TAS-20	Bagby et al. (1994)	x	x
Range and Differentiation of Emotional Experience Scale	RDEES	Kang & Shaver (2004)	x	x
Perceived Stress Scale, 4-item version	PSS4	Cohen et al. (1983)	x	x
Patient Health Questionnaire, Severity of Somatic Symptoms scale	PHQ-15	Kroenke et al. (2002)	x	x
Patient Health Questionnaire, Depression scale	PHQ-8	Kroenke et al. (2009)	x	x
Revised NEO Personality Inventory	NEO PI-R	Costa et al. (1992)		x
Barratt Impulsiveness Scale	BIS	Barratt (1985)		x
Domain-Specific Risk Taking Questionnaire	DSRTQ	Weber et al. (2002)		x
UCLA Loneliness Scale, 3-item version	UCLA-L53	Hughes et al. (2004)		x
Stimulating-Instrumental Risk Taking Questionnaire	SIRTQ	Zaleskiewicz (2001)		x

Table S2. Sample 2: Example Experience Sampling Calendar

Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
					In-lab session 1 Questionnaire 1 (any time)	
Daily diary 1 (before bed)	Questionnaire 2 (any time)	Questionnaire 3 (any time)	Questionnaire 4 (any time)	Daily diary 2 (before bed)	In-lab session 2	
	Daily diary 3 (before bed)	Questionnaire 5 (any time)	Questionnaire 6 (any time)	Questionnaire 7 (any time)	In-lab session 3	

Table S3. Sample 2: Questionnaire Measures for Experience Sampling, In-Lab Sessions

Questionnaire Name	Acronym	Reference	Online	In-lab 1	In-lab 2
World-Focused Emotional Experiences		(unpublished)	x		
Essentialism of Emotion		Lindquist et al. (2013)	x		
Socio-Economic Status Items			x		
Dimensions of Emotional Meaning (Adapted)		Geneva Group (2002)	x		
Goldberg-100 Personality Scale	BFAS	DeYoung et al. (2007)	x		
Range and Differentiation of Emotional Experiences Scale	RDEES	Kang & Shaver (2004)	x		
Toronto Alexithymia Scale, 20-item version	TAS-20	Bagby et al. (1994)	x		
Beck Anxiety Inventory	BAI	Beck et al. (1988)		x	
Beck Depression Inventory	BDI-I	Beck et al. (1961)		x	
Satisfaction with Life Scale	SWLS	Diener et al. (1985)			x
Social Status Ladder		Adler (2000)			x

Histograms and Scatter Plots

Sample 1

Measures derived from emotion networks.

Overall emotion networks.

Figure S1. Heat map of correlation matrix between granularity measures estimated from overall networks for sample 1.

Figure S2. Scatter plots of the correlations between granularity measures estimated from overall networks (off-diagonals) and histograms of individual measures (diagonal) for sample 1.

Time-varying emotion networks: mean estimates.

Figure S3. Heat map of correlation matrix between granularity measures estimated from time-varying means for sample 1.

Figure S4. Scatter plots of the correlations between granularity measures estimated from time-varying means (off-diagonals) and histograms of individual measures (diagonal) for sample 1.

Time-varying emotion networks: standard deviation estimates.

Figure S5. Heat map of correlation matrix between granularity measures estimated from time-varying standard deviations for sample 1.

Figure S6. Scatter plots of the correlations between granularity measures estimated from time-varying standard deviations (off-diagonals) and histograms of individual measures (diagonal) for sample 1.

Measures derived from experience sampling data.*Overall estimates.*

Figure S7. Histograms of measures derived as overall estimates of experience sampling data from sample 1: ICC (upper left), emotional instability (upper right), mean negative affect (lower left), standard deviation negative affect (lower right).

Mean estimates.

Figure S8. Histograms of measures derived as time-varying mean estimates from experience sampling data from sample 1: ICC (upper left), emotional instability (upper right), mean negative affect (lower left), standard deviation negative affect (lower right).

Standard deviation estimates.

Figure S9. Histograms of measures derived as time-varying standard deviation estimates from experience sampling data from sample 1: ICC (upper left), emotional instability (upper right), mean negative affect (lower left), standard deviation negative affect (lower right).

Self-report questionnaires.

Figure S10. Histograms of self-report questionnaire scores from sample 1: anxiety (GAD-7; upper left), depression (PHQ-8; upper right), alexithymia (TAS-20; lower left), emotion reactivity (ERS; lower right).

Sample 2**Measures derived from emotion networks.***Overall emotion networks.*

Figure S11. Heat map of correlation matrix between granularity measures estimated from overall networks for sample 2.

Figure S12. Scatter plots of the correlations between granularity measures estimated from overall networks (off-diagonals) and histograms of individual measures (diagonal) for sample 2.

Time-varying emotion networks: mean estimates.

Figure S13. Heat map of correlation matrix between granularity measures estimated from time-varying means for sample 2.

Figure S14. Scatter plots of the correlations between granularity measures estimated from time-varying means (off-diagonals) and histograms of individual measures (diagonal) for sample 2.

Time-varying emotion networks: standard deviation estimates.

Figure S15. Heat map of correlation matrix between granularity measures estimated from time-varying standard deviations for sample 2.

Figure S16. Scatter plots of the correlations between granularity measures estimated from time-varying standard deviations (off-diagonals) and histograms of individual measures (diagonal) for sample 2.

Measures derived from experience sampling data.*Overall estimates.*

Figure S17. Histograms of measures derived as overall estimates of experience sampling data from sample 2: ICC (upper left), emotional instability (upper right), mean negative affect (lower left), standard deviation negative affect (lower right).

Mean estimates.

Figure S18. Histograms of measures derived as time-varying mean estimates from experience sampling data from sample 2: ICC (upper left), emotional instability (upper right), mean negative affect (lower left), standard deviation negative affect (lower right).

Standard deviation estimates.

Figure S19. Histograms of measures derived as time-varying standard deviation estimates from experience sampling data from sample 2: ICC (upper left), emotional instability (upper right), mean negative affect (lower left), standard deviation negative affect (lower right).

Self-report questionnaires.

Figure S20. Histograms of self-report questionnaire scores from sample 2: anxiety (BAI; upper left), depression (BDI-I; upper right), alexithymia (TAS-20; lower left).

Supplemental Results

Network Visualizations

Figure S21. Time-varying emotion network for the example participant in sample 1 with higher granularity (i.e., a lower ICC): snapshots at window 1 (upper left panel), window 4 (upper right panel), window 8 (lower left panel) and window 12 (lower right panel). Node color represents community assignment; node size represents degree (i.e., number of edges). Edge thickness represents the absolute value of the Pearson correlation coefficient between two nodes. Edge color represents the sign of the correlation: dark gray edges are positive connections; light gray edges are negative connections. Data were pre-processed in MATLAB (The MathWorks, Inc., Natick, MA) before network visualization in Gephi (Bastian et al., 2009), with nodes assigned to communities within each window using the Louvain detection algorithm (Rubinov & Sporns, 2011). For purposes of visualization, edges were pruned using a backbone detection algorithm (Hagmann et al., 2008; Hidalgo et al., 2007) that identified the dominant connections while maintaining an average degree one half that of the fully-connected network (i.e., $k_N^w = \frac{1}{2n} \sum_{i,j \in N} w_{ij}$). Networks were generated using the Yifan Hu Proportional layout (Hu, 2005).

Figure S22. Time-varying emotion network for the example participant in sample 1 with lower granularity (i.e., a higher ICC): snapshots at window 1 (upper left panel), window 4 (upper right panel), window 8 (lower left panel) and window 12 (lower right panel). Node color represents community assignment; node size represents degree (i.e., number of edges). Edge thickness represents the absolute value of the Pearson correlation coefficient between two nodes. Edge color represents the sign of the correlation: dark gray edges are positive connections; light gray edges are negative connections. Data were pre-processed in MATLAB (The MathWorks, Inc., Natick, MA) before network visualization in Gephi (Bastian et al., 2009), with nodes assigned to communities within each window using the Louvain detection algorithm (Rubinov & Sporns, 2011). For purposes of visualization, edges were pruned using a backbone detection algorithm (Hagmann et al., 2008; Hidalgo et al., 2007) that identified the dominant connections while maintaining an average degree one half that of the fully-connected network (i.e., $k_N^w = \frac{1}{2n} \sum_{i,j \in N} w_{ij}$). Networks were generated using the Yifan Hu Proportional layout (Hu, 2005).

Figure S23. Overall emotion networks for example participants in sample 2 with higher granularity (i.e., a lower ICC; left panel) and lower granularity (i.e., a higher ICC; right panel). Node color represents community assignment; node size represents degree (i.e., number of edges). Edge thickness represents the absolute value of the Pearson correlation coefficient between two nodes. Edge color represents the sign of the correlation: dark gray edges are positive connections; light gray edges are negative connections. Data were pre-processed in MATLAB (The MathWorks, Inc., Natick, MA) before network visualization in Gephi (Bastian et al., 2009), with nodes assigned to communities using the Louvain detection algorithm (Rubinov & Sporns, 2011). For purposes of visualization, edges were pruned using a backbone detection algorithm (Hagmann et al., 2008; Hidalgo et al., 2007) that identified the dominant connections while maintaining an average degree one half that of the fully-connected network (i.e.,

$k_N^w = \frac{1}{2n} \sum_{i,j \in N} w_{ij}$). Networks were generated using the Yifan Hu Proportional layout (Hu, 2005).

Figure S24. Time-varying emotion network for the example participant in sample 2 with higher emotional granularity (i.e., a lower ICC): snapshots at window 1 (upper left panel), window 4 (upper right panel), window 8 (lower left panel) and window 12 (lower right panel). Node color represents community assignment; node size represents degree (i.e., number of edges). Edge thickness represents the absolute value of the Pearson correlation coefficient between two nodes. Edge color represents the sign of the correlation: dark gray edges are positive connections; light gray edges are negative connections. Data were pre-processed in MATLAB (The MathWorks, Inc., Natick, MA) before network visualization in Gephi (Bastian et al., 2009), with nodes assigned to communities within each window using the Louvain detection algorithm (Rubinov & Sporns, 2011). For purposes of visualization, edges were pruned using a backbone detection algorithm (Hagmann et al., 2008; Hidalgo et al., 2007) that identified the dominant connections while maintaining an average degree one half that of the fully-connected network (i.e.,

$k_N^w = \frac{1}{2n} \sum_{i,j \in N} w_{ij}$). Networks were generated using the Yifan Hu Proportional layout (Hu, 2005).

Figure S25. Time-varying emotion network for the example participant in sample 2 with lower emotional granularity (i.e., a higher ICC): snapshots at window 1 (upper left panel), window 4 (upper right panel), window 8 (lower left panel) and window 12 (lower right panel). Node color represents community assignment; node size represents degree (i.e., number of edges). Edge thickness represents the absolute value of the Pearson correlation coefficient between two nodes. Edge color represents the sign of the correlation: dark gray edges are positive connections; light gray edges are negative connections. Data were pre-processed in MATLAB (The MathWorks, Inc., Natick, MA) before network visualization in Gephi (Bastian et al., 2009), with nodes assigned to communities within each window using the Louvain detection algorithm (Rubinov & Sporns, 2011). For purposes of visualization, edges were pruned using a backbone detection algorithm (Hagmann et al., 2008; Hidalgo et al., 2007) that identified the dominant connections while maintaining an average degree one half that of the fully-connected network (i.e.,

$k_N^w = \frac{1}{2n} \sum_{i,j \in N} w_{ij}$). Networks were generated using the Yifan Hu Proportional layout (Hu, 2005).

Table S4. Summary of Exploratory Factor Analyses for Networks using Pearson Correlations

Sample	Variables with Low Communality (h^2)	Sampling Adequacy (KMO)	Factors Retained	Variance Explained	Rotation Used
<i>Mean Estimates</i>					
1	--	.60	3	75%	varimax
2	--	.68	3	84%	direct oblimin
<i>Standard Deviation Estimates</i>					
1	comRadius (.29)	.74	2	54%	varimax
2	comRadius (.32), numCom (.13)	.81	1	60%	N/A

Note: Sampling adequacy assessed with the Kaiser-Meyer-Olkin (KMO) test.

References

- Adler, N. (2000). Social status ladder. *John D and Catherine T MacArthur Research Network on Socioeconomic Status and Health*.
- Bagby, R. M., Parker, J. D. A., & Taylor, G. J. (1994). The twenty-item Toronto Alexithymia Scale—I. Item selection and cross-validation of the factor structure. *Journal of Psychosomatic Research*, 38(1), 23–32.
- Barratt, E. S. (1985). Impulsiveness subtraits: Arousal and information processing. *Motivation, Emotion, and Personality*, 5, 137–146.
- Bastian, M., Heymann, S., & Jacomy, M. (2009). Gephi: An open source software for exploring and manipulating networks. *Third International AAAI Conference on Weblogs and Social Media*.
- Beck, A. T., Epstein, N., Brown, G., & Steer, R. A. (1988). An inventory for measuring clinical anxiety: Psychometric properties. *Journal of Consulting and Clinical Psychology*, 56(6), 893–897.
- Beck, A. T., Ward, C., Mendelson, M., Mock, J., & Erbaugh, J. (1961). Beck Depression Inventory (BDI). *Archives of General Psychiatry*, 4(6), 561–571.
- Benton, A. L., Hamsher, K., & Sivan, A. B. (1983). Controlled oral word association test (COWAT). *Multilingual Aphasia Examination, 3rd Ed. Iowa City, IA: AJA Associates*.
- Beverdort, D. Q., Hughes, J. D., Steinberg, B. A., Lewis, L. D., & Heilman, K. M. (1999). Noradrenergic modulation of cognitive flexibility in problem solving. *Neuroreport*, 10(13), 2763–2767.
- Beverdort, D. Q., White, D. M., Chever, D. C., Hughes, J. D., & Bornstein, R. A. (2002). Central β -adrenergic modulation of cognitive flexibility. *Neuroreport*, 13(18), 2505–2507.
- Broadway, J. M., & Engle, R. W. (2010). Validating running memory span: Measurement of working memory capacity and links with fluid intelligence. *Behavior Research Methods*, 42(2), 563–570.
- Cohen, S., Kamarck, T., & Mermelstein, R. (1983). A global measure of perceived stress. *Journal of Health and Social Behavior*, 385–396.
- Costa, P. T., & McCrae, R. R. (1992). *Professional manual: Revised NEO Personality Inventory (NEO-PI-R) and NEO Five-Factor Inventory (NEO-FFI)* (p. 101).
- De Leersnyder, J., Mesquita, B., & Kim, H. S. (2011). Where do my emotions belong? A study of immigrants' emotional acculturation. *Personality and Social Psychology Bulletin*, 37(4), 451–463. <https://doi.org/10.1177/0146167211399103>
- DeSteno, D., Li, Y., Dickens, L., & Lerner, J. S. (2014). Gratitude: A tool for reducing economic impatience. *Psychological Science*, 25(6), 1262–1267.
- DeYoung, C. G., Quilty, L. C., & Peterson, J. B. (2007). Between facets and domains: 10 aspects of the Big Five. *Journal of Personality and Social Psychology*, 93(5), 880–896.
- Diener, E. D., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The satisfaction with life scale. *Journal of Personality Assessment*, 49(1), 71–75.
- Fan, J., McCandliss, B. D., Sommer, T., Raz, A., & Posner, M. I. (2002). Testing the efficiency and independence of attentional networks. *Journal of Cognitive Neuroscience*, 14(3), 340–347.
- Figner, B., Mackinlay, R. J., Wilkening, F., & Weber, E. U. (2009). Affective and deliberative processes in risky choice: Age differences in risk taking in the Columbia Card Task. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 35(3), 709–730.

- Geneva Emotion Research Group. (2002). *Geneva Appraisal Questionnaire (GAQ)*.
- Hagmann, P., Cammoun, L., Gigandet, X., Meuli, R., & Honey, C. J. (2008). Mapping the structural core of human cerebral cortex. *PloS Biology*, 6(7), e159.
- Hidalgo, C. A., Klinger, B., Barabási, A.-L., & Hausmann, R. (2007). The product space conditions the development of nations. *Science*, 317(5837), 482–487.
- Hoemann, K., Khan, Z., Feldman, M., Nielson, C., Devlin, M., Dy, J., Barrett, L. F., Wormwood, J. B., & Quigley, K. S. (in press). Context-aware experience sampling reveals the scale of variation in affective experience. *Scientific Reports*. <https://doi.org/10.31234/osf.io/cvjb8>
- Hout, M. C., Papesch, M. H., & Goldinger, S. D. (2013). Multidimensional scaling. *Wiley Interdisciplinary Reviews: Cognitive Science*, 4(1), 93–103.
- Hu, Y. (2005). Efficient, high-quality force-directed graph drawing. *Mathematica Journal*, 10(1), 37–71.
- Hughes, M. E., Waite, L. J., Hawkley, L. C., & Cacioppo, J. T. (2004). A short scale for measuring loneliness in large surveys: Results from two population-based studies. *Research on Aging*, 26(6), 655–672.
- Kahneman, D., Krueger, A. B., Schkade, D. A., Schwarz, N., & Stone, A. A. (2004). A survey method for characterizing daily life experience: The Day Reconstruction Method. *Science*, 306, 1776–1780.
- Kang, S.-M., & Shaver, P. R. (2004). Individual differences in emotional complexity: Their psychological implications. *Journal of Personality*, 72(4), 687–726. <https://doi.org/10.1111/j.0022-3506.2004.00277.x>
- Kirby, K., Petry, N., & Bickel, W. (1999). Heroin addicts have higher discount rates for delayed rewards than non-drug-using controls. *Journal of Experimental Psychology: General*, 128(1), 78–87.
- Kirschbaum, C., Pirke, K.-M., & Hellhammer, D. H. (1993). The ‘Trier Social Stress Test’: A tool for investigating psychobiological stress responses in a laboratory setting. *Neuropsychobiology*, 28(1–2), 76–81.
- Kroenke, K., Spitzer, R. L., & Williams, J. B. (2002). The PHQ-15: Validity of a new measure for evaluating the severity of somatic symptoms. *Psychosomatic Medicine*, 64(2), 258–266.
- Kroenke, K., Strine, T. W., Spitzer, R. L., Williams, J. B., Berry, J. T., & Mokdad, A. H. (2009). The PHQ-8 as a measure of current depression in the general population. *Journal of Affective Disorders*, 114(1–3), 163–173.
- Lane, R. D., Quinlan, D. M., Schwartz, G. E., Walker, P. A., & Zeitlin, S. B. (1990). The Levels of Emotional Awareness Scale: A cognitive-developmental measure of emotion. *Journal of Personality Assessment*, 55(1–2), 124–134. <https://doi.org/10.1080/00223891.1990.9674052>
- Lindquist, K. A., Gendron, M., Barrett, L. F., & Dickerson, B. C. (2014). Emotion perception, but not affect perception, is impaired with semantic memory loss. *Emotion*, 14(2), 375–387. <https://doi.org/10.1037/a0035293>
- Lindquist, K. A., Gendron, M., Oosterwijk, S., & Barrett, L. F. (2013). Do people essentialize emotions? Individual differences in emotion essentialism and emotional experience. *Emotion*, 13(4), 629–644. <https://doi.org/10.1037/a0032283>
- Nock, M. K., Wedig, M. M., Holmberg, E. B., & Hooley, J. M. (2008). The Emotion Reactivity Scale: Development, evaluation, and relation to self-injurious thoughts and behaviors. *Behavior Therapy*, 39(2), 107–116.

- Rubinov, M., & Sporns, O. (2011). Weight-conserving characterization of complex functional brain networks. *NeuroImage*, 56(4), 2068–2079.
<https://doi.org/10.1016/j.neuroimage.2011.03.069>
- Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, 39, 1161–1178.
- Scherer, K. R. (2001). Appraisal considered as a process of multilevel sequential checking. In K. R. Scherer, A. Schorr, & T. Johnstone (Eds.), *Appraisal Processes in Emotion: Theory, Methods, Research* (pp. 92–120).
- Spitzer, R. L., Kroenke, K., Williams, J. B., & Löwe, B. (2006). A brief measure for assessing generalized anxiety disorder: The GAD-7. *Archives of Internal Medicine*, 166(10), 1092–1097.
- Stone, A. A., Schwartz, J. E., Schkade, D., Schwarz, N., Krueger, A., & Kahneman, D. (2006). A population approach to the study of emotion: Diurnal rhythms of a working day examined with the Day Reconstruction Method. *Emotion*, 6(1), 139–149.
- Taylor, S., Zvolensky, M. J., Cox, B. J., Deacon, B., Heimberg, R. G., Ledley, D. R., Abramowitz, J. S., Holaway, R. M., Sandin, B., & Stewart, S. H. (2007). Robust dimensions of anxiety sensitivity: Development and initial validation of the Anxiety Sensitivity Index-3. *Psychological Assessment*, 19(2), 176–188.
- Unsworth, N., & Engle, R. W. (2005). Working memory capacity and fluid abilities: Examining the correlation between Operation Span and Raven. *Intelligence*, 33(1), 67–81.
- Weber, E. U., Blais, A.-R., & Betz, N. E. (2002). A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *Journal of Behavioral Decision Making*, 15(4), 263–290.
- Wilson-Mendenhall, C. D., Barrett, L. F., & Barsalou, L. W. (2013). Situating emotional experience. *Frontiers in Human Neuroscience*, 7, 1–16.
- Wilson-Mendenhall, C. D., Barrett, L. F., & Barsalou, L. W. (2015). Variety in emotional life: Within-category typicality of emotional experiences is associated with neural activity in large-scale brain networks. *Social Cognitive and Affective Neuroscience*, 10(1), 62–71.
<https://doi.org/10.1093/scan/nsu037>
- Zachary, R. A. (1986). *Shipley Institute of Living Scale, Revised Manual*. Western Psychological Services.
- Zaleskiewicz, T. (2001). Beyond risk seeking and risk aversion: Personality and the dual nature of economic risk taking. *European Journal of Personality*, 15(S1), S105–S122.