

Emotional Granularity: Definition, Measurement, and Relationship to Cardiovascular
Physiological Activity

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Dedication

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Abstract of Dissertation

Emotional granularity describes an individual's ability to create instances of emotion that are diverse and context-specific. Considerable evidence suggests that higher granularity is a protective factor for mental and physical well-being. Despite this evidence, however, research on granularity is lacking in three critical respects.

First, a fuller definition of emotional granularity is needed that situates it with regard to neighboring individual difference constructs in affective science. A more nuanced understanding of the features that describe granularity is necessary for future research to be able to make tailored predictions about granularity's relationship with health and well-being. In Chapter 1, I offer a unifying framework for understanding and studying the mental representation of one's own emotional experience. To create this framework, I used domain-general accounts of expertise to deductively generate a list of core features. I then used this framework to structure the findings from a systematic review of constructs for the mental representation of emotional experience, including emotional granularity. This approach, I argue, has the capacity to not only organize scientific knowledge, but reveal potential underlying mechanisms and motivate future programs of research and intervention.

Second, measures of emotional granularity are needed that capture various dimensions of granularity and intra-individual fluctuations therein. Multi-dimensional and time-varying estimates of granularity are necessary to represent the complex dynamics of emotional experience. In Chapter 2, I study granularity using measures provided by network analyses. I used experience sampling data to generate person-specific (i.e., idiographic) networks, and characterized these networks using a variety of network measures, estimated based on the average network structure as well as the change in network structure over time. I found that network measures of 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. These findings serve as a proof-of-concept demonstration of the efficacy of network analysis for describing the dynamic structure of emotional experience.

Third, the relationship between emotional granularity and mechanisms underlying physical health is under-investigated. Investigations that incorporate peripheral physiology into the study of granularity can be used to test specific hypotheses about the biological underpinnings of emotional experience and their implications for health. In Chapter 3, I investigated the relationship between granularity and cardiovascular physiological activity using data collected using experience sampling with ambulatory peripheral physiological monitoring. I compared granularity with three variables: respiratory sinus arrhythmia during seated rest, the number of patterns of physiological activity discovered during seated rest, and the performance of classifiers trained on event-related changes in physiological activity. Individuals with higher granularity exhibited more, and more specific, patterns of physiological activity during seated rest as well as during emotional events. These findings are consistent with constructionist accounts of emotion, which propose concepts as a key mechanism underlying individual differences in emotional experience and physical health.

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Introduction

Emotional granularity describes an individual's ability to create instances of emotion that are diverse and context-specific (Barrett, 2017a; Tugade et al., 2004). As a psychological construct, emotional granularity reflects the number of emotion categories an individual's brain can create, as well as the features of those categories (Hoemann & Barrett, 2018). For individuals lower in granularity, instances of rage may not be distinct from instances of frustration or anger, and instances of anger may not be distinct from sadness (i.e., the words "irritated", "furious", and "unhappy" are synonyms for 'unpleasant'). Individuals higher in granularity make finer, more situated categories, such that "irritated", "furious", and "unhappy" refer to distinct emotional instances.

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; Smidt & Suvak, 2015). For example, when compared to individuals with lower granularity, those with higher 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, Danoff-Burg, et al., 2002).

Despite this evidence, however, research on emotional granularity is lacking in three critical respects. First, a fuller definition of granularity is needed that situates it with regard to neighboring individual difference constructs in affective science. A more nuanced understanding of the features that describe granularity is necessary for future research to be able to make tailored predictions about granularity's relationship with health and well-being. Second, measures of granularity are needed that capture various dimensions of granularity and intra-individual fluctuations therein. Multi-dimensional and time-varying estimates of granularity are necessary to represent the complex dynamics of emotional experience. Third, the relationship between granularity and mechanisms underlying physical health is under-investigated. Investigations that incorporate peripheral physiology into the study of granularity can be used to test specific hypotheses about the biological underpinnings of emotional experience and their implications for health.

I address each of these three goals in turn, as a separate chapter of this dissertation. These chapters are formatted as free-standing manuscripts for submission at peer-reviewed journals in domain-general psychological science, affective science, and behavioral medicine. Each chapter includes relevant tables, and figures, and is immediately followed by an appendix of supplemental materials. References have been consolidated and are presented at the end of the document.

Defining Emotional Granularity in Relation to Other Similar Constructs

The phenomenon of precise and detailed emotional experience has been discovered again and again in psychological science. Today, emotional granularity goes by several different names in the scientific literature (e.g., emotion differentiation, emotional complexity, emotional awareness, and alexithymia; Bagby et al., 1994; Barrett et al., 2001; Kang & Shaver, 2004; Lane & Schwartz, 1987). These constructs speak to the intuition, shared by researchers and the general public alike, that some people are better at a range of competencies related to understanding and regulating their emotions, and these competencies may help them lead healthier lives. This can be thought of as a sort of 'emotional expertise' for its reference to outstanding skill or ability in a particular domain (Ericsson et al., 2018). However, there are differences in the competencies highlighted by constructs for emotional expertise. There are also differences in how constructs are operationalized and measured, and in the theoretical perspectives that inform them. The full set of relationships between constructs remains unclear, hindering the ability to evaluate and compare findings. This splintering of work cripples a body of research with

clear ties to mental and physical well-being. For scientists and clinicians to understand how constructs relate to one another, they must first be integrated within a shared conceptual space.

In Chapter 1, I offer a unifying framework for understanding and studying a central aspect of emotional expertise: the mental representation of one's own emotional experience. A comprehensive account of emotional expertise would also include, for example, constructs related to the representation of others' emotional experiences, and those related to the regulation of emotion in oneself. In the present work, my goal is to provide a framework for emotional expertise that can be expanded in future research to incorporate other aspects. To create this framework, I used domain-general accounts of expertise to deductively generate a list of core features. I then used this framework to structure the findings from a systematic review of constructs for the mental representation of emotional experience, including emotional granularity. This approach, I argue, has the capacity to not only organize scientific knowledge, but to reveal potential underlying mechanisms and motivate future programs of research and intervention.

Measuring Granularity using Multi-Dimensional, Time-Varying Estimates

Emotional granularity is most commonly measured using data from experience sampling studies, in which participants rate the intensity of their momentary experiences according to experimenter-provided terms (e.g., “angry”, “sad”, “calm”, “excited”). Participants are prompted to report their experiences multiple time per day, across multiple days, and their ratings are used to assess the extent of shared information across emotion terms via 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” are rated consistently across sampling instances. Higher consistency or agreement (ICC value near 1) indicates that the ratings have little unique variance and is interpreted as lower granularity. Lower consistency or agreement (ICC value near 0) indicates that the ratings have more unique variance and is interpreted as higher granularity. Unfortunately, assessing granularity via within-person correlational (i.e., ICC-based) approaches produces only a single, aggregate estimate of granularity for each individual (but see Erbas et al., 2019; Willroth et al., 2020).

In Chapter 2, I study emotional granularity using multidimensional, time-varying measures provided by network analyses (Boccaletti et al., 2006). Using experience sampling data to generate person-specific (i.e., idiographic) networks, I estimated the number of distinct emotion categories and the complex relationships between these categories captured by each participant's momentary ratings of emotional experience. These time-varying networks described dynamic relationships between emotion categories. I characterized these networks using a variety of network measures, estimated based on the average network structure as well as the variation or change in network structure over time. I also visualized a representative subset of networks as a way of describing the variety in structures of emotional experience. I found that 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 efficacy of network analysis for describing the dynamic structure of emotional experience.

Assessing the Relationship between Granularity and Cardiovascular Physiological Activity

Previous research has established a strong association between depression and cardiovascular disease (CVD; e.g., Carney et al., 2005; Stein et al., 2000; Vaccarino et al., 2008), and identified a number of emotion-related risk factors for CVD (Krantz & McCeney, 2002; Rozanski, 2014) and metabolic syndrome – a cluster of precipitating factors for CVD, including hypertension, high cholesterol, (pre)diabetes, and abdominal obesity (Alberti et al., 2005; Grundy et al., 2004). Detrimental shifts in the contributions of the two branches of the autonomic nervous system (ANS) to visceral functions throughout the body, in particular a reduction in resting parasympathetic activity, are observed with both emotional dysregulation and disordered mood (Bleil et al., 2008; Carney et al., 2005; J. L. Hamilton & Alloy, 2017; Kapczynski et al., 2008), and may be a common, core vulnerability for CVD and metabolic syndrome (e.g., Buccelletti et al., 2009; Stein et al., 2007; Togo & Takahashi, 2009; Villareal et al.,

2002). Reduced resting parasympathetic activity is often measured using respiratory sinus arrhythmia (RSA), an index of vagal influence on the heart that is associated with positive mental and physical health outcomes (e.g., Beauchaine, 2015; Curtis & O’Keefe, 2002). Analyses that characterize patterns of cardiovascular physiological activity in everyday life, including resting RSA, can provide further insight into the relationship between psychological and physiological (dys)regulation.

In Chapter 3, I investigated the relationship between emotional granularity and cardiovascular physiological activity with data collected using experience sampling with ambulatory peripheral physiological monitoring. I derived estimates of emotional granularity as well as several measures of cardiovascular activity from these data. In a series of pre-registered analyses, I compared granularity with three variables: RSA during seated rest, the number of patterns of physiological activity discovered during seated rest, and the performance of classifiers trained on event-related changes in physiological activity. Individuals with higher granularity exhibited more, and more specific, patterns of physiological activity during seated rest as well as during emotional events. These findings are consistent with constructionist accounts of emotion, which propose concepts as a key mechanism underlying individual differences in emotional experience and physical health.

Chapter 1: Expertise as a Unifying Framework for Individual Differences in the Mental Representation of Emotional Experience

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Abstract

Expertise refers to outstanding skill or ability in a particular domain. In the domain of emotion, expertise represents the intuition that some people are better at a range of competencies related to understanding and managing emotions, and these competencies may help them lead healthier lives. Individual differences in emotional expertise are represented by a wide variety of psychological constructs, including emotional awareness, clarity, complexity, granularity, and intelligence. Each of these constructs highlights different competencies. There are also differences in how these constructs are operationalized and measured, and in the theoretical perspectives that inform them. Yet the full set of relationships between these constructs remains unclear, hindering the ability to evaluate and compare findings. This splintering of work cripples a body of research with clear ties to mental and physical well-being. To understand how these constructs relate to one another, we must first integrate them within a shared conceptual space. In this paper, we offer a unifying framework for a central aspect of emotional expertise: the mental representation of one's own emotional experience. This approach has the capacity to organize scientific knowledge, reveal potential underlying mechanisms of individual differences in emotion, motivate future programs of research, and direct clinical interventions.

Keywords: alexithymia, emotional awareness, emotional creativity, emotional granularity, emotional intelligence

Remember the old story about the blind men and the elephant? Each touching a different part of an elephant to learn what it is like, they proclaim it have different properties. The blind men is a particularly useful analogy for how important constructs in psychology are discovered again and again, defined in slightly different ways and labeled with slightly different words. The topic of this paper, *emotional expertise*, is an example of one of these situations. We adopt the term ‘expertise’ for its reference to outstanding skill or ability in a particular domain (Ericsson et al., 2018). Emotional expertise is our elephant (Russell & Barrett, 1999): it represents the intuition, shared by scientists and the general public alike, that some people are better than others at a range of competencies related to understanding and regulating emotions, and these competencies may help them lead healthier lives.

At present, individual differences in emotional expertise are represented by a wide variety of psychological constructs, including *emotional awareness*, *emotional clarity*, *emotional complexity*, *emotional granularity*, and *emotional intelligence*. Each of these constructs highlights different competencies. There are also differences in how these constructs are operationalized and measured, and in the theoretical perspectives that inform them. Yet the full set of relationships between constructs remains unclear, hindering the ability to evaluate and compare findings. This splintering of work cripples a body of research with clear ties to mental and physical well-being. To understand how constructs relate to one another, we must first integrate them within a shared conceptual space.

In this paper, we offer a unifying framework for understanding and studying a central aspect of emotional expertise: the mental representation of one’s own emotional experience. A comprehensive account of emotional expertise would also include, for example, constructs related to the representation of others’ emotional experiences, and those related to the regulation of emotion in oneself. In the present work, our goal is to provide a framework for emotional expertise that can be expanded in future research to incorporate other aspects. To create this framework, we use domain-general accounts of expertise to deductively generate a list of core features. We then use this framework to structure the findings from a systematic review of constructs for the mental representation of emotional experience. This approach, we argue, has the capacity to not only organize scientific knowledge, but reveal potential underlying mechanisms and motivate future programs of research and intervention.

Parts of the Elephant

Interest in individual differences in the understanding and experience of emotions can be found within the psychoanalytic tradition around the beginning of the 20th century (e.g., Freud, 1891, 1895). With few exceptions (e.g., Meltzoff & Litwin, 1956; Saul, 1947; Wessman & Ricks, 1966), the early scientific study of such individual differences was focused on clinical diagnosis and treatment (e.g., Freedman & Sweet, 1954; Henry & Shlien, 1958; Ruesch, 1948)¹. This research often centered on patients with psychosomatic disorders (e.g., Alexander, 1950; MacLean, 1949; Marty & de M’Uzan, 1963), leading to the formalization of the construct of alexithymia in the 1970s (e.g., Nemiah, 1970; Nemiah et al., 1976; Sifneos, 1972). In the 1980s and 1990s, an explosion of emotion-related research produced seminal work on constructs such as emotional intelligence (e.g., Goleman, 1995; Salovey & Mayer, 1990a), emotional awareness (Lane et al., 1990; Lane & Schwartz, 1987), emotional complexity (e.g., Larsen & Cutler, 1996; Tobacyk, 1980), and emotional creativity (Averill & Thomas-Knowles, 1991). These constructs captured the attention of the scientific community; emotional intelligence, in particular, soon became a hotspot of activity in both the academy (e.g., Bar-On, 1997; Mayer & Salovey, 1997; Schutte et al., 1998) and industry (e.g., Cooper & Sawaf, 1997; Grandey, 2000; Law et al., 2004).

As emotion-related research gained traction, other constructs followed, such as emotion differentiation (Barrett et al., 2001) and its synonym emotional granularity (Tugade et al., 2004), emotional clarity (e.g., Palmieri et al., 2009), and emotional flexibility (Vaughn et al., 2011). Today, one has only to do a quick Internet search to get a sense of the variety of terms in use: emotional agility

¹ The study of individual differences in social intelligence also originated around the beginning of the 20th century (e.g., Thorndike, 1920). This research later came to be regarded as the foundation of emotional intelligence (e.g., Bar-On, 2000; Mayer & Salovey, 1993; for review and discussion, see Landy, 2005, 2006).

(David, 2016), emotional fitness (Cooper & Sawaf, 1997), emotional literacy (e.g., Steiner, 1984), and emotional stability (e.g., Hills & Argyle, 2001) are only a few of the dozens of constructs currently in circulation. Research on individual differences in emotion continues apace, with new constructs still being introduced, including emodiversity (Quoidbach et al., 2014) and affective agnosia (Lane et al., 2015a). To make matters more complex, most constructs are associated with multiple measures (e.g., there are nine adult measures for alexithymia reviewed in Bermond et al., 2015 alone), and measures are often used to assess for multiple constructs. For example, the Toronto Alexithymia Scale (e.g., Bagby et al., 1994) has been used as an index of emotional clarity (e.g., Erbas et al., 2018).

At present, the nature of the relationships between the variety of constructs and measures for individual differences in the mental representation of emotional experience is not clear. This is an issue for scientific practice: the proliferation of theoretical and methodological tools makes the conceptual workspace untidy. A lack of conceptual clarity leads to issues with reproducibility and obscures common underlying mechanisms. Scientific progress requires that each term maps onto a clearly-defined construct, and that each construct has a valid measure (Cronbach & Meehl, 1955). There should be alignment between labels, constructs, and measurement. We are far from this level of clarity, leading to ambiguity about how to integrate results across studies.

A lack of conceptual clarity is also an issue for the instrumental utility and applied value of research on emotional expertise: each of these constructs purports to – and often does – predict indicators of mental and physical health, among other positive real-world outcomes. For example, alexithymia is associated with mental health disorders, substance abuse and eating disorders, chronic pain and functional gastrointestinal disorders, and coronary heart disease (for reviews, see Bermond et al., 2015; Lumley et al., 2007; G. J. Taylor, 2000). Emotional intelligence is positively correlated with subjective well-being, and negatively correlated with self-reported symptoms of depression and anxiety, physical health complaints, and substance abuse (for reviews, see Bar-On, 2000; Mayer, Roberts, et al., 2008; Salovey et al., 2002; Zeidner et al., 2012). These constructs clearly capture individual differences in emotional experience and understanding that are meaningful and clinically-relevant. However, conceptual ambiguity hampers scientists' and clinicians' ability to understand why they are protective and how to intervene.

There is an elephant, and it is consequential (or perhaps weighty?). A growing number of publications have called for direct comparison and integration of constructs and their measures (e.g., Gohm & Clore, 2000; Grossmann et al., 2016; Grühn et al., 2013a; Ivcevic et al., 2007; Joseph & Newman, 2010; Kang & Shaver, 2004; Kashdan et al., 2015; Lindquist & Barrett, 2008; Lumley et al., 2005; Maroti et al., 2018; Schimmack et al., 2000). However, work has yet to systematically address a fuller range of the constructs we believe underlie emotional expertise. A conceptual synthesis has yet to be conducted that will allow the field to view the elephant in its entire form. Here, we create a unifying framework into which existing constructs and measures can be integrated. We create this framework using a set of features identified from studies of domain-general expertise, as we describe next.

Features of Expertise

As mentioned above, expertise can be broadly defined as outstanding skill or ability in a particular domain (Ericsson et al., 2018). Expertise has previously been mentioned in connection with emotion-related abilities (e.g., Mayer et al., 2001; McBrien et al., 2018; Pistoia et al., 2018; Salisch, 2001), but has not been used as a framework for systematic investigation and synthesis. Expertise has several defining characteristics that are particularly relevant to the domain of emotions, as it is: (i) supported by extensive and specific domain knowledge, (ii) characterized by information processing capacities, (iii) demonstrated through reliable task performance, and (iv) developed through metacognitive awareness and deliberate practice. We briefly review each of these in turn.

Expertise requires a *broad and efficiently structured* body of specialized domain knowledge (Bédard & Chi, 1992). This knowledge includes both explicit, declarative knowledge of domain-relevant concepts, as well as implicit, functional knowledge of how those concepts might be deployed in specific situations (Sternberg et al., 1995; Sternberg, 1998; see also the distinction between deep and surface knowledge by Steels, 1990). In other words, there are specific *types of knowledge* that experts must

possess. Experts' concepts are organized into highly-interconnected networks, as opposed to novices who have fewer and weaker links between concepts (Bédard & Chi, 1992; Sternberg, 1998). Experts' concepts are also more specific, and translate into a subordinate-level shift in domain-relevant categorization (e.g., Bukach et al., 2006). For novices, categorization proceeds according to boundaries established as 'cognitively basic' in a given cultural context (Rosch et al., 1976). In contrast, experts are able to differentiate between more specific categories, performing subordinate-level categorizations as if they were basic-level categorizations (Tanaka & Taylor, 1991). While novices might see only yellow versus green, color experts such as painters might distinguish lime, olive, and chartreuse. This differentiation extends to how experts *verbally represent* their experience by using language to label specific categories or describe specific properties (Tanaka & Taylor, 1991).

Experts also differ from novices in how they implement domain-relevant knowledge (Steels, 1990), and exhibit enhanced abilities to process information and meet situation-specific needs (e.g., via problem-solving strategies; Bédard & Chi, 1992; Sternberg, 1998; Ullén et al., 2016). Whereas novices rely on surface-level perceptual features to make decisions and predictions, experts harness abstract, functional features (Bédard & Chi, 1992). For example, a novice may believe olive and chartreuse to work equally well for painting a wall 'green', whereas an expert would consider the impacts of undertone and lighting on perceived color – and may ultimately suggest emerald to create a balanced calm. Experts easily construct sophisticated *mental representations* of situations, and use non-obvious properties (e.g., the mood associated with a color) to determine which action is maximally effective at achieving a given goal (Sternberg, 1998). This type of holistic and relational processing is a hallmark of expertise, and extends to how new knowledge is acquired. While novices learn by rote, experts can efficiently generalize to new exemplars by means of abstract, functional similarities (Bukach et al., 2006).

As illustrated by the preceding example, expertise is not only a matter of having domain-relevant knowledge; it must also be demonstrated through measureable behavioral outcomes. Experts are distinguished from non-experts on the basis of their *performance on tasks* that produce concrete results, and this performance must be reliable and replicable (Ericsson & Lehmann, 1996; Ericsson & Ward, 2007). This suggests that it is not sufficient to measure expertise using global self-report measures, such as scales and questionnaires, which ask individuals to endorse beliefs about themselves. Rather, individual differences in expertise should be derived from a series of *adaptive responses*, observed over time or across contexts and judged according to their *context-specific* efficacy (Ericsson & Lehmann, 1996; Ericsson & Smith, 1991). In contrast to novices, experts flexibly adapt their actions to the situation at hand. Different aspects of color expertise might be demonstrated via perceptual discrimination, verbal fluency, or practical application (interior design that leads to shorter recovery time, reduced pain medication, and increased satisfaction in hospital patients; Rubin et al., 1998), but would not be attested to by statements about an individual's interests or self-assessed facility.

Scientists debate the extent to which expertise is due to trait-level dispositions or genetic factors (e.g., Ericsson, 2014; Plomin et al., 2014b, 2014a). There is overall consensus, however, that substantial training is critical to developing expertise and that expertise can be enhanced through *deliberate practice* (for discussion, see Ullén et al., 2016). Deliberate practice involves both improving existing skills and expanding the set and scope of skills. This is done by updating knowledge, identifying alternative solutions, and encountering novel experiences (Ericsson, 2006; Ericsson & Charness, 1994). An expert painter might seek out opportunities to work with new colors, subject matter, or materials, and might spend time learning about pigments and application techniques to create specific impressions (Ford, 2016; Protter, 1997). These processes require metacognitive *awareness* and sustained *attention* (Ericsson, 2007; Ullén et al., 2016). Experts engage in reflective and careful monitoring of their domain understanding and ability to meet situation-specific needs (Sternberg, 1998). This regular evaluation leads to more effective resource allocation (Sternberg, 1984; Sternberg & Kagan, 1986), such that experts are better at determining what information to attend to, and how to anticipate and prepare for upcoming energy needs. That is, experts are better at *predicting* what will happen next, and proactively planning and adjusting their actions accordingly.

In summary, expertise can be described according to the following set of features: structure, breadth, and type of knowledge (i.e., differentiated, elaborated, domain-relevant concepts); mental representation (i.e., information processing); verbal representation (i.e., labeling, description); ability (i.e., skill in performance on tasks); adaptive responses (i.e., effective actions, outcomes); context-specificity (i.e., flexibility); awareness (i.e., metacognition); monitoring (i.e., attention); deliberate practice (i.e., self-evaluation, improvement); and prediction (i.e., proactive resource allocation). These features describe expertise as skilled performance within a given domain and relative to situation-specific needs. Experts must possess the ‘basic’ domain knowledge shared by other culture members (e.g., primary and secondary color categories, their prototypical hues, boundaries, and names) as well as more specific knowledge shared by other domain experts (e.g., the difference between hue, saturation, and lightness). Experts can also flexibly deploy this knowledge, depending on context-driven goals: for example, an expert uses different language when describing the color of a toy apple to an American toddler (“red”) than when suggesting a pigment for painting a stormy night sky (“Pantone 7545c”). There are few, if any, context-invariant criteria for gauging expertise, independent of domain-relevant knowledge and goal-relevant actions. This becomes an important point as we return to the discussion of expertise in the domain of emotions.

Systematic Review and Interpretation

Now that the above features of domain-general expertise have been clarified, we can extend this perspective to emotion. In particular, we can build an organizational framework that synthesizes constructs and measures underlying emotional expertise. We accomplish this through a scoping review procedure. Scoping reviews are used to generate overviews of large and diverse literatures; they seek to map a given body of research in a rigorous and transparent manner, while identifying key constructs as well as gaps and inconsistencies (Pham et al., 2014). As recommended by Arksey and O’Malley (2005), we conducted a scoping review in an iterative, five-stage process: formulating the research question; identifying relevant constructs; selecting publications; extracting and organizing the data; and summarizing, illustrating, and synthesizing the results. Throughout this process, we were guided by the materials from the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) workgroup (Liberati et al., 2009; Moher et al., 2009). We also looked to qualitative synthesis methods (e.g., framework synthesis; Pope et al., 2000) to inform our use of expertise as an a priori framework for situating and re-mapping the included constructs (for details, see Data Organization section, below; see also Kastner et al., 2012).

In the present review, we seek to address the research question: What is the nature of emotional expertise, as it pertains to the mental representation of one’s own emotional experience? To do so, we systematically review the emotion literature to identify psychological constructs that describe individual differences in this aspect of expertise. For each of these constructs, we consult key publications in which either the construct itself, or a measure of it, is either introduced or redefined. We further consult publications in which constructs or measures are compared to each other. This survey of the literature is intentionally representative, rather than comprehensive: our goal is to capture the features of expertise exhibited by constructs, not to review every paper in which they are mentioned. Similarly, our review of empirical research is qualitative rather than quantitative: we seek to understand how constructs are measured and how they relate to one another, not to provide a definitive estimate of a meta-analytic effect size. Using our set of key publications as data, we then inductively generate a list of core features for each psychological construct, and use these features to re-map constructs onto a common framework for emotional expertise. This re-mapping process interrogates the theoretical perspectives and assumptions about emotion underlying different constructs, as well as the relationship between construct and measurement. Finally, we consider the methodological and analytical advances suggested by our unifying framework, as well as their potential impacts on future work.

Method

Construct Identification

We identified potential constructs to include in the review via several sources, with the goal of being as inclusive as possible. The constructs reviewed in Kashdan et al (2015) – alexithymia, awareness, clarity, complexity, and differentiation/granularity² – served as an initial base. To these, we added any other constructs thought to cover individual differences in emotional knowledge, repertoire, or skill (i.e., those that describe how people understand and experience their own emotions). The first and senior authors developed a preliminary list of constructs based on their knowledge of the literature, frequent Google Scholar search terms (e.g., which words are suggested after typing “emotion(al)”), and popular science pieces on emotional health. Constructs were iteratively added to the list during publication selection, screening, and full-text review, as described below.

We excluded constructs from further consideration if they dealt specifically with the perception, expression, or regulation of emotion, as these processes go beyond the mental representation of emotional experience in oneself. Constructs were also excluded if they: were not specific to emotion (e.g., ‘social skill’ (Riggio, 1986), ‘resilience’ (Connor & Davidson, 2003)); had strictly interpersonal (i.e., transactional) meanings (e.g., ‘affective sensitivity’ (Kagan & Schneider, 1987), ‘emotional literacy’ (Steiner, 1984)); were formulated only within a developmental, lifespan, or applied (i.e., industrial/organizational) context (e.g., ‘affective social competence’ (Halberstadt et al., 2001), ‘emotional fitness’ (Cooper & Sawaf, 1997)). Critically, because we are interested in the mental representation of emotional experiences, we excluded constructs dealing with overall affect (i.e., positive vs. negative mood) and the dynamics therein (e.g., ‘affect intensity’ (Larsen & Diener, 1987), ‘affective instability’ (Trull et al., 2008)), as well as constructs covering individual differences in temperament and disposition (e.g., ‘emotional stability’ (Hills & Argyle, 2001), ‘trait affect’ (D. Watson & Walker, 1996)). Although we were interested in constructs and measures with impacts for health and well-being, this was not a formalized criterion.

For each potential construct, the first author reviewed example publications to determine if it met criteria for inclusion. Final decisions regarding inclusion were made through discussion with the senior author. In cases of uncertainty or disagreement, we erred on the side of inclusion. In total, we considered 133 constructs, of which 40 were included. For a full list of included constructs and corresponding publication search results, see Table S1-1. For a full list of excluded constructs, example publications, and reason for exclusion, see Table S1-2.

Publication Selection

The American Psychological Association’s PsycINFO database was used to locate literature published up to the date of search; primary searches were conducted between May and October of 2018. Literature for each construct was searched separately, with the construct name as the keyword for the search (e.g., “alexithymia”). Multi-word constructs were searched using several keyword phrases to ensure all possible variants were included in review: “emotional [CONSTRUCT]” (e.g., “emotional awareness”), “emotion [CONSTRUCT]” (e.g., “emotion awareness”), “affective [CONSTRUCT]” (e.g., “affective awareness”), and “affect [CONSTRUCT]” (e.g., “affect awareness”)³. Results were filtered to include only publications written in English, in a peer-reviewed journal or edited volume, in which the keyword (phrase) was included in the title or abstract. See Figure 1-1 for a flowchart of publication identification, screening, and review. For a full list of search terms, dates, and hits, see Table S1-1.

Four search terms generated more than 500 hits in PsycINFO, even after filters were applied: “alexithymia” (2,529 records), “emotional awareness” (548 records), “emotional competence” (681 records), and “emotional intelligence” (3,428 records). Because the volume of results for these four constructs far outweighed that of the others (which together yielded 1,316 records), and would have been

² From now on, we refer to constructs (e.g., emotional awareness, emotional granularity) as “awareness”, “granularity”, etc. for ease of reading.

³ The phrase “affect [CONSTRUCT]” (e.g., “affect awareness”) often did not include any publications relevant to the present research, because “affect” can be used as a verb. If a given search yielded no relevant publications (as determined by visual inspection by the first author), the search results were excluded from further review.

unfeasible to review, we followed a two-part procedure to select relevant literature. First, we entered these search terms in Clarivate's Web of Science database, where we could sort search results based on the number of citations. As before, we searched only for phrases appearing in the publication 'topic', with publications limited to articles, reviews, and book chapters written in English. In this case, however, we only selected those publications with at least 100 citations. This resulted in a much-reduced set of 382 records to be screened across the four constructs (Table S1-1). Second, to ensure we captured all key publications, we consulted a set of reviews for each construct (Table S1-3). Based on and including these reviews, we identified 66 publications potentially related to construct definition and measurement. These records were individually added to the list for further screening. Altogether, this process yielded 1,764 publications; 95 duplicates were removed, leaving 1,669 unique records.

Two trained undergraduate research assistants (author A.Y. and one other) screened abstracts for identified publications to confirm they met the criteria for inclusion in the review. Publications had to meet the overall criteria introduced above, and were excluded from further review if they: (a) described the construct or measure only in relation to a specific domain (e.g., art appreciation, romantic relationships); (b) assessed the construct using only biological measures (e.g., fMRI or EEG); or (c) merely applied an existing measure to a sample of participants, without modifying that measure or directly comparing it to another (Table S1-4). Throughout this screening process, our goal was to identify publications that introduced, reformulated, critiqued, or compared the constructs of interest and their corresponding measures. Of note, comparisons between constructs or measures could be either theoretical or empirical. All abstracts were screened independently by both research assistants, with the first and/or senior author adjudicating in difficult or ambiguous cases. Of the 1,669 publications screened, only 196 met the rigorous inclusion criteria (1,473 were excluded).

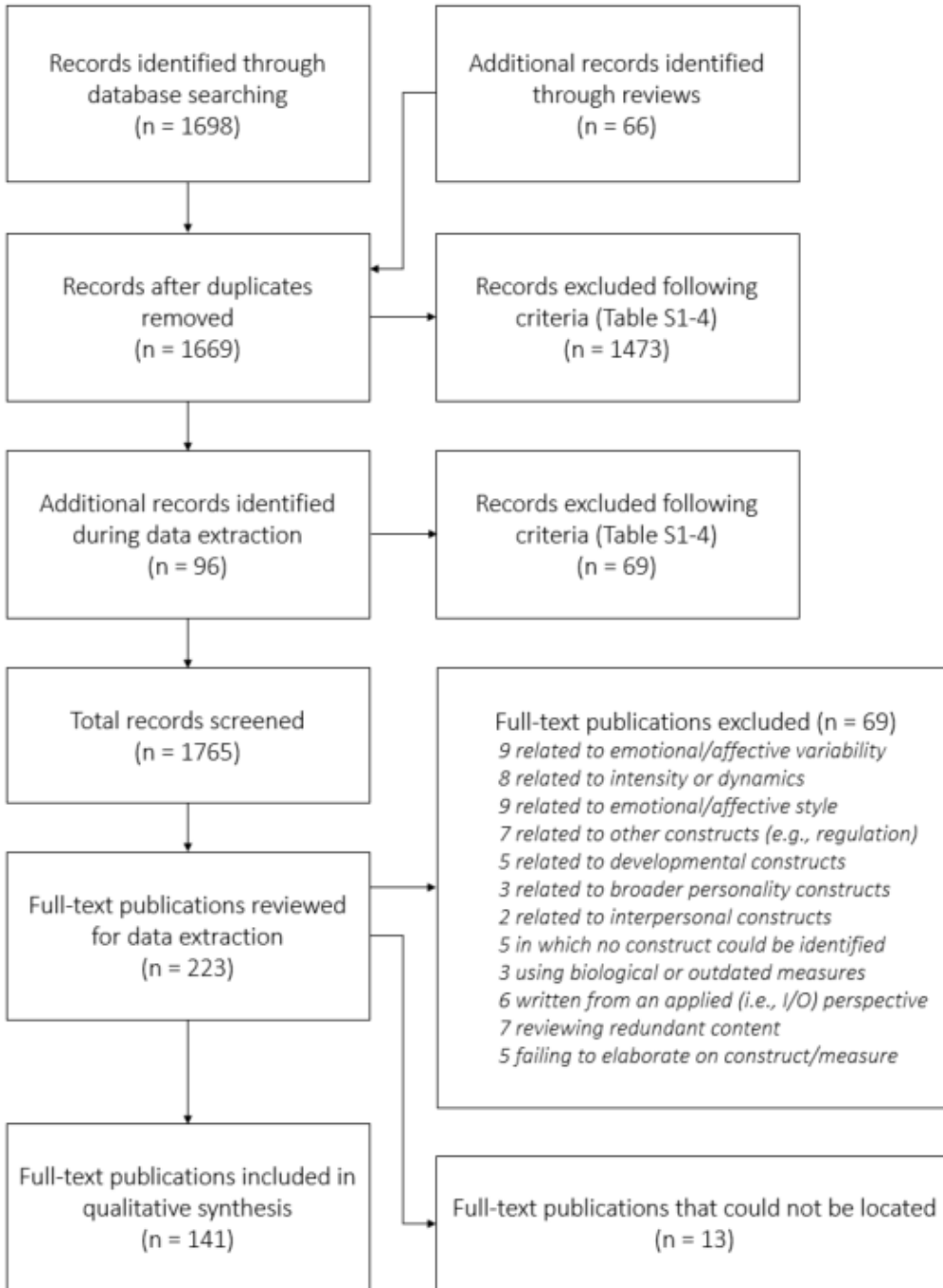


Figure 1-1. PRISMA flow chart describing identification, screening, and full review of publications, based on guidelines by Moher et al. (2009).

Data Extraction

Data from publications were extracted following a coding procedure designed to capture each construct's definition, measurement, validity, and relationships with other psychological and health variables, as well as historical and theoretical background. For each publication, we recorded the information provided in Figure 1-2. Because publications could describe more than one construct, construct-specific items (Figure 1-2, inset box) could be repeated until all constructs were documented.

<i>Bibliographic Information</i>	
Authors	(free response)
Year	(free response)
Title	(free response)
Format	Journal article; Book chapter; Other
Journal/book title	(free response)
Type	Empirical; Review; Meta-analysis; Theory
<i>Construct Information</i>	
Construct name	(free response)
New construct introduced?	Yes; No; Not sure
Definition offered?	Yes; No
Definition	(free response)
Explicitly described as a(n)...	Trait; Ability; State; Implied trait; Not sure; More than one (comment); Other (comment)
Measure used	(free response)
How measure analyzed	(free response)
Measure type	Global self-report; Retrospective self-report; Momentary self-report, repeated over time; Behavioral/performance; Other (comment)
New measure introduced?	Yes; No; Not sure
Construct validity approach(es)	Reliability analysis; Factor/principal components analysis; Convergent validity; Discriminant validity; Concurrent validity; Predictive validity; Other (comment)
Relationship(s) with other constructs	(free response)
Relationship(s) with health/well-being	(free response)
Predicted associations not tested	(free response)
Personality traits (e.g., Big Five) analyzed?	Yes; No; Other (comment)
<i>Theoretical Information</i>	
Particular theoretical approach evidenced?	Yes, mentioned explicitly; Yes, but it's implicit; No
Name of approach (if applicable)	Appraisal; Basic emotion; Constructionist; Psychoanalytic/psychodynamic; Other (comment)
Evidence for approach	(free response)
<i>Review Information</i>	
Reviewer name	(free response)
Flag for discussion/exclusion?	Yes; No
Overall notes/conclusions	(free response)
Anything to add to the list to review?	(free response)

Figure 1-2. Data extraction template completed for each fully-reviewed publication. Questions regarding a specific construct (inset box) were repeated until all included constructs had been documented.

Publications were randomly assigned to a team of two reviewers (K.H. & A.Y. or C.N. & J.G.). Both members of the team independently read and coded the publication, and resolved any discrepancies through discussion to produce a consensus record⁴. Difficult or ambiguous cases were also addressed in meetings with all reviewers. As part of data extraction, reviewers were asked to identify, from the works cited, any additional publications that may be relevant. This iterative identification method extended our previous search and selection steps, as it was not constrained by the presence of specific keywords.

⁴ Because our primary variables of interest were free-text responses, we were not able to compute meaningful measures of inter-rater reliability such as intraclass correlations or kappa coefficients.

Ninety six publications were added in this way, 27 of which passed screening for further review, bringing the total to 223 publications. Full print or online versions could not be located for 13 records (e.g., they were published in books only held by European libraries), such that data were extracted for 210 publications.

Reviewers also had the opportunity to recommend a publication be excluded from further review and analysis. For example, in some cases, the full version of an article clarified (in contrast to the abstract) that one or more of the inclusion criteria had not been met (see Figure 1-1 for list of reasons for exclusion). Through reading and discussion, we also decided to exclude all publications related to affective and emotional style, as well as those related to affective and emotional variability. Style (e.g., Davidson, 1992, 1998, 2000) was initially included in our search due to its prominence in the literature; however, we found that it did not provide sufficient treatment of the mental representation and behavioral measurement of specific emotional experiences (instead focusing on overall tendencies such as approach vs. withdraw, affective dynamics and chronometry, and underlying brain systems). Variability was initially included in our search due to its multiple possible meanings: although it typically refers to fluctuations in the intensity of emotion or affect over time (e.g., Kuppens, Van Mechelen, Smits, et al., 2007; Larsen, 1987), less commonly it can also refer to range, variation, or context-specificity in experienced emotion (e.g., Barrett, 2009; Waugh et al., 2011). While we would have been interested in publications covering the latter, our selected publications only covered the former, dealing exclusively with affective dynamics that do not invoke mental representation or (necessarily) specific emotions. With these records removed, 141 publications remained in the extracted data. See Table 1-1 for a final list of included constructs and the number of publications representing each. An abridged version of the final database is provided via our online data repository (<https://osf.io/a6vzk/>).

Data Organization

The principle goal of the present review is to map research on emotional expertise. We approached this goal in three ways. First, we summarized the definition, common measures, and dominant theoretical perspective of each construct. To do this, we reviewed the definitions extracted for a given construct, and selected a representative (and typically recent) definition based on one or two of the included publications. We also used the extracted data to identify commonly-used measures for the construct, as well as their corresponding measurement type. For example, we identified two commonly-used measures for emotional awareness. Most of the publications we reviewed used the Levels of Emotional Awareness Scale (LEAS; Lane et al., 1990), which is a performance-based measure, but there were also publications that used the Clarity and Attention subscales of the Trait Meta-Mood Scales (TMMS; Salovey et al., 1995), which is a global self-report measure. In a similar manner, we identified the dominant theoretical approaches or perspectives adopted in publications about the construct. We summarize these data in Table 1-1 to provide a high-level overview of the constructs pertaining to the mental representation of emotional experience, and illustrate key commonalities and differences among constructs.

Second, we illustrated the interrelationships between constructs, taking into account both theoretical and empirical connections. To determine theoretical connections, we reviewed all the definitions extracted for a given construct, as well as any other notes made from the included publications' discussion sections. Definitions often indicated that constructs were comprised of multiple facets (i.e., subordinate constructs). For example, Kang and Shaver (2004) define emotional complexity as comprised of range and differentiation; as such, we documented 'range' and 'differentiation' as facets of complexity, as well as links between each facet and the superordinate construct. Furthermore, publications often referred to relationships between the constructs in our review. For example, Kang and Shaver (2004) also discuss the relationship between emotional complexity and emotional intelligence; as such, we documented a link between complexity and intelligence. In this way, we compiled a list of all the constructs and their facets, and a matrix of the theoretical connections between them.

Given that we were interested in the mental representation of emotional experience, we excluded from review any construct that specifically targeted the perception, expression, and regulation of emotion.

However, some constructs that met our criteria included perception, expression, or regulation as facets (e.g., the model of emotional intelligence proposed by Mayer & Salovey, 1997). We incorporated these facets into our network to avoid discarding data from the publications in our review.

We followed a similar procedure to build a matrix of empirical connections between constructs. Specifically, empirical connections were established whenever publications reported correlations between two or more constructs for emotional expertise (extracted in the “relationships with other constructs” field). For each empirical connection, we documented the average effect size of the relationship (i.e., the r value), as well as the specific measures used. We used the matrices of theoretical connections and empirical connections (available via our OSF repository) to build a series of networks. This allowed us to examine the hypothesized relationships between constructs as well as the relationships between constructs demonstrated in the literature.

Third, we inductively generated a list of the features of emotional expertise represented by each construct. To do this, we reviewed the definitions, measurement information, and other notes extracted from each publication, and noted salient characteristics about the construct in question. We then compared these characteristics to the features of domain-general expertise described above: structure, breadth, and type of knowledge; mental representation; verbal representation; ability or skill; adaptive responses; context specificity; awareness; monitoring; deliberate practice; and prediction. For example, emotional awareness stresses the role of conscious cognition in emotional experience (Lane et al., 1990; Lane & Schwartz, 1987), and so it fulfills the feature of ‘awareness’. Likewise, emotional granularity stresses the presence of differentiated emotion concepts (Barrett, 2004, 2017a), and so it fulfills the feature of ‘structure of knowledge’. In this way, we used constructs’ key characteristics to synthesize and map them onto an integrated framework for emotional expertise. We present the results of this synthesis as a pair of polar plots illustrating the distribution of features across constructs for the mental representation of emotional expertise.

Results

Summarizing Constructs for the Mental Representation of Emotional Experience

Table 1-1 presents the final list of included constructs along with their definition, common measures, dominant theoretical perspective, number of reviewed publications, and key publications (for individual construct summaries, see pages 11-20 of the supplemental materials). Ignoring modifiers (e.g., “emotion(al)”, “affect(ive)”), there are 15 constructs represented in the extracted data. Two pairs of constructs are synonymous: differentiation and granularity (Kashdan et al., 2015; Smidt & Suvak, 2015)⁵, and intelligence and quotient (e.g., Bar-On, 1997, 2000). For the present analyses, we adopt the labels “granularity” and “intelligence”. Four constructs – agnosia, diversity, utilization, and range – were represented by only one or two publications each. Based on this small literature size and the constructs’ definitions, we (i) merged diversity and range, (ii) subsumed agnosia under alexithymia, and (iii) subsumed utilization under competence. Together, these decisions account for the final total of ten summarized constructs.

Two constructs – alexithymia and emotional intelligence – had particularly large literatures to summarize, with 43 and 44 included publications, respectively. In each case, there are several competing definitions and measures, the history and details of which are out of scope for the present review⁶. For current purposes, we focus on the work of Taylor, Bagby, and Parker for alexithymia (e.g., Bagby et al., 1994; G. J. Taylor et al., 1985) and the work of Mayer, Salovey, and Caruso for intelligence (e.g., Mayer et al., 2002; Salovey & Mayer, 1990a). The definitions and measures introduced by these research groups

⁵ We also included “emotional heterogeneity” (e.g., Charles, 2005) in our list of search terms. None of the resulting publications were selected for inclusion in the final database because they described the construct strictly within a lifespan development context. However, based on the definition of heterogeneity as the simultaneous experience of multiple negative emotions, we would have also considered it a type of (low) granularity. See Table S1-1 for details.

⁶ Interested readers are referred to the following reviews: for alexithymia (Bar-On, 2004; Bermond et al., 2015; Sifneos, 1996); for emotional intelligence (Akerjordet & Severinsson, 2007; Conte, 2005; Siegling et al., 2015).

are the most widely-used and/or psychometrically-validated in their respective literatures (alexithymia: Lumley et al., 2007; but see Kooiman et al., 2002; emotional intelligence: Cherniss, 2010; Joseph & Newman, 2010; Livingstone & Day, 2005; but see Maul, 2012; Roberts et al., 2010). Even so, we highlight common measures advanced by other research groups (e.g., the Emotional Quotient Inventory [EQ-i]; Bar-On, 1997; the Bermond-Vorst Alexithymia Questionnaire [BVAQ]; Bermond & Oosterveld, 1994).

Table 1-1. Summary of Constructs for the Mental Representation of Emotional Experience

Construct	Definition	Common Measure(s)	Measure Type	Dominant Theoretical Perspective(s)	Reviewed*	Included	Key Publication(s)
Alexithymia ¹	The inability to identify, describe, and introspect about one's emotional experiences (Aaron et al., 2018); the inability to mentally represent one's emotional experiences (Lane et al., 2015)	Toronto Alexithymia Scale, 20-item version (TAS-20; Bagby et al., 1994); Bermond-Vorst Alexithymia Questionnaire (BVAQ; Bermond et al., 1994)	Global self-report	Psychoanalytic	164	43	Nemiah & Sifneos (1970); Taylor et al. (1985)
Awareness	The extent to which one understands, describes, and attends to one's emotional experiences (Mankus et al., 2016)	Levels of Emotional Awareness Scale (LEAS; Lane et al., 1990); Trait Meta-Mood Scales (TMMS) for Clarity, Attention (Salovey et al., 1995)	Task performance; Global self-report	Cognitive-developmental; Appraisal	148	13	Lane & Schwartz (1987); Thompson et al. (2009)
Clarity	The extent to which one unambiguously identifies, labels, and describes one's own emotional experiences (Boden & Thompson, 2017)	TMMS, Clarity subscale (Salovey et al., 1995); TAS-20, Identification subscale (TAS-20, DIF; Bagby et al., 1994)	Global self-report	Appraisal	148	12	Salovey et al. (1995); Boden & Berenbaum (2011)
Competence ²	The extent to which one identifies, expresses, understands, regulates, and uses one's own emotions and those of others (Brasseur et al., 2013) to facilitate appropriate actions (Izard, 2009)	Emotional Competence Inventory (ECI; Boyatzis et al., 2000); Profile of Emotional Competence (PEC; Brasseur et al., 2013) [†]	Multi-rater assessment; Global self-report	Basic emotion; Appraisal	44	5	Boyatzis et al. (2000); Brasseur et al. (2013)
Complexity	The extent to which one simultaneously experiences different(ly valenced) emotions, and/or differentiates between a varied and nuanced set of emotions (Grühn et al., 2013)	Range and Differentiation of Emotional Experiences Scale (RDEES; Kang & Shaver, 2004); Empirically-derived indices computed from emotion intensity ratings	Global self-report; Momentary self-report, repeated over time	Cognitive-developmental; Appraisal	126	18	Kang & Shaver (2004); Grühn et al. (2013a)
Creativity	The ability to produce emotional responses that are novel, authentic, and effective, as well as one's preparedness to use this ability (Averill, 1999)	Emotional Creativity Inventory (Averill, 1999); Emotional Consequences, Emotional Triads (Averill & Thomas-Knowles, 1991)	Global self-report; Task performance	Constructionist	33	6	Averill & Thomas-Knowles (1991); Averill (1999)

Construct	Definition	Common Measure(s)	Measure Type	Dominant Theoretical Perspective(s)	Reviewed*	Included	Key Publication(s)
Diversity ³	The variety and relative abundance of the emotions one experiences (Quoidbach et al., 2014); the breadth of emotions one experiences (Kang & Shaver, 2004)	Empirically-derived index computed across emotion frequency ratings; RDEES, Range subscale (Kang & Shaver, 2004)	Retrospective self-report; Global self-report	Appraisal	53	4	Quoidbach et al. (2014); Sommers (1981)
Flexibility	The ability to adapt (i.e., regulate) one's emotional experiences in a situation-specific manner (Fu et al., 2018)	Changes in emotion intensity ratings after mood induction; Emotional Flexibility Scale (Fu et al., 2018)	Momentary self-report; Global self-report	Appraisal	54	4	Waugh et al. (2011); Zhu & Bonanno (2017)
Granularity ⁴	The ability to represent one's emotional experience in a nuanced and specific manner, as marked through language (Lee et al., 2017; Tugade et al., 2004)	Within-person correlations (e.g., intraclass correlations) across emotion intensity ratings; RDEES, Differentiation subscale (Kang & Shaver, 2004)	Momentary self-report, repeated over time; Global self-report	Constructionist	153	24	Barrett et al. (2001); Tugade et al. (2004)
Intelligence ⁵	The ability to perceive and express emotion, understand and reason with emotion, and regulate emotion in the self and others (Mayer et al., 2000)	Mayer-Salovey-Caruso Emotional Intelligence Test (MSCEIT; Mayer et al., 2002); Emotional Quotient Inventory (EQ-i; Bar-On, 1997); Schutte Emotional Intelligence Scale (SEIS; Schutte et al., 1998); Trait Emotional Intelligence Questionnaire (TEIQue; Petrides, 2009)	Task performance; Global self-report	Basic emotion; Appraisal	353	44	Mayer & Salovey (1997); Bar-On (1997); Siegling et al. (2015)

Note: * Number of publications identified through database searching and/or key reviews; † Also assessed as emotional intelligence. Superscripts: ¹ Includes agnosia; ² Includes utilization; ³ Includes range; ⁴ Includes differentiation; ⁵ Includes quotient.

The first trend this summary makes particularly clear is a similarity in construct measurement. All ten constructs can be measured using global self-report instruments (e.g., the Toronto Alexithymia Scale, 20-item version [TAS-20]; Bagby et al., 1994). Such measures have been criticized, however, for their tendency to capture individuals' beliefs about themselves and other biases, rather than providing insight into how emotional experience itself is mentally represented (e.g., M. D. Robinson & Clore, 2002). Global self-report measures can be susceptible to socially-desirable responding (Paulhus, 1984), as individuals may overestimate their abilities relative to norms (Mayer et al., 2001) and may even go as far as to fake their responses (e.g., Grubb & McDaniel, 2007). Conversely, individuals may be limited in how well they can self-report on their own ability to introspect if this ability is impaired (Lane et al., 1997; Lundh et al., 2002). Global self-report measures can also be susceptible to shifts in momentary affect, such that they capture an overall sense of how good or bad an individual is feeling, rather than the specific skills or qualities the instruments purport to measure (e.g., Leising et al., 2009).

However, the level of measurement employed should correspond with the construct definition. While it may arguably be appropriate to capture emotion-related traits using global self-report, skills or abilities are more appropriately measured behaviorally (Joseph & Newman, 2010; Kashdan et al., 2015; Siegling et al., 2015). Indeed, seven of the ten constructs are (also) measured using scores or other indices derived from performance-based tasks (e.g., the Levels of Emotional Awareness Scale [LEAS]; Lane et al., 1990), retrospective emotion frequency ratings (e.g., emodiversity; Quoidbach et al., 2014), or in-the-moment emotion intensity ratings (e.g., intraclass correlations for granularity; Tugade et al., 2004).

Another key take-away from Table 1-1 is the role played by various theoretical perspectives on emotion. Across all ten constructs, appraisal-theoretic influences appear most often. These influences include both 'causal' appraisal perspectives (e.g., Frijda, 1986; Lazarus, 1991; Plutchik, 1980; Roseman, 1991; Scherer, 1984), which hold that appraisals are mental processes that give rise to the experience of emotion, as well as 'descriptive' appraisal perspectives (e.g., Clore & Ortony, 2000, 2008; Moors et al., 2013; Scherer, 2009a, 2009b; see also Gross & Barrett, 2011), which hold that appraisals capture the content or meaning of emotional experience. Work on clarity, diversity, and flexibility appears to be mostly influenced by appraisal perspectives, whereas work on intelligence and competence has also been influenced by basic emotion perspectives (e.g., Ekman, 1972; Izard, 1993; Tomkins, 1962, 1963), and work on awareness and complexity has also been influenced by cognitive-developmental perspectives (e.g., Labouvie-Vief & Medler, 2002; Lane & Schwartz, 1987; Piaget, 1937; Werner & Kaplan, 1963).

From a largely separate perspective, work on alexithymia has been historically situated within a psychoanalytic or psychodynamic tradition (e.g., Freud, 1891; Marty & de M'Uzan, 1963; Ruesch, 1948), which understands emotional experience as a way of symbolizing or processing internal or unconscious conflicts (e.g., Krystal, 1979; Lesser, 1981; Nemiah & Sifneos, 1970; G. J. Taylor, 1984). In a similarly separate vein, work on creativity and granularity has been anchored in a (social) constructionist framework (e.g., Averill, 1980; Barrett, 2009; James, 1884; Russell, 2003), which emphasizes the influence of individual history, cultural background, and physical and situational context on the experience of emotion. Each of these theoretical perspectives carries implications for the understanding of individual differences in the mental representation of emotional experience, how they can be measured, and whether they can be improved. We return to this point in the Data Synthesis section, below.

Illustrating Relationships between Constructs

Figure 1-3 provides a network illustration of the theoretical interrelationships between constructs. In this network, constructs are shown in relation to each other and their facets, as determined based on the reviewed publications. Nodes corresponding to constructs are colored in green, while nodes corresponding to facets are colored in gray; for clarity of viewing (and in keeping with Table 1-1), all nodes are labeled without modifiers (e.g., "emotion(al)"). Connections linking a facet to a broader construct are indicated with an arrow directed at the construct; connections linking two 'peer' constructs are indicated with an arrow at either end. Connections are weighted by the number of publications represented, from a scale of one (a single publication; thinnest lines) to five (five or more publications; thickest lines). Weights were capped at five to provide a representative sense of endorsement rates, while

accounting for differences in publication selection for high-volume constructs such as alexithymia and emotional intelligence. Finally, facets have been renamed to facilitate integration in the network. For example, source clarity (Boden & Berenbaum, 2011; Boden & Thompson, 2015; Cameron et al., 2013; Lischetzke & Eid, 2017) is referred to as “appraisal” to highlight connections to appraisal-theoretic perspectives as well as to other constructs such as competence (Scherer, 2007) and intelligence (Salovey & Mayer, 1990a). Furthermore, constructs and facets defined as inabilities have been conceptually inverted. For example, alexithymia is defined as “the inability to identify, describe, and introspect about one’s emotional experiences” (Aaron et al., 2018); when inverted as “(a)lexithymia”, these facets become the abilities of identification, description, and introspection⁷. As ‘identification’ is also a facet of awareness (Bagby et al., 2006; Boden & Thompson, 2015), clarity (Boden & Berenbaum, 2011; Lischetzke & Eid, 2017), and competence (Brasseur et al., 2013), this node can be connected accordingly.

As made evident by Figure 1-3, the literature on emotional expertise can be broken down into several, interrelated clusters of constructs. The hubs of these clusters are intelligence, alexithymia, and awareness/clarity. The intelligence cluster is the largest, and includes constructs oriented toward applied contexts, such as competence and flexibility. Creativity also forms a part of this cluster, although as a satellite of intelligence; this relationship reflects the theoretical context in which creativity was introduced as a constructionist alternative to intelligence (e.g., Averill, 2004; Ivcevic et al., 2007). The (a)lexithymia cluster, the second largest, evidences its clinical origins through the psychoanalytic construct of (a)gnosia (Lane et al., 2015a), and facets such as introspection (i.e., the inverse of externally-oriented thinking) and imagination (i.e., the inverse of reduced fantasy). Still, this cluster has many nodes in common with the awareness/clarity cluster, which bridges clinical application with a basic science interest in the mechanisms underlying mental representation of emotional experience (e.g., voluntary vs. involuntary attention; Huang et al., 2013; source vs. type clarity; Boden & Berenbaum, 2011). This emphasis on mechanism is shared by the complexity cluster, whose constructs additionally seek to capture individual differences across the lifespan (e.g., Grünh et al., 2013a) and across cultures (e.g., Grossmann et al., 2016). Across the network as a whole, connections between constructs reflect underlying relationships between domains of research, research groups, and theoretical perspectives. Missing connections between constructs at the periphery reflect, then, opportunities for theoretical integration.

⁷ Moormann et al. (2008) also adopts the term “lexithymics” to describe emotionally intelligent individuals.

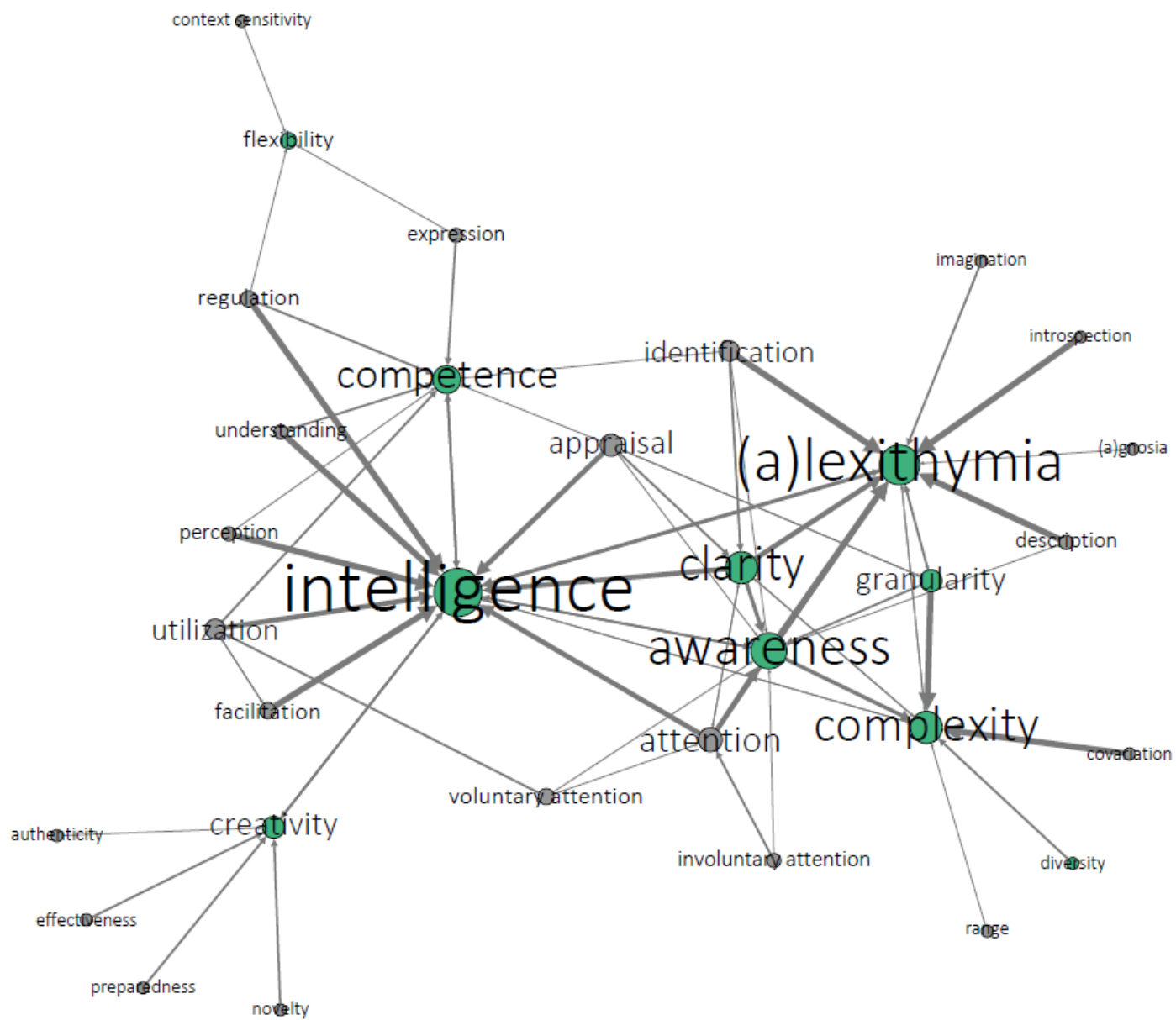


Figure 1-3. Network based on theoretical interrelationships documented between constructs and their facets. Node color distinguishes constructs summarized in Table 1-1 (green) from facets added during data extraction (gray). Only publications by Taylor, Bagby, and colleagues (e.g., Bagby et al., 1994; G. J. Taylor et al., 1985) and Mayer, Salovey, and colleagues (e.g., Mayer et al., 2002; Salovey & Mayer, 1990a) are represented for alexithymia and intelligence, respectively. For a version of this network including other definitions of these constructs, see Figure S1-1. Nodes are sized (along with their labels) according to their number of connections (i.e., degree). Facets are connected to broader constructs with an arrow directed at the construct; constructs are connected to each other with an arrow at both ends. Connections are weighted counts of the number of publications represented, such that the thinnest lines represent a single publication, and the thickest lines represent five or more publications. Nodes renamed from the original publications to facilitate integration: “granularity” also refers to differentiation (e.g., Barrett et al., 2001); “covariation” also refers to dialecticism (e.g., Grossmann et al., 2016); “regulation” also refers to repair (Salovey et al., 1995); “appraisal” also refers to source clarity (e.g., Boden & Berenbaum, 2011); “identification” also refers to type clarity (e.g., Boden & Berenbaum, 2011); “voluntary attention” (e.g., Boden & Thompson, 2015) also refers to redirected attention (Salovey & Mayer, 1990a). Facets noting the use of language to verbalize emotion (e.g., labeling; Swinkels & Giuliano, 1995) are referred to as “description” (following Bagby et al., 1994). Nodes conceptually inverted: (a)gnosia; (a)lexithymia and its facets identification, description, introspection (vs. externally-oriented thinking), and imagination (vs. reduced fantasy). Network visualization created in Gephi (Bastian et al., 2009) using the Yifan Hu Proportional layout (Hu, 2005).

Figure 1-4 provides network illustrations of the empirical interrelationships between constructs. As in Figure 1-3, constructs are represented by green nodes, whereas facets are represented by gray nodes. In these networks, however, connections between nodes represent statistical relationships (i.e., correlations) documented between the constructs/facets, regardless of the measure used to collect this data. These relationships are visualized in two ways. In the upper panel, connections represent mean effect sizes (r) of all reported correlations and are colored according to the direction of correlation (blue for positive, orange for negative). Importantly, because (a)lexithymia and its facets were conceptually inverted, so were corresponding connections: publications documenting negative correlations between alexithymia and emotional intelligence (e.g., Parker et al., 2001), for example, are displayed as positive (blue) connections between the two nodes. The position of nodes in Figure 1-3 has been maintained to facilitate comparison with theoretical connections. In the lower panel, the network layout has been restructured according to the strength of the mean effect sizes. In both panels, connections are undirected (i.e., there are no arrows), indicating the bidirectionality of the relationships.

In contrast to Figure 1-3, what Figure 1-4 makes evident is the number of empirical comparisons between the wider network of constructs representing aspects of emotional expertise. Although it is rare for more than two constructs to be compared within a single publication (cf. Lumley et al., 2005), Figure 1-4 reveals the extent of comparisons made across the literature. There are several nodes that remain unconnected in this network. Note, however, that because our goal was to review a representative rather than comprehensive set of publications – particularly for the high-volume constructs of alexithymia and emotional intelligence – it is likely that there are missing comparisons. Moreover, publications focused on excluded constructs (e.g., [emotion] regulation, a facet of intelligence and competence) were, by design, never reviewed. Nevertheless, Figure 1-4 provides a high-level snapshot of how data are collected and analyzed in relation to the constructs of interest.

The overall relationship, after inverting (a)lexithymia, is positive; only involuntary attention evidences negative correlations. Comparisons between facets of intelligence (e.g., regulation, perception, understanding) and facets of (a)lexithymia (e.g., identification, description, introspection) are by far the most common (e.g., Lumley et al., 2005; Parker et al., 2001), suggesting a reliable correlation between the two largest clusters of constructs and their measures. The stability of relationships between constructs for emotional expertise is further underscored by prior meta-analytic comparisons of common measures for (a)lexithymia (TAS-20) and awareness (LEAS; Maroti et al., 2018), and by studies comparing multiple constructs and measures for each (e.g., Gohm & Clore, 2002; Ivcevic et al., 2007; Kang & Shaver, 2004; Lumley et al., 2005). Findings of positive but weak correlations between measures are typically interpreted as discriminant validity for the constructs in question. For example, a significant but weak meta-analytic correlation of $r = .12$ was used to argue that (a)lexithymia and awareness are separate but related (Maroti et al., 2018). However, this interpretation is called into question by the extent of empirical interrelations demonstrated in Figure 1-4, especially when we structure the network according to the strength of these relationships, allowing nodes to form one large, tight cluster (right panel). Taken together, these findings suggest reliable convergent validity between constructs, and lend credibility to our proposal to integrate these constructs within an expertise framework.

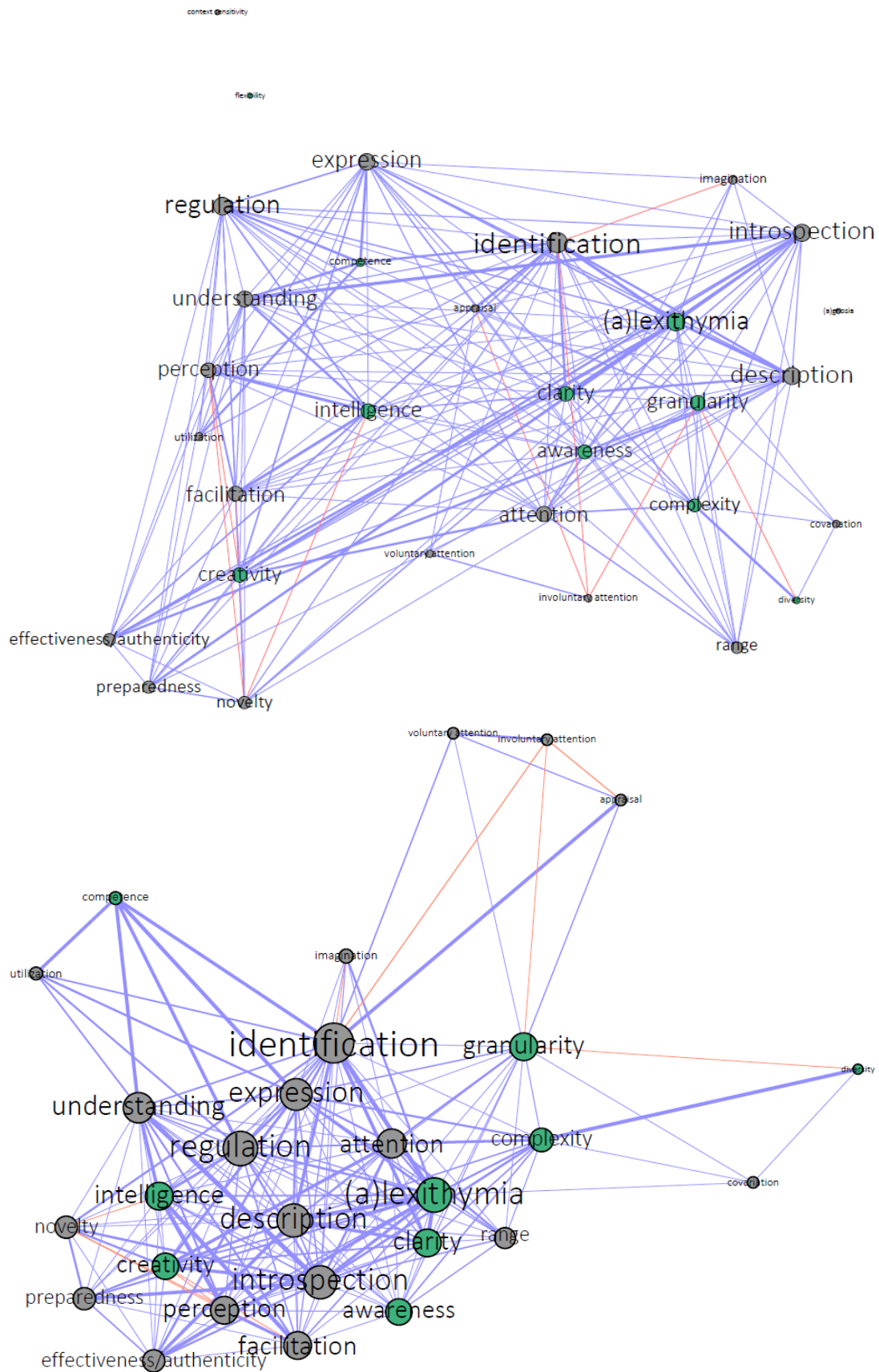


Figure 1-4. Networks based on empirical interrelationships documented between constructs and their facets. Node color distinguishes constructs summarized in Table 1-1 (green) from facets added during data extraction (gray). Only publications by Taylor, Bagby, and colleagues (e.g., Bagby et al., 1994; G. J. Taylor et al., 1985) and Mayer, Salovey, and colleagues (e.g., Mayer et al., 2002; Salovey & Mayer, 1990a) are represented for alexithymia and intelligence, respectively. For a version of this network including other definitions and measures of these constructs, see Figure S1-2. Nodes are sized (along with their labels) according to their number of connections (i.e., degree). Connections are undirected. *Upper panel:* Connections represent mean effect sizes (r) of all reported correlations, and are colored according to the direction of correlation (blue = positive, orange = negative). Unconnected nodes (e.g., flexibility) represent measures not directly compared within the publications selected for review. Node positions have been maintained from Figure 3 to facilitate side-by-side comparison. *Lower panel:* The network layout has been restructured according to the strength of the mean effect sizes. Nodes renamed from the original publications to facilitate integration: “granularity” also refers to differentiation (e.g., Barrett et al., 2001); “covariation” also refers to dialecticism (e.g., Grossmann et al., 2016); “regulation” also refers to repair (Salovey et al., 1995); “appraisal” also refers to source clarity (e.g., Boden & Berenbaum, 2011); “identification” also refers to type clarity (e.g., Boden & Berenbaum, 2011); “voluntary attention” (e.g., Boden & Thompson, 2015) also refers to redirected attention (Salovey & Mayer, 1990a). Facets noting the use of language to verbalize emotion (e.g., labeling; Swinkels & Giuliano, 1995) are referred to as “description” (following Bagby et al., 1994). Nodes conceptually inverted: (a)gnosia; (a)lexithymia and its facets identification, description, introspection (vs. externally-oriented thinking), and imagination (vs. reduced fantasy). Network visualizations created in Gephi (Bastian et al., 2009): for the upper panel, all connections from the theoretical network (Figure 1-3) were removed, and the identified empirical connections were manually added to maintain network layout; for the lower panel, the Yifan Hu Proportional layout (Hu, 2005) was used to structure the network.

Synthesizing Constructs based on Features of Emotional Expertise

Figure 1-5 presents the set of twelve features hypothesized to constitute emotional expertise, as determined deductively from accounts of domain-general expertise. These features are presented in the same order as they were summarized in the introduction: structure, breadth, and type of knowledge; mental representation; verbal representation; ability or skill; adaptive responses; context specificity; awareness; monitoring; deliberate practice; and prediction. The two polar plots summarize which features are represented by the constructs included in this review. The left panel highlights which features are evidenced by each construct: constructs are plotted along radial lines, with features plotted along concentric circles in numerical order from 1 (the innermost circle) to 12 (the outermost circle). The right panel highlights which construct evidences each feature: features are plotted along radial lines, with constructs plotted along concentric circles in alphabetical order from (a)lexithymia (the innermost circle) to intelligence (the outermost circle). In both plots, data points indicate where a feature is present; in cases of disagreement or conflicting accounts within the literature, the data point is not filled (see Table S1-5 for example publications in support of each point).

Two things are immediately evident from Figure 1-5. First, every construct satisfies the feature of *mental representation*. This is by design, as this feature was a conceptual prerequisite for inclusion in a review about individual differences in the mental representation of one's own emotional experience. Second, some constructs cover more features than others. Intelligence, granularity, and creativity are the most comprehensive, while flexibility and diversity exhibit the fewest features. However, the number of features covered by a particular construct is not intended as an index of quality or utility. Rather, as we discuss next, the presence of individual features is largely driven by underlying theoretical assumptions about the nature of emotions and appropriate methods of measurement.

One of the primary dimensions on which constructs differ is the nature of the conceptual knowledge that underlies the mental representation of emotional experience. Most construct definitions explicitly acknowledge that knowledge or 'mental content' is a central feature of expertise. The majority of constructs specify something about the *structure (i.e., quality) of knowledge*: granularity, for example, requires emotion concepts (i.e., accrued knowledge and experience) that are nuanced and precise (e.g., Barrett et al., 2001; Tugade et al., 2004), while complexity emphasizes high-dimensionality (e.g., Carstensen et al., 2000; Ong et al., 2017), and creativity underscores the accrual of knowledge that is person-specific (e.g., Averill, 1999; Fuchs et al., 2007). Creativity and granularity – along with diversity and complexity – also highlight the *breadth of knowledge* supporting emotional experience. In the case of diversity and complexity, this can be seen in the emphasis on range of emotional experience (e.g., Kang & Shaver, 2004; Quoidbach et al., 2014). For creativity, breadth is captured by the emphasis on novelty (e.g., Averill, 1999; Ivcevic et al., 2017), whereas for granularity breadth is implied by having emotion concepts that are precise rather than overlapping (thereby covering more conceptual 'space'; Barrett, 2017a).

Instead of speaking to the structure or breadth of knowledge, work on intelligence and competence focuses on the *type of knowledge*. That is, these constructs follow the assumption (from basic and/or causal appraisal accounts of emotion) that one can be 'correct' or 'incorrect' in one's knowledge – and that accuracy is critical for expertise (e.g., Izard et al., 2011; Mayer & Salovey, 1997; Scherer, 2007). By these accounts, having more, or differently structured, knowledge will not necessarily provide more expertise, if one does not already know the specific things one should know about emotions, such as their (evolutionary-endowed) expressions and functions (e.g., Izard, 2009; Salovey & Mayer, 1990a; Scherer, 2007).

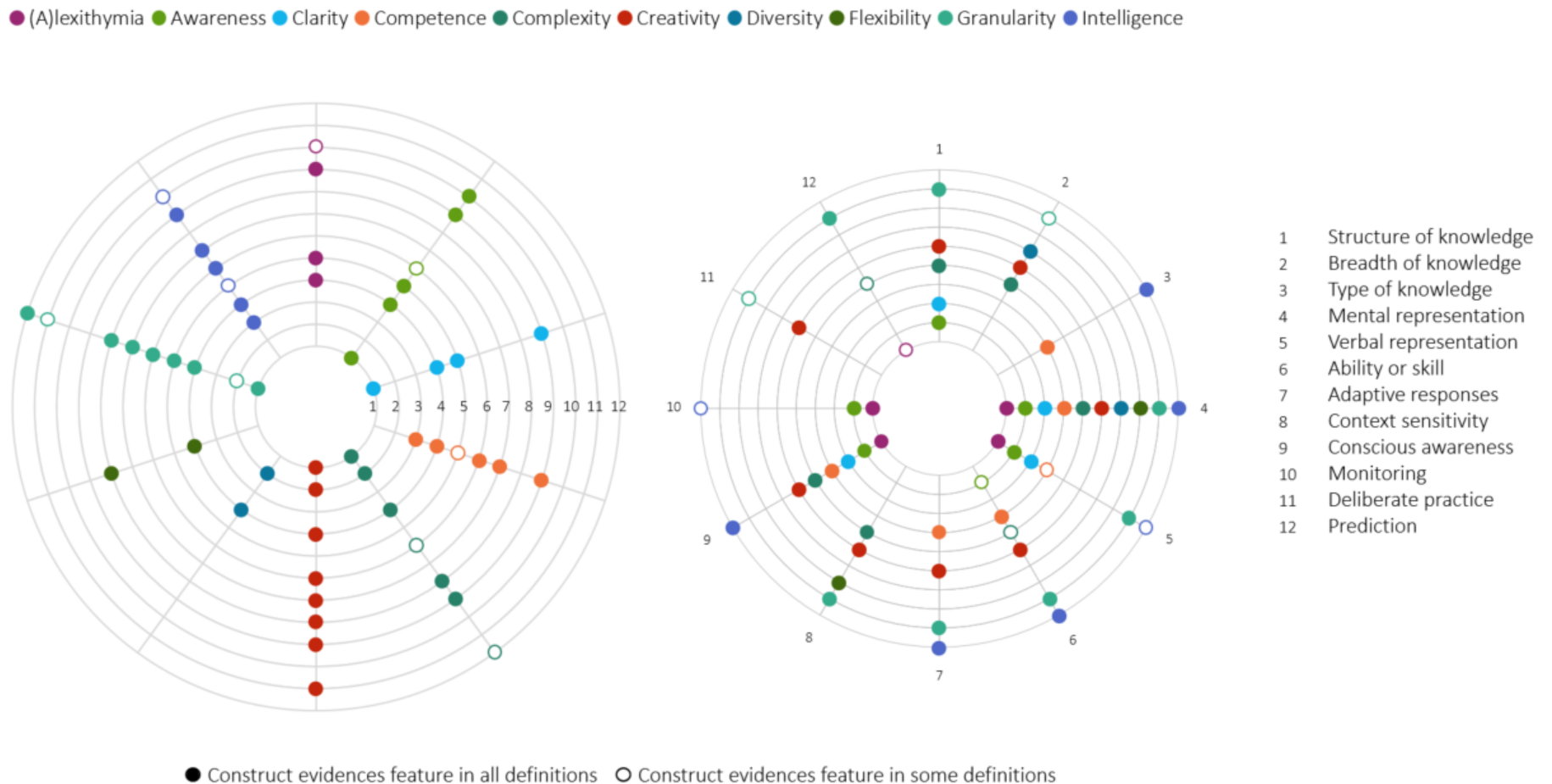


Figure 1-5. Features of emotional expertise, as determined deductively through consultation of accounts of domain-general expertise. For an alternative presentation of these data, see Table S1-5. *Left panel:* Constructs are plotted along radial lines, with features plotted along concentric circles in numerical order from 1 (the innermost circle) to 12 (the outermost circle). *Right panel:* Features are plotted along radial lines, with constructs plotted along concentric circles in alphabetical order from (a)lexithymia (the innermost circle) to intelligence (the outermost circle).

Another primary dimension of emotional expertise is whether it is considered to be an *ability or skill* versus a trait. Four of the ten constructs we reviewed were conceptualized predominantly as abilities or skills: competence (e.g., Brasseur et al., 2013), creativity (e.g., Averill, 1999), granularity (e.g., Kashdan et al., 2015), and intelligence (e.g., Mayer et al., 2000). Outside of Mayer and colleagues' 'ability model' of intelligence, there are also several competing 'trait' or 'mixed model' accounts (e.g., Bar-On, 1997; Petrides et al., 2007). Ability models broadly assume that expertise is not a latent capacity or personality variable, but a skill that is continually acquired throughout the lifespan, and can be actively improved (e.g., Kashdan et al., 2015; Mayer et al., 2016). However, the nature of the emotion knowledge that undergirds that skill varies according to the theoretical framework of the construct, with some ability constructs emphasizing the type of knowledge (i.e., competence and intelligence, which take inspiration from basic emotion perspectives) and others emphasizing the structure or quality (i.e., creativity and granularity, which are based on constructionist perspectives). In contrast, five constructs were described, either implicitly or explicitly, as traits: (a)lexithymia, awareness, clarity, complexity, and diversity. Awareness (e.g., Lane & Schwartz, 1992) and complexity (e.g., Lindquist & Barrett, 2008) have alternatively been conceptualized as abilities or skills.

Three features capture the types of behaviors that indicate expertise. By most accounts, *verbal representation* of emotional experience provides key – if not unparalleled – insight into mental representation. 'Verbal representation' includes the identification (i.e., labeling) and description of emotion, and forms a central part of (a)lexithymia (e.g., Bermond et al., 1999; Sifneos, 1973; G. J. Taylor, 1984), awareness (e.g., Lane & Schwartz, 1987; Swinkels & Giuliano, 1995; R. J. Thompson et al., 2009), clarity (e.g., Boden & Thompson, 2017; Lischetzke & Eid, 2017), and granularity (e.g., Barrett, 2004; Lee et al., 2017a). The appropriate (i.e., normative) use of language is also included in some conceptualizations of competence (e.g., Scherer, 2007) and intelligence (e.g., Ivcevic et al., 2007).

Adaptive responses are a further concomitant of competence, intelligence, creativity, and granularity, although these constructs differ in their understanding of 'adaptive'. As noted above, measures of competence and intelligence tend to look for universal or at least strongly normative operationalizations of emotional behaviors (e.g., Izard, 2009; Mayer et al., 2000), whereas measures of creativity and granularity prioritize behaviors that are situation-specific and personally- and culturally- efficacious. As such, constructs inspired by basic emotion perspectives – competence and intelligence – assume that expertise should meet criteria that are more-or-less context-invariant (e.g., Averill, 2004; Petrides, 2010). These criteria can be taken from hypotheses about evolutionarily-endowed forms and functions (e.g., Izard, 2009; Scherer, 2007), established by a panel of emotion researchers (Mayer et al., 2000), or derived from the performance of a normative sample of US-culture participants (Mayer et al., 2000). In all of these cases, there is an assumption of a 'best' way to respond to a given emotional situation. Individual variability in response is thereby considered an undesirable deviation from this norm⁸.

By comparison, constructs such as complexity, creativity, and granularity stress *context sensitivity* in assessment and interpretation (e.g., Averill, 1999; Kashdan et al., 2015; Lindquist & Barrett, 2008). The cross-cutting assumption – based largely on constructionist and descriptive appraisal perspectives – is that expertise is a relative rather than absolute measure, and varies naturally as a function of culturally-, personally-, and situationally-relevant goals and constraints (e.g., Averill, 1999; Barrett, 2017a).

Two features have to do with how expertise shapes emotional experience. Most constructs specify that expertise includes *awareness* of emotion – that individuals consciously represent and navigate emotional experience (e.g., Lane & Schwartz, 1987; Subic-Wrana et al., 2005; R. J. Thompson et al.,

⁸ The need for normative criteria for assessing adaptive responses (i.e., behaviors) is specifically a problem for ability models of intelligence and competence, which we follow in the present review. Trait or mixed-model accounts of intelligence and competence do not suffer these same criticisms because they are predominantly assessed using global self-report measures (e.g., Bar-On, 1997; Petrides et al., 2007). For further reading on the debate between ability and mixed or trait models of emotional intelligence with regard to measurement, the interested reader is referred to Averill (2004), Conte (2005), Petrides (2010), Roberts et al. (2010).

2009). Granularity is a notable exception to this trend. Although the measurement of emotional granularity invokes the use of verbal representation (which requires conscious cognition), the experience of granular emotions does not per se require internally-directed attention; emotion concepts may be used to construct an emotion without this process entering into subjective awareness (Barrett, 2017a, 2017b; see also Lambie & Marcel, 2002). Constructs such as (a)lexithymia and awareness expand conscious awareness further to include attention to emotions in terms of active scanning or *monitoring* (e.g., Coffey et al., 2003; Gohm & Clore, 2002; Salovey et al., 1995; Swinkels & Giuliano, 1995). This monitoring can take the form of introspection or internally-oriented thought (e.g., Marty & de M'Uzan, 1963; G. J. Taylor et al., 1985), and can be voluntary or involuntary (e.g., Boden & Thompson, 2015; Elfenbein & MacCann, 2017)⁹.

Two final features have to do with how expertise is acquired and how it is implemented. Many accounts of domain-general expertise speak to its acquisition via *deliberate practice* (e.g., Ullén et al., 2016), yet the only constructs to explicitly advocate for such an approach to emotion are creativity and granularity. With its facet of 'preparedness', creativity directly taps the intuition that individuals develop expertise through intentional engagement with and reflection upon their emotions – and that these exercises are done purposefully, to grow and organize knowledge (Averill, 1999). Similarly, individuals can improve their granularity by being “collectors of experience” (Barrett, 2017a), seeking out new ways to expand their perspective and gain new, more nuanced concepts. Granularity further emphasizes that these new concepts lead to improved *prediction*, or more effective resource allocation (Barrett, 2017a). Individuals with greater expertise are more skilled at implementing their knowledge, and can better anticipate and adjust to upcoming challenges. While constructs such as creativity and flexibility do emphasize context sensitivity, as discussed above, they do not capture the proactive planning accounted for by prediction. Along with granularity, prediction is discussed in some accounts of (a)lexithymia (Lane et al., 2015a) and complexity (Lindquist & Barrett, 2008).

Discussion

The idea that some people are better or worse at understanding and managing emotions than others is so widely held and so seemingly obvious as to be common sense. Decades of research support the existence of individual differences in emotional competencies, with thousands of studies demonstrating the various ways in which individuals can excel or be deficient in this ability, and the downstream consequences of these individual differences for mental health, physical health, and other real-world outcomes. Yet the volume of research and variety of individual differences can also be a hindrance to scientific discovery and practical application. There are dozens of psychological constructs (and an even greater number of measures) pertaining to individual differences in the mental representation of emotional experience, and research on these constructs is often fragmented into separate literatures with separate audiences, research goals, and theoretical assumptions.

In the present paper, we have conceptualized the mental representation of emotional experience as a central aspect of emotional expertise, and we have proposed a means to integrate related constructs within a unifying framework based on features of domain-general expertise. Through a scoping review procedure, we conducted an iterative, systematic review of the literature. We identified ten core constructs: alexithymia, awareness, clarity, complexity, competence, creativity, diversity, flexibility, granularity, and intelligence. For each construct, we interrogated a representative set of publications to determine the features of expertise represented, the primary methods of measurement, and their underlying theoretical perspectives. We also situated constructs with respect to each other in terms of definition and measurement, and we illustrated these theoretical and empirical relationships using networks. Finally, we re-mapped constructs to a set of deductively-generated features for emotional expertise, and we compared them within this framework. Throughout this process, we observed overlaps, gaps, and inconsistencies in construct definition and measurement that provide insight into the nature of

⁹ Involuntary attention to emotion is itself negatively associated with other facets of awareness, clarity, and overall expertise (Boden & Thompson, 2015; Huang et al., 2013; Mankus et al., 2016).

emotional expertise, as it pertains to the mental representation of emotional experience. These findings provide a clear framework for interpreting a broader set of emotion-related individual differences, and have implications for future research.

The Nature of Emotional Expertise

By using networks to illustrate the relationships between constructs, we were able to examine the nomological network for the mental representation of emotional experience as an aspect of emotional expertise. The theoretical connections posited between constructs revealed the structure of this body of research: there are several interrelated clusters of constructs, anchored by emotional intelligence, alexithymia, and emotional awareness and clarity. This network, based primarily on construct definitions, represents the motivations behind hypothesis generation and testing. In it, we discerned several clusters of constructs, which we interpret as evidence of the conceptual splintering or re-discovery that has produced the different ‘parts of the elephant’.

Conceptual splintering was not as evident, however, when we examined the empirical connections between constructs. Indeed, the thick web of correlations between these constructs and their facets suggests that there is reliable convergent validity across the network as a whole – that these parts are all part of the same elephant, even if scholars wish to say that they differ in some way or another. In the present review, we excluded constructs that dealt exclusively with the perception, expression, and regulation of emotion. Yet these processes emerged as facets of competence (e.g., Brasseur et al., 2013), flexibility (e.g., Fu et al., 2018), and intelligence (e.g., Mayer & Salovey, 1997). We interpret this not as a limitation of our construct selection procedure, but as an indication of the overlap between our focal aspect of emotional expertise and a broader set of interrelated bodies of research.

When interpreting these networks, it is important to remember that we have ‘zoomed in on’ only one portion of a much larger nomological network of emotional expertise. The mental representation of one’s own emotional experience is a central aspect of expertise, but it is not the only aspect. As such, the connections between our sub-network and its neighboring networks are not visible from this paper alone. This means that the full extent of conceptual splintering (in the theoretical network) and discriminant validity (in the empirical networks) – both within the portion we have covered in this paper and how this portion relates to other aspects of emotional expertise – cannot be determined. The networks we have created are, by their nature, designed to illustrate overlap and convergence.

As mentioned in the introduction, a comprehensive account of emotional expertise would also include constructs related to the representation of others’ emotional experiences (e.g., recognition, empathy), those related to the regulation of emotion in oneself (e.g., coping, control), and those related to the management of emotion with others (e.g., capital, attunement; see Table 2 for example publications). It may further include research on affective dynamics and temperament, changes across the lifespan, and disordered emotional health. We conceptualize the understanding and management of emotions as an umbrella, the exact structure of which should be determined through systematic review and synthesis of relevant constructs. In this regard, we echo and extend prior work that has conceptualized emotional intelligence as a broad, multi-faceted domain (e.g., Bar-On, 1997; Elfenbein & MacCann, 2017; Palmer et al., 2008; Tett et al., 2005). In particular, in their initial 1990 publication, Salovey and Mayer proposed a taxonomic framework for emotional intelligence as a set of skills related to emotion in oneself and others. Here, we have built upon this framework by introducing a set of principled and domain-general features that serve as the basis for interpretation of emotional expertise writ broadly.

In surveying over fifteen constructs for emotional expertise, the present paper echoes and extends recent work by Lumley and colleagues. In a 2005 article, the team gathered and compared data for five constructs of emotional ability (emotional intelligence, trait metamood skills, alexithymia, emotional approach coping, and emotional awareness). On the basis of a confirmatory factor analysis, Lumley and colleagues concluded that emotional ability is not a unitary construct, because it differs as a function of measurement type (e.g., global self-report vs. task performance). This general conclusion about the role of measurement method has received further support from a meta-analysis of emotional intelligence models by Joseph and Newman (2010). Both of these prior studies, like the present review, focused on the

existence of multiple overlapping constructs (or construct definitions), and both underscored the difference – and relationship – between a construct and its measurement in their analyses. In the present review, however, we undertook a qualitative comparison of the constructs in question. This comparison allowed us to expand the scope of our investigation in several ways. First, we were able to include a larger number of constructs than could have reasonably been compared within a single sample. Second, we were able to juxtapose not only methods of measurement, but also theoretical background, assumptions, and goals. In this way, we could examine conceptual features and concomitants of each construct, going beyond effect sizes of local comparisons to parse this research domain at a higher level.

Our approach allowed us to identify both common and distinguishing features across the current literature. We identified several features of emotional expertise that were shared by many of the constructs that we surveyed, beyond that which served as a prerequisite for inclusion (i.e., mental representation). Among the largest commonalities were that emotional experts are consciously aware of their experiences as emotions per se, and that experts use specific language to label and describe their emotional experiences. In line with domain-general accounts, emotional expertise is often seen as an ability or skill. However, the degree to which a given construct is uniformly or explicitly described as evidencing these features varies, with constructs such as alexithymia, awareness, and intelligence comprising multiple different definitions and models.

There are also clear distinctions to be made between constructs. Perhaps the largest is between constructs that look for specific knowledge and responses in determining expertise, such as competence and intelligence, and those that look at the structure of the knowledge and context-sensitivity of the response, such as creativity and granularity. These differences are often rooted in the theoretical assumptions about emotion made by a group of researchers. In our interpretation, we have highlighted the contrast between basic emotion and causal appraisal accounts of emotion espoused by competence and intelligence with the constructionist accounts espoused by creativity and granularity. Differences between constructs are also influenced by other motivating factors, such as the goals of a program of research (e.g., to help managers work with personnel, to help clinicians treat patients, to better understand underlying mechanisms). Yet the distinction between theoretical accounts of emotion also facilitates comparison with domain-general accounts of expertise, as we discuss next.

Support for Constructionist Accounts of Emotional Expertise

In the present review, we have used features of domain-general expertise to scaffold our interpretation of constructs for emotional expertise. Specifically, we have drawn upon a set of core features that describe expertise in terms of a broad and structured knowledge base, sophisticated mental and verbal representation, situation-specific adaptive responses, self-awareness, and active monitoring. These characteristics are understood as reflecting abilities (rather than traits), which is optimally measured via task performance, can be acquired and improved through deliberate practice, and leads to more efficacious prediction of upcoming challenges and how to address them. Further, in our interpretation of expertise, we have emphasized the lack of context-invariant criteria for its assessment. That is, what distinguishes an expert is not just how much they know, how precisely they can describe it, and how effectively they wield it, but whether these processes are performed in the service of context-dependent goals. An expert is nimble, sensitive and responsive to their ever-changing environment. Adept at predicting how the environment will change next, an expert also seems to always be one step ahead. These features are generally manifested by many, if not most, of the constructs included in this review, but are exemplified by granularity and creativity – both of which evidence features, such as the role of deliberate practice and prediction, that are not addressed by other constructs. As introduced previously, these constructs also have a shared foundation in constructionist accounts of emotion.

In particular, an expertise framework for emotion is consistent with the theory of constructed emotion (TCE; Barrett, 2017a, 2017b). According to the TCE, the brain implements an internal model of the body in the world, which uses accrued knowledge (i.e., concepts) to process the current sensory array and issue predictions about what sensory input is likely to occur next. In each instance, the brain compares the current sensory array with that of prior instances with similar situation-specific goals. The

prior instance determined to be most similar serves as the prediction for how the next instance will unfold; the meaning of this prior instance also becomes the inferred cause of incoming sensory input, and processing of this input is tailored accordingly. By functioning predictively, the brain is able to anticipate probable motor actions as well as the accompanying visceromotor changes necessary to meet upcoming energy needs. The experience of emotion occurs when the brain makes meaning of the array of internal sensations – what could be perceived as tingles, aches, fatigue, hunger, etc. – in the context of the current situation, giving rise to the sense that the latter has caused the former. Given a sunny afternoon amid a group of friends at the park, a feeling of indolence might be experienced as the height of pleasant relaxation; given a rainy morning, alone and facing a day of work, the exact same feeling might be experienced as insurmountable torpor.

By specifying the body as a context for prediction, and linking predictive outcomes to efficient resource allocation, the TCE grounds the experience of emotion in biological terms. At the same time, the TCE specifies that the previously-acquired knowledge that shapes predictions is the product of individuals' prior experience as well as enculturation. When to expect certain affective sensations and what to call those sensations are learned throughout the lifetime from fellow culture members. This transmission can be direct, such as a mother instructing a child not to be “angry”, or it can be indirect, such as observing a friend's reaction to an insult. Cultural norms about affect are also communicated through media, such as books and films (e.g., Tsai et al., 2007). As different sets of expectations are accrued, they are associated with different categories of emotion, each with its own associated label. According to the TCE, these categories are not fixed in nature, with necessary or sufficient causes; rather, they depend upon social reality. There are no observer-independent criteria to determine what someone is feeling or when they should feel it. Instead, there is consensus among a group of people about what typically constitutes category membership in a given context. In this way, the TCE also grounds the experience of emotion in social terms. This shared knowledge is further shaped by individuals' (idiosyncratic) prior experience, including the effort they expend in ‘practicing’ their emotions. Whereas activities such as introspecting, chatting with a friend, or engaging in fantasy or counterfactual thinking may not seem like emotional ‘practice’, the TCE holds that these are the processes by which a broad and efficiently structured knowledge of emotions is built.

Altogether, the TCE views emotions as constructed through the interaction of biological, psychological, and social processes. This approach has profound implications for the notion of emotional expertise. Indeed, it is predominantly in the context of the TCE that the construct of emotional granularity (i.e., emotion differentiation) has been and continues to be elaborated (e.g., Barrett, 2004, 2017a; Barrett et al., 2001). Ultimately, however, emotional granularity and the TCE are not alone in providing a comprehensive and mechanistic approach to understanding individual differences in the mental representation of emotional experience. Models of emotional intelligence (e.g., Bar-On, 1997; Mayer & Salovey, 1997; Salovey & Mayer, 1990a), competence (e.g., Brasseur et al., 2013), and creativity (e.g., Averill, 1999) are also comprehensive. Accounts of emotional awareness (e.g., Lane et al., 1990; Lane & Schwartz, 1987) and complexity (e.g., Grossmann et al., 2016; Labouvie-Vief & Medler, 2002) are also mechanistic. In particular, recent work by Smith and colleagues (2018) has explored the underlying processes by which emotional experiences are generated and represented, and has proposed testable hypotheses linking these processes to individual differences in emotional awareness. The authors argue that a better understanding of the mechanisms underlying these individual differences can shed light onto the known relationships between emotional experience and mental and physical health. We concur with their argument, but expand upon their goal to suggest a more inclusive framework for emotional expertise based on the domain-general processes and features outlined by the TCE and accounts of expertise not specific to emotion. By emphasizing the intrinsic links between the brain and the body, and by integrating the study of emotion within a broader understanding of social and biological functioning, such a unifying framework impacts the questions we as scientists ask, and the methods we use to answer them. In the next section, we expand on the benefits of taking a TCE approach.

Implications for Future Research

Translating constructs for emotional expertise into a shared theoretical space guided by the TCE requires a shift in how constructs are defined and how they are measured. Certain measures will be better suited to capturing expertise, and certain measures will be better suited to testing questions of mechanism and links to health. An important task for future research will be to identify and validate these measures. Yet the proposed framework for emotional expertise does offer some suggestions. In particular, it suggests that measures must allow individuals to demonstrate expert performance as an ability or skill, and that this performance must be related to situation-specific goals and needs. Global, self-report measures of expertise are less valid, because expertise cannot be assessed outside of the context in which it is performed. Domain-general expertise, and emotional expertise especially, emphasize facility of verbal representation, such that individuals' use of language to describe emotions can also be considered a key aspect of performance. Taken together, these criteria promote the use of behavioral tasks (e.g., responses to scenarios gathered using the LEAS; Lane et al., 1990) and momentary self-reports, repeated over time (e.g., data gathered using experience sampling methods; Barrett & Barrett, 2001) as a means of capturing expertise.

Future research can expand upon these recommendations in three respects. Firstly, to address the biological mechanisms underlying emotional expertise, biological measures are needed that can be used along with behavioral measures to triangulate the constructs in question. For example, prior research suggests that respiratory sinus arrhythmia (RSA; also known as high frequency heart rate variability or (hf)HRV) is broadly associated with emotional health, such that individuals with lower resting RSA and blunted or excessive RSA reactivity demonstrate poorer regulation capabilities and higher incidence of psychopathology (e.g., Beauchaine, 2015), whereas individuals with higher resting RSA report greater subjective well-being that is mediated by adaptive emotion regulation (e.g., Geisler et al., 2010). To better understand how both biological and behavioral indices of expertise vary within individuals, measures are needed that can capture fluctuations over time, on multiple dimensions, and in everyday life. One possible path forward is to use network analysis to estimate individual differences in the complex dynamics of emotional experience (Hoemann et al., in prep) and interrelations between specific emotions (e.g., Pe et al., 2015) as well as their components (e.g., Howe et al., 2020; Lange et al., 2020). Network analysis allows for multiple properties of the overall construct of interest to be characterized, while simultaneously modeling the relationships between features or facets, and quantifying variation in all of these over time (for discussion, see Epskamp et al., 2018). In particular, future research can integrate network analyses of self-report data with data from ambulatory peripheral physiological monitoring (e.g., Hoemann et al., 2020; Wilhelm & Grossman, 2010) and other forms of in-the-world recording and observation (e.g., Mehl et al., 2012) to examine how the biology and behavior of emotional expertise covary with and predict one another.

Secondly, to address the social mechanisms of emotional expertise, research is needed that can provide insight into how emotion concepts are developed and practiced as a form of cultural learning. Here, computational models can leverage data from in-lab experiments (e.g., S. Kirby et al., 2008) and large-scale repositories (e.g., Lupyan & Dale, 2010) to simulate and predict the spread and maintenance of emotion knowledge, as has been done for language. To ground these models, future research can look to theoretical principles from discursive psychology as well as sociolinguistics and linguistic anthropology. Work in these disciplines examines how emotions are drawn upon and represented in everyday interaction (e.g., D. Edwards, 1999; Parkinson, 1996), and the kinds of work performed by emotion discourse (e.g., storytelling, reporting, assigning motives and blame; Bamberg, 1997). As individuals are socialized within communities of practice (e.g., Wenger, 2010) and emotional collectives (Van Kleef & Fischer, 2016), they develop relevant knowledge. A better understanding of these interactional and group-level processes is therefore critical to charting the development of emotional expertise and understanding how it translates into observable skills. Combined, these methods may provide a means of not only tracking, but also improving expertise. Recent findings suggest that granularity improves naturally as a function of experience sampling and other means of encouraging self-monitoring (Van der Gucht et al., 2019; Widdershoven et al., 2019). Further longitudinal investigations

and more targeted interventions, conducted in future research, can add depth and detail to these promising results.

Thirdly, to address the real-world outcomes of emotional expertise, research is needed that can link specific features of expertise with aspects of mental and physical health. All of the constructs we reviewed are associated with positive outcomes in one or more domains, yet it remains unclear to what extent these relationships differ as a function of the features of expertise each construct represents. It is also unclear whether these relationships extend to other aspects of emotional expertise, and how they emerge as a function of underlying biological, psychological, and social mechanisms. For example, higher granularity is related to more effective emotion regulation (Barrett et al., 2001; Kalokerinos et al., 2019) and buffers against the impact of stress (Nook et al., 2020; Starr et al., 2019). However, the path from granularity in the mental representation of emotional experience, to the regulation of that experience and overarching psychological processes such as resilience is unknown (but see e.g., Bonanno, 2005; Kashdan et al., 2015; Tugade et al., 2004 for hypotheses). With an integrative framework for expertise, informed by the TCE, future research is on a stronger footing to systematically answer these questions. By incorporating biological measures for emotional expertise, future research will be able to more directly test relationships with physical health (for discussion related to cardiovascular disease, see Gianaros & Jennings, 2018). By gathering insights into social processes, future research will also be able to establish and foster emotional expertise within larger communities of practice.

Author Notes

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K.H., K.S.Q., and L.F.B. designed the scoping review. K.H. and L.F.B. determined constructs for inclusion and criteria for publication selection. K.H. performed database searches; K.H. and A.Y. reviewed the abstracts; K.H., A.Y., C.N., and J.G. reviewed the full publications and extracted the data. K.H. synthesized and visualized the data, and wrote the manuscript. All authors reviewed and revised the manuscript.

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A database of all publications reviewed in this paper, as well as data underlying network visualizations, are available via a repository hosted by the Center for Open Science at <https://osf.io/a6vzk/>.

Chapter 1 Supplemental Materials

Methods

Table S1-1. Constructs Included and Search History

Construct Search Term	Search Date	PsycINFO		Web of Science			Notes
		Raw	Filtered	Raw	Filtered	> 100 Citations	
Affective agnosia	10/21/2018	4	4				Merged with alexithymia
Affective anomia	10/21/2018	0	N/A				
Alexithymia	7/25/2018	4211	2529*	5384	3386	160	
Emotional awareness	7/25/2018	876	548*	1017	580	38	
Emotion awareness	5/24/2018	134	89				
Affective awareness	5/24/2018	37	21				
Affect awareness	5/24/2018	33	N/A				
Emotional clarity	5/24/2018	172	145				
Emotion clarity	5/24/2018	5	N/A				
Affective clarity	5/24/2018	3	3				
Affect clarity	5/24/2018	1	N/A				
Emotional competence	7/25/2018	1158	681*	1108	594	21	
Emotion competence	7/5/2018	30	13				
Emotional complexity	5/24/2018	109	85				
Emotion complexity	5/24/2018	7	5				
Affective complexity	5/24/2018	24	19				
Affect complexity	5/24/2018	18	17				
Emotional creativity	7/5/2018	56	33				
Emotion creativity	7/5/2018	8	N/A				
Affective creativity	7/5/2018	3	N/A				
Emotion differentiation	5/17/2018	87	61				Merged with granularity
Emotional differentiation	5/17/2018	55	32				
Affective differentiation	5/17/2018	15	13				
Affect differentiation	5/24/2018	34	28				
Emodiversity	5/24/2018	7	6				
Emotional diversity	5/24/2018	7	6				
Emotion diversity	5/24/2018	2	N/A				
Affective diversity	5/24/2018	8	N/A				
Affect diversity	5/24/2018	8	N/A				
Emotional flexibility	5/24/2018	52	41				
Emotion flexibility	5/24/2018	5	N/A				
Affective flexibility	5/24/2018	20	13				

Construct Search Term	Search Date	PsycINFO		Web of Science			Notes
		Raw	Filtered	Raw	Filtered	> 100 Citations	
Affect flexibility	5/24/2018	8	N/A				
Emotional granularity	5/17/2018	20	13				
Emotion granularity	5/17/2018	0	N/A				
Affective granularity	5/17/2018	0	N/A				
Affect granularity	5/24/2018	30	N/A				
Emotional heterogeneity	10/21/2018	3	2				No papers included in final database (Would be merged with granularity)
Emotion heterogeneity	10/21/2018	2	2				
Affective heterogeneity	10/21/2018	1	1				
Affect heterogeneity	10/21/2018	2	1				
Emotional intelligence	7/25/2018	7045	3428*	9261	4157	163	
Emotion intelligence	5/24/2018	35	22				
Affective intelligence	5/24/2018	32	22				
Affect intelligence	5/24/2018	25	N/A				
Emotional quotient	5/24/2018	559	146				Merged with intelligence
Emotion quotient	5/24/2018	7	N/A				
Affective quotient	5/24/2018	0	N/A				
Emotional range	5/24/2018	45	41				
Emotion range	5/24/2018	1	N/A				
Affective range	5/24/2018	14	N/A				
Affect range	5/24/2018	7	N/A				
Emotional style	5/24/2018	148	70				Excluded from final database
Emotion style	5/24/2018	9	N/A				
Affective style	5/24/2018	215	146				
Affect style	5/24/2018	8	N/A				
Emotion utilization	10/21/2018	12	10				Merged with competence
Emotional variability	5/24/2018	46	37				Excluded from final database
Emotion variability	5/24/2018	10	6				
Affective variability	5/24/2018	25	23				
Affect variability	5/24/2018	59	53				
Mood variability	7/5/2018	110	87				

Note: N/A Full search results were empty or did not include any relevant publications; * Over 500 PsycINFO results after filters applied; alternative search procedure conducted using Web of Science.

Table S1-2. Constructs Excluded

Construct	Example Publication(s)	Reason Excluded
Trait <i>affect</i>	Watson & Walker (1996)	Related to temperament
Trait <i>affectivity</i>	Heller et al. (2002)	Related to temperament
Emotional <i>agility</i>	David (2016)	No peer-reviewed literature
Emotional <i>alchemy</i>	Cooper & Sawaf (1997)	From I/O literature
Emotional <i>ambivalence</i>	Rees et al. (2013)	Unrelated to knowledge/skill
Feeling <i>aphasia</i>	Sifneos (1996)	Captured as part of alexithymia
Emotional <i>approach coping</i>	Stanton et al. (1994)	Related to emotion regulation
Trait <i>arousability</i>	Mehrabian (1995)	Related to temperament
<i>Attention</i> to emotions	Huang et al. (2013)	Captured as part of emotional awareness
Emotion <i>attention regulation</i>	Elfenbein & MacCann (2017)	Captured as part of emotional intelligence
Emotional <i>attunement</i>	Gottman (2011)	Interpersonal construct
Emotional <i>availability</i>	Biringer & Robinson (1991)	Interpersonal construct
Interoceptive <i>awareness</i>	Herbert et al. (2011); Mehling et al. (2012)	Not specific to emotion
<i>Affect balance</i>	Bradburn (1969); Schwartz & Garamoni (1989)	Related to temperament
<i>Affective bipolarity</i>	Dejonckheere et al. (2019)	Unrelated to knowledge/skill
<i>Callous-unemotional</i> traits	Frick et al. (2003)	From developmental literature
Emotional <i>capability</i>	Huy (1999)	From I/O literature
Emotional <i>capital</i>	Cottingham (2016)	Interpersonal construct
<i>Affective chronometry</i>	Hemenover (2003)	Unrelated to knowledge/skill
<i>Affective coherence</i>	Centerbar et al. (2008)	Unrelated to knowledge/skill
Emotional <i>coherence</i>	Mauss et al. (2005)	Unrelated to knowledge/skill
<i>Affective coloring</i>	Helson & Klohnen (1998)	Related to temperament
<i>Affective (social) competence</i>	Halberstadt et al. (2001)	From developmental literature
<i>Affective control</i>	Meltzoff & Litwin (1956)	Related to emotion regulation
Emotion <i>control</i>	Roger & Najarian (1989)	Related to emotion regulation
Emotional <i>control</i>	Watson & Greer (1983)	Related to emotion regulation
Emotional <i>depth</i>	Cooper & Sawaf (1997)	From I/O literature
(Emotional) <i>dialecticism</i>	Schimmack et al. (2002)	Unrelated to knowledge/skill
Emotion <i>disposition</i>	Scherer & Brosch (2009)	Related to temperament
Emotional <i>disposition</i>	Skaggs (1942)	Related to temperament
Emotion-network <i>density</i>	Pe et al. (2015); Bringmann et al. (2016)	Unrelated to knowledge/skill
Negative/positive <i>emotionality</i>	Eisenberg et al. (2001)	Related to temperament
Emotion <i>expression</i>	Banase & Scherer (1996); Malatesta & Haviland (1982)	Process rather than individual difference
Emotional <i>expressiveness</i>	King & Emmons (1990)	Unrelated to knowledge/skill
Emotional <i>fitness</i>	Cooper & Sawaf (1997)	From I/O literature
Expressive <i>flexibility</i>	Westphal et al. (2010)	Related to emotion regulation
(Emotional) <i>flux</i>	Moskowitz & Zuroff (2004)	Unrelated to knowledge/skill
<i>Affective forecasting</i>	Wilson & Gilbert (2003)	Related to emotion regulation
Emotional <i>geography</i>	Hochschild (1996)	Interpersonal construct
Emotional <i>inflexibility</i>	Brose et al. (2015)	Inverse of emotional flexibility
Emotion-related <i>impulsivity</i>	Whiteside & Lynam (2001)	Unrelated to knowledge/skill
Emotional <i>impulsivity</i>	Barkley & Fischer (2010)	Unrelated to knowledge/skill
Emotional <i>inertia</i>	Kuppens et al. (2010)	Unrelated to knowledge/skill
<i>Affective instability</i>	Trull et al. (2008)	Unrelated to knowledge/skill
Emotional <i>instability</i>	Thompson et al. (2012)	Unrelated to knowledge/skill
Social <i>intelligence</i>	Weis & Süß (2007)	Not specific to emotion
<i>Affect intensity</i>	Larsen & Diener (1987)	Unrelated to knowledge/skill
<i>Affective intensity</i>	Keltner (1996)	Unrelated to knowledge/skill
Emotion <i>intensity</i>	Frijda et al. (1992)	Unrelated to knowledge/skill
Emotional <i>intensity</i>	Diener et al. (1985)	Unrelated to knowledge/skill

Construct	Example Publication(s)	Reason Excluded
(Emotional) <i>irregularity</i>	Pincus et al. (2008)	Unrelated to knowledge/skill
Emotion <i>knowledge</i>	Izard et al. (2001)	From developmental literature
Emotional <i>knowledge</i>	Garner & Power (1996)	From developmental literature
Affective <i>lability</i>	Gerson et al. (1996)	Unrelated to knowledge/skill
Emotional <i>lability</i>	Morris et al. (1993)	Unrelated to knowledge/skill
Mood <i>level</i>	Underwood & Froming (1980)	Related to temperament
Emotional <i>literacy</i>	Cooper & Sawaf (1997); Steiner (1984)	From I/O literature; Interpersonal construct
Affect <i>maturity</i>	Thompson (1985)	Captured as part of alexithymia
Emotional <i>maturity</i>	Saul (1947)	Not specific to emotion
Meta-mood <i>experience</i>	Mayer & Gaschke (1988)	Captured as part of emotional intelligence
Mixed <i>emotions</i>	Barford & Smillie (2016); Hershfield et al. (2008)	Unrelated to knowledge/skill
Emotional <i>openness</i>	Komiya et al. (2000)	Unrelated to knowledge/skill
Affect <i>optimization</i>	Labouvie-Vief & Medler (2002)	Related to emotion regulation
Emotion <i>perception</i>	Phillips et al. (2003a, 2003b); Barrett et al. (2011)	Process rather than individual difference
(Emotional) <i>pulse</i>	Kuppens et al (2007); Moskowitz & Zuroff (2004)	Unrelated to knowledge/skill
Affective <i>reactivity</i>	Emmons & King (1989)	Unrelated to knowledge/skill
Emotion <i>reactivity</i>	Nock et al. (2008)	Unrelated to knowledge/skill
Emotional <i>reactivity</i>	Suls et al. (1998)	Unrelated to knowledge/skill
Mood <i>reactivity</i>	Underwood & Froming (1980)	Unrelated to knowledge/skill
Emotion <i>recognition</i>	Elfenbein & Ambady (2002)	Process rather than individual difference
Emotion <i>regulation</i>	Gross (1998b)	Process rather than individual difference
(Emotional) <i>resilience</i>	Bonanno et al. (2007); Connor & Davidson (2003)	Unrelated to knowledge/skill
Mood <i>seasonality</i>	Murray (2003)	Unrelated to knowledge/skill
Affective <i>sensitivity</i>	Kagan & Schneider (1987)	Interpersonal construct
Emotion <i>sensitivity</i>	Carpenter & Trull (2013)	Unrelated to knowledge/skill
Emotional <i>sensitivity</i>	Martin et al. (1996)	Related to emotion perception
Social <i>skill</i>	Riggio (1986)	Not specific to emotion
(Emotional) <i>spikiness</i>	Pincus et al. (2008)	Unrelated to knowledge/skill
Affect <i>spin</i>	Park (2015)	Unrelated to knowledge/skill
(Emotional) <i>spin</i>	Kuppens et al. (2007); Moskowitz & Zuroff (2004)	Unrelated to knowledge/skill
Emotional <i>stability</i>	Hills & Argyle (2001)	Related to temperament
Emotional <i>susceptibility</i>	Caprara et al. (1985)	Unrelated to knowledge/skill
Emotional <i>switching</i>	Houben et al. (2016)	Specific to borderline personality disorder
Affective <i>synchrony</i>	Rafeali et al. (2007)	Unrelated to knowledge/skill
Affective <i>tone</i>	Mason & Griffin (2003)	From I/O literature
Emotional <i>tone</i>	Williams et al. (2012)	Interpersonal construct
Affective <i>understanding</i>	Anders et al. (2016)	From developmental literature; Interpersonal construct
Emotion <i>understanding</i>	Denham et al. (1994)	From developmental literature; Interpersonal construct
Emotional <i>understanding</i>	Thompson (1987)	From developmental literature; Interpersonal construct
Affective <i>volatility</i>	Adams et al. (2014)	Unrelated to knowledge/skill
Emotional <i>volatility</i>	Blair (2013)	Unrelated to knowledge/skill
Affective <i>vulnerability</i>	Gregor et al. (2005)	Unrelated to knowledge/skill
Emotional <i>vulnerability</i>	MacLeod & Hagan (1992)	Unrelated to knowledge/skill

Table S1-3. Reviews Consulted for Large-Literature Constructs

Construct	Review
Alexithymia	Kanbara & Fukugana (2016) Kooiman et al. (2002) Lane et al. (2015a) Lesser (1981) Lumley et al. (2007) Maroti et al. (2018) Taylor et al. (1991) Taylor (2000) Taylor et al. (2016)
Emotional awareness	Gu et al. (2013) Lane (2008) Smith et al. (2018)
Emotional competence	Scherer (2018)
Emotional intelligence	Akerjordet & Severinsson (2007) Andrei et al. (2016) Cartwright & Pappas (2008) Cherniss (2010) Conte (2005) Davis & Nichols (2016) Elfenbein & MacCann (2017) Fiori (2009) Gómez-Leal et al. (2018) Maul (2012) Mayer et al. (2008) Mayer et al. (2004) Mayer & Salovey (1995) Peña-Sarrionandia et al. (2015) Van Rooy et al. (2005) Zeidner et al. (2012)

Note: Selected publications were narrative reviews or meta-analyses identified by searching Google Scholar for the construct name along with the word “review” (e.g., “alexithymia review”).

Table S1-4. Exclusion Criteria

A Priori Criterion	Applied To
Not specific to emotion	Construct
Interpersonal construct	Construct
From developmental or lifespan literature	Construct
From I/O (work) literature	Construct
Unrelated to knowledge/skill	Construct
Related to temperament/disposition	Construct
Dealt only with affect (e.g., positive vs. negative mood) rather than emotion	Publication
Discussed only within a developmental, lifespan, or applied (i.e., industrial/organizational) context	Publication
Described only in relation to a specific domain (e.g., art appreciation, romantic relationships)	Publication
Measured using only biological measures (e.g., fMRI or EEG)	Publication
Merely applied an existing measure to a sample of participants	Publication

Results

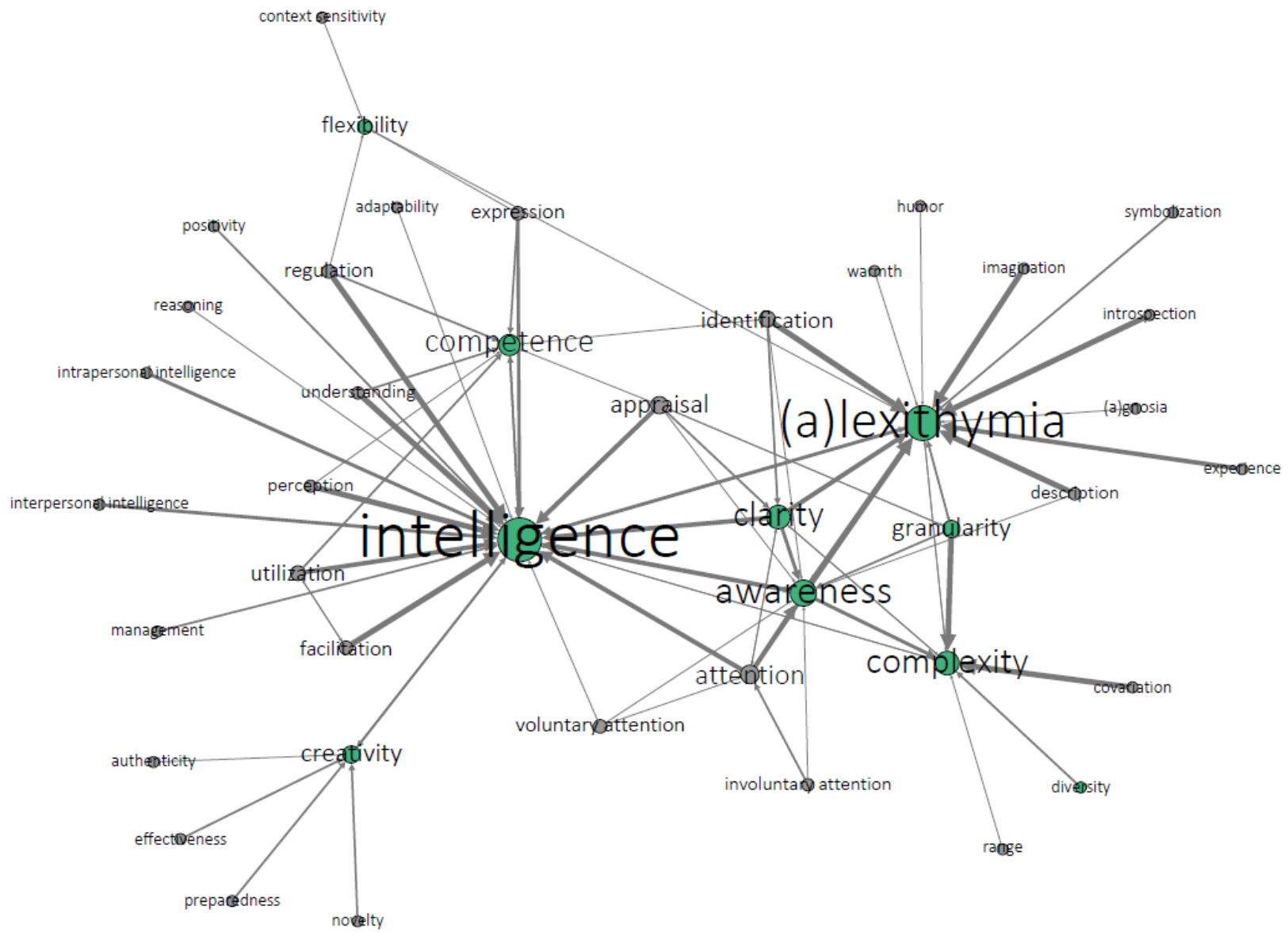


Figure S1-1. Network based on theoretical interrelationships documented between constructs and their facets, including all definitions for alexithymia and intelligence (i.e., not limited to those by Taylor, Bagby, and colleagues and Mayer, Salovey and colleagues, respectively). Node color distinguishes constructs summarized in Table 1-1 (green) from facets or constructs added during data extraction (gray). In cases where definitions included two levels of facets and ‘subfacets’ (e.g., Bar-On, 1997 defines awareness as a facet of intrapersonal intelligence, which is itself a facet of intelligence), only the first level of facets are displayed (e.g., the link between awareness and intrapersonal intelligence has been omitted). Nodes are labeled without any modifiers (e.g., “emotion(al)”, “affect(ive)”), and sized (along with their labels) according to their number of connections (i.e., degree). Facets are connected to broader constructs with an arrow directed at the construct; constructs are connected to each other with an arrow at both ends. Connections are weighted counts of number of publications represented, such that the thinnest lines represent a single publication, and the thickest lines represent five or more publications. Nodes renamed from the original publications to facilitate integration: “granularity” also refers to differentiation (e.g., Barrett et al., 2001); “covariation” also refers to dialecticism (e.g., Grossmann et al., 2016); “regulation” also refers to repair (Salovey et al., 1995); “appraisal” also refers to source clarity (e.g., Boden & Berenbaum, 2011); “identification” also refers to type clarity (e.g., Boden & Berenbaum, 2011); “voluntary attention” (e.g., Boden & Thompson, 2015) also refers to emotion attention regulation (Elfenbein & MacCann, 2017) and redirected attention (Salovey & Mayer, 1990a). Facets noting the use of language to verbalize emotion (e.g., labeling; Swinkels & Giuliano, 1995) are referred to as “description” (following Bagby et al., 1994). Whereas “regulation” refers to an intrapersonal process, “management” refers to the regulation of emotions in others. Nodes conceptually inverted: (a)gnosia; (a)lexithymia and its facets identification, description, introspection (vs. externally-oriented thinking), and imagination (vs. reduced fantasy). Network visualization created in Gephi (Bastian et al., 2009) using the Yifan Hu Proportional layout (Hu, 2005).

Figure S1-2. Network based on empirical interrelationships documented between constructs and their facets, including all definitions for alexithymia and intelligence (i.e., not limited to those by Taylor, Bagby, and colleagues and Mayer, Salovey and colleagues, respectively). Node color distinguishes constructs summarized in Table 1-1 (green) from facets or constructs added during data extraction (gray). Connections are undirected. *Upper panel:* Connections represent mean effect sizes (r) of all reported correlations, and are colored according to the direction of correlation (blue = positive, orange = negative). Unconnected nodes (e.g., flexibility) represent measures not directly compared within the publications selected for review. Node positions have been maintained from Figure S1 to facilitate side-by-side comparison. *Lower panel:* The network layout has been restructured according to the strength of the mean effect sizes. Nodes renamed from the original publications to facilitate integration: “granularity” also refers to differentiation (e.g., Barrett et al., 2001); “covariation” also refers to dialecticism (e.g., Grossmann et al., 2016); “regulation” also refers to repair (Salovey et al., 1995); “appraisal” also refers to source clarity (e.g., Boden & Berenbaum, 2011); “identification” also refers to type clarity (e.g., Boden & Berenbaum, 2011); “voluntary attention” (e.g., Boden & Thompson, 2015) also refers to emotion attention regulation (Elfenbein & MacCann, 2017) and redirected attention (Salovey & Mayer, 1990a). Facets noting the use of language to verbalize emotion (e.g., labeling; Swinkels & Giuliano, 1995) are referred to as “description” (following Bagby et al., 1994). Whereas “regulation” refers to an intrapersonal process, “management” refers to the regulation of emotions in others. Nodes conceptually inverted: (a)gnosia; (a)lexithymia and its facets identification, description, introspection (vs. externally-oriented thinking), and imagination (vs. reduced fantasy). Network visualizations created in Gephi (Bastian et al., 2009): for the upper panel, all connections from the theoretical network (Figure S1-1) were removed, and the identified empirical connections were manually added to maintain network layout; for the lower panel, the Yifan Hu Proportional layout (Hu, 2005) was used to structure the network.

Table S1-5. Features for Emotional Expertise

Feature	(A)lexithymia ¹	Awareness	Clarity	Competence ²	Complexity	Creativity	Diversity ³	Flexibility	Granularity ⁴	Intelligence ⁵
Structure of knowledge		✓	✓		✓	✓			✓	
Breadth of knowledge					✓	✓	✓		Barrett (2017a)	
Type of knowledge				✓						✓
Mental representation	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Verbal representation	✓	✓	✓	Scherer (2007)					✓	Ivcevic et al. (2007)
Ability or skill		Lane & Schwartz (1992)		✓	Lindquist & Barrett (2008)	✓			✓	✓
Adaptive responses				✓		✓			✓	✓
Context specificity					✓	✓		✓	✓	
Awareness	✓	✓	✓	✓	✓	✓				✓
Monitoring	✓	✓								Salovey & Mayer (1990a)
Deliberate practice						✓			Barrett (2017a)	
Prediction	Lane et al. (2015a)				Lindquist & Barrett (2008)				✓	

Note: Column 1 lists the features hypothesized to constitute emotional expertise, as determined deductively through consultation of accounts of domain-general expertise. Columns 2 through 11 summarize which features are represented by the constructs and measures included in this review: check marks indicate where a feature is present; in cases of disagreement or conflicting accounts within the literature, example publication(s) in support of the feature are noted. Features for (a)lexithymia and emotional intelligence are predominantly based upon, respectively, the work of Taylor, Bagby, and colleagues and Mayer, Salovey, and colleagues. Superscripts: ¹ Includes agnosia; ² Includes utilization; ³ Includes range; ⁴ Includes differentiation; ⁵ Includes quotient.

Construct Summaries

Below, we provide individual summaries of the constructs included in the present review. Additional details are available in an abridged version of the final database of reviewed publications, which is provided via our online data repository (<https://osf.io/a6vzk/>). This database includes, for each of the 141 publications included in the final review: bibliographic information, constructs covered, page locations of construct definitions, measurement method(s), relationships with other constructs and/or measures of health/well-being, the theoretical approach adopted by the authors, and any review notes.

Alexithymia

The word “alexithymia” literally translates to ‘a lack of words for feelings’ (Nemiah et al., 1976; Nemiah & Sifneos, 1970; Sifneos, 1972) and refers to a condition “involving a severe affective experiential deficit” (Lane et al., 2015b, p. 597). The construct itself is complexly defined, typically including a set of inter-related difficulties in the processing of emotional information, such that individuals with alexithymia are unable to identify, describe, and introspect about their own emotional experiences (Aaron et al., 2018; Bagby et al., 1994; E. R. Edwards & Wupperman, 2017; Erbas et al., 2014; Saklofske et al., 2003; Sifneos, 1973; G. J. Taylor & Bagby, 2004). Further, the definition of alexithymia often includes a reduction in daydreaming, fantasy, and overall imaginal ability (Bagby et al., 1986; Bermond et al., 2015; Gori et al., 2012; Kleiger & Kinsman, 1980; Kooiman et al., 2002; Koven & Thomas, 2010; Lesser, 1981; Maroti et al., 2018; Sifneos, 1972; G. J. Taylor et al., 1985; Zech et al., 1999). Broadly, these four facets of alexithymia can be understood as difficulties with awareness of emotional experience (subsuming identification and description) and difficulties with the analysis or symbolization of experience (subsuming imagination and introspection; Bagby et al., 2006; Porcelli & Mihura, 2010). Bermond and colleagues (1999) further elaborated the construct with a (fifth) facet describing difficulties in experiencing emotions (see also Gori et al., 2012; Vorst & Bermond, 2001). These difficulties (in *identification*, *description*, *introspection*, *imagination*, and *experience*) represent the modal definitions of alexithymia, although the exact nature and number of facets varies by research group as well as over time.

The construct of alexithymia has been predominantly anchored in a psychoanalytic or psychodynamic theory of emotion, in which conflicts that are not expressed and dealt with through words or images (i.e., symbolically) are expressed through bodily symptoms (i.e., they are somatized; Haviland et al., 2000; Lesser, 1981). In this view, alexithymia can be seen as a defense against anxiety and neurotic conflicts (G. J. Taylor & Bagby, 2013). Research on alexithymia evolved from clinical observations of patients presenting with psychosomatic disorders: corresponding features were first described by Ruesch (1948) and MacLean (1949) as “infantile personality” and underdeveloped symbolic ability¹⁰. Although the term “alexithymia” was coined by Sifneos (1972), independent groups of researchers documented similar sets of features that have likewise influenced the construct. For example, Marty and de M’Uzan (1963) described “pensée opératoire”, in which patients were noted as having a concrete, utilitarian, ‘operative’ thinking style that involved little to no affective or figurative content. In contemporary research, alexithymia can also be understood more generally, as a global impairment in the processing of emotional information (e.g., Donges & Suslow, 2017; Lane et al., 2000; Maroti et al., 2018). In this view, alexithymia is considered a deficit or deficiency (rather than a psychological defense; Lane et al., 2000; Lumley et al., 2007), or “an impoverished conceptual system for emotion” (Kashdan et al., 2015, p. 12). More recent work has also expanded the description of alexithymia to involve problems with empathy or recognizing the emotional experiences of others (e.g., Kashdan et al., 2015; Lane et al., 1996; G. J. Taylor & Bagby, 2013). In 2015, Lane and colleagues introduced the related construct of affective agnosia to describe “a deficit in the ability to mentally represent the meaning of emotional responses” (Lane et al., 2015b, p. 595) which, they contend, can be contrasted with a predominantly ‘anomia’ model of alexithymia in which experiences are mentally represented but cannot be labeled (i.e., symbolized or described).

¹⁰ These patients have also been referred to as “emotional illiterates” (Freedman & Sweet, 1954).

Alexithymia has been assessed using a variety of measurements, including projective tests and content analysis, observational scales and interviews, and self-report questionnaires (for reviews, see Bermond et al., 2015; Linden et al., 1995; G. J. Taylor et al., 2000). Projective tests and content analysis are used to assess individuals' verbal expression of emotion and capacity for fantasy or symbolization (G. J. Taylor, 1984), and include the Thematic Apperception Test (TAT; H. A. Murray, 1943), the Rorschach Inkblot Test (Exner, 1993) and Rorschach Alexithymia Scale (RAS; Porcelli & Mihura, 2010), the objectively-scored Archetypal9 test (SAT9; K. R. Cohen et al., 1985; Demers-Desrosiers et al., 1983), and various verbal content analysis techniques (e.g., Gottschalk & Gleser, 1969; G. J. Taylor & Doody, 1982; von Rad et al., 1977). Observational scales and interviews are completed by clinicians or relatives and acquaintances, and include versions of the Beth Israel Hospital Psychosomatic Questionnaire (Apfel & Sifneos, 1979; Sifneos, 1973), the Alexithymia Provoked Questionnaire (APRQ; Krystal et al., 1986), the California Q-set Alexithymia Prototype (CAQ-AP; Haviland & Reise, 1996), the Observation Alexithymia Scale (OAS; Haviland et al., 2000), the Diagnostic Criteria for Psychosomatic Research (DCPR; Galeazzi et al., 2004), and the Toronto Structured Interview for Alexithymia (TSIA; Bagby et al., 2006).

Self-report measures, however, are by far the most widely-used means of assessing alexithymia. Furthermore, other types of measures have often suffered from methodological flaws or lack of adequate psychometric data that have led researchers to caution against their use (Bermond et al., 2015; Parker et al., 1991; Zech et al., 1999). Two self-report measures have received particular attention: the 20-item Toronto Alexithymia Scale (TAS-20; Bagby et al., 1994), and the Bermond-Vorst Alexithymia Questionnaire (BVAQ; Vorst & Bermond, 2001). The TAS-20 is the latest version of the Toronto Alexithymia Scale (e.g., G. J. Taylor et al., 1985, 1992) and the dominant measure in the literature. It is comprised of subscales for Difficulty Identifying Feelings (DIF), Difficulty Describing Feelings (DDF), and Externally-Oriented Thought (EOT). The BVAQ extends upon the Amsterdam Alexithymia Scale (Bermond et al., 1999) and is comprised of subscales for Emotionalizing, Fantasizing, Identifying, Analyzing, and Verbalizing. Less-common self-report measures include the Psychological Treatment Inventory – Alexithymia Scale (PTI-AS; Gori et al., 2012), the Minnesota Multiphasic Personality Inventory Alexithymia Scale (MMPI-A; Kleiger & Kinsman, 1980), and the Schalling-Sifneos Personality Scale (SSPS; Apfel & Sifneos, 1979).

Research on alexithymia's relationship to clinical and non-clinical outcomes has been extensive. Alexithymia is associated with, among others, anxiety disorders (Berardis et al., 2008; L. J. Robinson & Freeston, 2014), depression (Honkalampi et al., 2000), post-traumatic stress disorder (Frewen et al., 2008), schizophrenia (O'Driscoll et al., 2014), autism spectrum disorders (Kinnaird et al., 2019; Poquérousse et al., 2018), addiction and substance abuse disorders (Mahapatra & Sharma, 2018; Marchetti et al., 2019; Morie et al., 2016; Thorberg et al., 2009), eating disorders (Nowakowski et al., 2013; Westwood et al., 2017), Parkinson's Disease (Assogna et al., 2016), immune dysregulation (Uher, 2010), chronic pain (Aaron et al., 2019), functional gastrointestinal disorders (Carrozzino & Porcelli, 2018), and coronary heart disease (Beresnevaite, 2000).

Awareness

Emotional awareness is broadly defined as “how people understand, describe, and attend to their emotional experience” (Mankus et al., 2016, p. 28). This construct was introduced by Lane and Schwartz (1987), who proposed that there are five levels of emotional awareness: bodily sensations, action tendencies, single emotions, blends of emotions, and combinations of blends (Lane & Schwartz, 1987; see also Lane et al., 1990). Anchoring on a cognitive-developmental (e.g., Piaget, 1937; Werner & Kaplan, 1963) approach to emotion, Lane and Schwartz (1987) proposed that these five levels are arranged hierarchically and achieved through cognitive development. For example, if an individual were to describe their current experience as a “stomachache” (bodily sensation), this would be considered a lower level of emotional awareness than a description of “makes me want to punch something” (action tendency) or “upset” (single emotion). Lane and colleagues (1990) also introduced the Levels of Emotional Awareness Scale (LEAS), a performance-based measure of emotional awareness. In the

LEAS, participants are presented with a variety of evocative written scenarios and asked to describe, in free response, how each person in the scenario ('you' and another person) would feel. Responses are scored based on the demonstrated level of emotional awareness (Lane et al., 1990). The LEAS has been shown to predict both behavioral and physiological outcomes (Lane et al., 1995, 1996), and to be sensitive to changes in psychosomatic patients over the course of treatment (Subic-Wrana et al., 2005).

In 2009, Thompson, Dizen, and Berenbaum introduced a new formulation of emotional awareness defined in terms of facets rather than levels, and based on appraisal models of emotion and emotion regulation (e.g., Gross, 1998b, 1998a; Lazarus, 1991; Schwarz & Clore, 1983). Thompson and colleagues' (2009) original facets of emotional awareness were *attention* (i.e., "the extent to which one notices, thinks about, and monitors one's mood", p. 875) and *clarity* (i.e., "how clearly one understands one's own emotions, discriminates among one's own emotions, and knows how to label these emotions", p. 875). These facets were measured using the attention and clarity subscales from the self-report Trait Meta-Mood Scales (TMMS; Salovey et al., 1995).

Boden and Thompson (2015) further developed emotional awareness by defining subfacets for clarity and attention. They differentiated between *type clarity* (measured using items from the clarity subscale of the TMMS and from the Difficulty Identifying Feelings [DIF] subscale of the 20-item Toronto Alexithymia Scale [TAS-20; Bagby et al., 1994]) and *source clarity* (measured using items from the Source of Emotions Scale [SES; Boden & Berenbaum, 2011]). For attention, Boden and Thompson (2015) delimited *voluntary attention* (measured using items from the attention scale of the TMMS and from the Externally-Oriented Thought [EOT] subscale of the TAS-20) and *involuntary attention* (measured using items from Huang et al., 2013). To these facets and subfacets, Mankus and colleagues (2016) added negative emotional granularity (i.e., differentiation), "the complexity with which people identify, distinguish, and label specific negative emotions" (p. 29), which they estimated using the intra-class correlation (ICC) of emotion intensity ratings to negatively-valenced photographs (as in e.g., Erbas et al., 2014; for more details, see the "Granularity" section below). With the exception of involuntary attention to emotion, these facets of emotional awareness have been shown to predict adaptive emotion regulation strategies and fewer depression symptoms (e.g., Boden & Thompson, 2015).

A closely related construct is mood awareness, which describes "a form of attention directed toward one's mood states" (Swinkels & Giuliano, 1995, p. 934). Mood awareness is parsed into two facets: mood monitoring, "the tendency to scrutinize and focus on one's moods" (p. 934) and mood labeling, "the ability to identify and categorize one's moods" (p. 934). Both facets are measured using the self-report Mood Awareness Scale (MAS; Swinkels & Giuliano, 1995). Whereas mood labeling is associated with positive outcomes such as satisfaction with social support and life, mood monitoring is associated with negative outcomes such as rumination and poor emotion regulation (Swinkels & Giuliano, 1995).

Clarity

Emotional clarity, also known as affective clarity (e.g., Lischetzke et al., 2005), is defined as the extent to which an individual takes a meta-emotional perspective to unambiguously identify, label, and characterize their emotional experiences (Boden et al., 2013; Boden & Thompson, 2017; Eckland et al., 2018; Gohm & Clore, 2002; Lischetzke & Eid, 2017). Research on emotional clarity has typically focused on trait-level assessments of how individuals understand their moods and emotions (e.g., Boden et al., 2013; Gohm & Clore, 2002), although some studies have measured momentary, state-level emotional clarity (e.g., Lischetzke et al., 2005). Boden and Berenbaum (2011) proposed two facets of emotional clarity: *source awareness* (i.e., the degree to which individuals understand the causes of their emotional experiences) and *type awareness* (i.e., the degree to which individuals can distinguish between the experiences of specific emotion categories, such as discriminating anger vs. fear; see Boden & Thompson, 2015 for a similar formulation, as addressed in the "Awareness" section above).

Common measures for trait-level emotional clarity include the Trait Meta Mood Scale (TMMS – Clarity of Feelings subscale; Salovey et al., 1995), the 20-item Toronto Alexithymia Scale (TAS-20 – Difficulty Identifying Feelings subscale; Bagby et al., 1994), the Mood Awareness Scale (MAS – Mood

Labeling subscale; Swinkels & Giuliano, 1995), and the Difficulties in Emotion Regulation Scale (DERS – Lack of Emotional Clarity subscale; Gratz & Roemer, 2004). Boden and Berenbaum (2011) measured the subfacet of source awareness using a set of custom items, and measured the subfacet of type awareness using items from the TMMS and TAS-20. Momentary emotional clarity has been assessed using state-level forms of the subscales mentioned above or, as an indirect measure, by calculating response latencies to momentary affect ratings (Lischetzke et al., 2005). This indirect assessment of emotional clarity assumes that the clearer an individual's emotions are, the fewer cognitive resources are required to identify and label these emotions, resulting in faster responses to affect ratings. Higher levels of emotional clarity have been shown to be related to emotional intelligence (Schutte et al., 1998) and may facilitate emotion regulation processes (Boden et al., 2013; Boden & Thompson, 2017; Lischetzke et al., 2005).

Competence

Emotional competence is defined as how an individual “identifies, expresses, understands, regulates, and uses his emotions or those of others” (Brasseur et al., 2013, p. 1). Some perspectives have further elaborated emotional competence by breaking the construct down into constituent facets. For example, Scherer (2007) suggested that emotional competence consists of *appraisal competence* (i.e., accurate judgment of important emotion events to inform subsequent response), *regulation competence* (i.e., correction of inappropriate responses to emotion events due to inaccurate appraisals), *communication competence* (i.e., appropriate signaling of emotion response to others), and *perception competence* (i.e., accurate perception of emotion responses signaled by others). Izard and colleagues (2009; 2011) dissected emotional competence into two facets: *emotion knowledge* (i.e., an understanding of one's own or another's emotions; Izard et al., 2011) and *emotion utilization* (i.e., the ability to effectively exploit such understanding for constructive purposes and actions; Izard, 2009). Other perspectives have incorporated emotional and social competence into a single construct (ESC; Boyatzis et al., 2004). Originally created to characterize an individual's performance in a workplace setting, this perspective proposed four basic competency clusters: self-awareness, self-management, social awareness, and relationship management (Boyatzis et al., 2004).

Emotional competence is typically assessed using self-report measures, including the Profile of Emotional Competence (PEC; Brasseur et al., 2013), the Emotion Questionnaire (EQ; Rydell et al., 2003), the Emotional Competence Inventory (ECI; Boyatzis et al., 2000), and the Mayer-Salovey-Caruso Emotional Intelligence Test (MSCEIT; Mayer & Salovey, 1997). These measures have been used to assess the sub-competencies theorized to comprise emotional competence, such as emotion knowledge (e.g., using the MSCEIT) and emotion utilization (e.g., using the EQ). In developmental samples, emotion knowledge has also been assessed using a performance-based measure, the Emotion Matching Task (EMT; Morgan et al., 2010). Greater emotional competence is thought to benefit mental health, social skills, and academic performance (Trentacosta & Schultz, 2015). Studies have shown positive relationships between emotional competence and trait positive affect, subjective health, and quality of social relationships (Brasseur et al., 2013).

Complexity

Emotional complexity has been defined in several ways in the emotion literature. Broadly, it describes a combination of *covariation*, *granularity* (i.e., differentiation), and/or *range* in emotional experience, as well as elaboration in *propositional knowledge* of emotion categories (e.g., Grossmann et al., 2016; Grossmann & Ellsworth, 2017; Hay & Diehl, 2011; Lindquist & Barrett, 2008). Some researchers focus on covariation and granularity (e.g., Grossmann & Ellsworth, 2017; Hay & Diehl, 2011), while others emphasize granularity and range (e.g., Kang & Shaver, 2004; Ong et al., 2017) or covariation, granularity, and knowledge (e.g., Lindquist & Barrett, 2008). Each of these facets (i.e., covariation, granularity, range, and propositional knowledge) is summarized in turn.

Covariation – also referred to as dialecticism (e.g., Grossmann & Ellsworth, 2017) and poignancy (e.g., Carstensen et al., 2000; Hay & Diehl, 2011) – describes an individual's tendency to simultaneously

experience positive and negative emotions. Previous work investigating covariation has hypothesized that greater co-occurrence of positive and negative affect is indicative of greater emotional complexity (Brose et al., 2015; Carstensen et al., 2000; Charles et al., 2017; Grossmann et al., 2016; Grühn et al., 2013b; Hay & Diehl, 2011; Kashdan et al., 2015). Data for measuring covariation are typically collected via experience sampling or daily diary reports of positive and negative affect, most commonly using the Positive and Negative Affect Scale (PANAS; David Watson et al., 1988). These data are then used to compute intra-individual correlations between positive and negative affect (e.g., following Grühn et al., 2013b). Covariation has also been indexed at an absolute level, in which mean positive and negative emotion levels are calculated from daily ratings of emotional experience (Ready et al., 2008).

Emotional granularity (i.e., emotion differentiation) describes the precision with which an individual differentiates their emotional experiences (e.g., Brose et al., 2015; Grühn et al., 2013b; Hay & Diehl, 2011; Kang & Shaver, 2004; Ready et al., 2008). Individuals showing a propensity to distinguish nuance within emotion categories are thought to have greater emotional granularity and therefore greater emotional complexity (Kang & Shaver, 2004). Measurement of emotional granularity typically relies on experience sampling data, which are used to compute intra-individual estimates of overlap in intensity ratings across emotions (e.g., intra-class correlations [ICCs], following Tugade et al., 2004). Other studies have assessed self-reported emotional granularity using the Range and Differentiation of Emotional Experiences Scale (RDEES; Kang & Shaver, 2004). For more details about emotional granularity, see the corresponding section below.

Emotional range refers to the variety in an individual's emotion experiences (e.g., Kang & Shaver, 2004; Ong et al., 2017). It has been measured using the RDEES and with experience sampling and daily diary measures (for a review, see Ong et al., 2017). For more details about emotional range, see the "Diversity" section below.

Propositional knowledge describes an individual's explicit understanding of emotional experiences in specific situations (Lane et al., 1990; Lane & Pollermann, 2002; Lane & Schwartz, 1987). The complexity of propositional knowledge is frequently assessed using the Levels of Emotional Awareness Scale (LEAS; Lane et al., 1990). In the LEAS, participants are presented with evocative written scenarios and asked to describe how each person in the scenario would feel (see the "Awareness" section above for more details). Participants who score higher on the LEAS are considered to have greater emotional complexity (Lindquist & Barrett, 2008).

Another, related construct is affect (or affective) complexity, which has been defined as "the ability to coordinate positive and negative affect into flexible and differentiated structures" (Labouvie-Vief & Medler, 2002, p. 571). Early measures of affect complexity involved clinician-scoring of the Thematic Apperception Test (TAT; H. A. Murray, 1943) for subjective complexity (e.g., Henry & Shlien, 1958; Kantrowitz et al., 1986). More recent studies generally use measures of range or covariation on the PANAS or other mood reports (e.g., Bodner et al., 2013; Brose et al., 2015; Larsen & Cutler, 1996; Tobacyk, 1980). However, Labouvie-Vief and Medler (2002) assessed affect complexity using performance-based tasks. For example, in one task participants were asked to generate statements about themselves, which were then scored according to how complexly the self and others are represented (following Labouvie-Vief, 1994).

Creativity

Emotional creativity is generally defined as an individual's ability to produce emotional responses that are *novel*, *authentic*, and *effective*, as well as their *preparedness* to use this ability (Averill, 1999, 2004; Ivcevic et al., 2017). Introduced by Averill and Thomas-Knowles (1991), emotional creativity is rooted in Averill's social constructionist theory of emotion which posits that emotions are performances based on sociocultural expectations and learned experience, heavily influenced by the current social and environmental context. An emotionally creative person, then, is a more creative performer: an individual who combines social scripts in new and effective ways. In this way, emotional creativity is theorized as a type of creativity, in a similar way and around the same time that emotional intelligence was posited as a type of intelligence (Salovey & Mayer, 1990b). In fact, Averill (2004)

compares these two constructs theoretically, arguing that emotional creativity is more comprehensive than emotional intelligence due to its ability to account for the role of culture and context in emotional expression and experience, while emotional intelligence is more narrow and presumes that there is a “correct” or agreed upon emotional response in a given scenario.

Emotional creativity is typically assessed using the self-report Emotional Creativity Inventory (Averill, 1999). It has also been assessed using performance-based measures: the Emotional Consequences task, which assesses individuals’ originality and quantity of their responses to a unique emotion situation, and the Emotional Triads task, where participants are given three dissimilar emotion words (e.g., “calm”, “confused”, and “joyous”) and asked to generate a situation in which someone could experience all three (Averill & Thomas-Knowles, 1991; described in Ivcevic et al., 2017). At least one study has shown empirical support for convergent validity between these measures (Fuchs et al., 2007). Studies have also shown that emotional creativity is positively related to emotional intelligence (Ivcevic et al., 2007) and negatively related to alexithymia (Fuchs et al., 2007), although these constructs are empirically distinguishable. Studies have further shown that emotional creativity is positively correlated with artistic creativity, such as poetry writing (Ivcevic et al., 2007, 2017).

Diversity

The variety of emotions that an individual experiences has been variously called emotional range (Sommers, 1981) and emodiversity (a blended form of “emotional diversity”; Quoidbach et al., 2014). The term “emotional range” was introduced first by Sommers (1981). She measured emotional range by asking participants to tell a story based on a vignette with emotional content and then coding the number of unique emotion words freely generated in their stories. Using this measure, Sommers (1981) found that higher emotional range was related to better social cognitive ability, or the ability to know how to act around social others. More recent work has situated emotional range as a feature of emotional complexity (e.g., as measured using the Range and Differentiation of Emotional Experience Scale [RDEES; Kang & Shaver, 2004]).

The term “emodiversity” was introduced several decades later by Quoidbach and colleagues (2014). Emodiversity draws conceptually on Shannon’s entropy (Shannon, 1948) and a biodiversity index (Magurran, 2013), which captures both the variety (i.e., range) and relative amounts (i.e., evenness) of organisms in an ecosystem. To measure emodiversity, Quoidbach and colleagues (2014) asked participants to report the relative frequency with which they experience a set of positive and negative emotions. These data were used to calculate a custom measure of emodiversity, with higher values indicating that an individual reported experiencing a greater number of emotions at about the same frequency. Higher emodiversity was found to predict lower depressive and physical health symptoms over and above mean frequency of overall emotional experience (Quoidbach et al., 2014). However, this model was challenged by Brown and Coyne (2017), who questioned whether it was theoretically appropriate to measure emodiversity in a similar way as biodiversity. Brown and Coyne (2017) also reanalyzed Quoidbach and colleagues’ (2014) data and found evidence of multicollinearity between emotion frequency and emodiversity, significantly impacting their interpretation that emodiversity explains unique variance in positive outcomes. Thus, despite the theoretical importance of accounting for range or diversity in emotional experience, more research is necessary in this area to determine the appropriate measures for predicting greater well-being.

Flexibility

Emotional flexibility, also referred to as affective flexibility (e.g., Zhu & Bonanno, 2017), is defined as the capability to adapt to changing emotional contexts (Beshai et al., 2018; Fu et al., 2018). Fu and colleagues (2018) elaborate upon this definition by specifying two core facets of emotional flexibility: *sensitivity* to situational demands, and the ability to regulate emotions accordingly (i.e., *emotion regulation*). Emotional flexibility has been conceptualized as both an ability (e.g., Fu et al., 2018; Zhu & Bonanno, 2017) and a trait (e.g., Beshai et al., 2018).

Emotional flexibility has been assessed using both self-report and performance-based measures. The Emotional Flexibility Scale (EFS; Fu et al., 2018) is a self-report measure that assesses how likely the individuals are to either enhance or suppress their emotions based on situations-specific needs. EFS items have been found to load onto three factors, described by Fu and colleagues (2018) as: tuning of negative emotions, tuning of positive emotions, and emotion communication. EFS scores have been found to be positively correlated with self-reported psychological well-being (Fu et al., 2018).

There are two performance-based measures of emotional flexibility: the Affective Flexibility Task (AFT; Zhu & Bonanno, 2017) and the Visual Analogue Mood Scale (VAMS; Beshai et al., 2018). In the AFT, participants are asked to rate the intensity of their affective experience in response to negatively-valenced and neutral photographs (Zhu & Bonanno, 2017). Participants are told to enhance, suppress, or only view the photographs; “enhancement ability” and “suppression ability” scores are derived by subtracting the intensity ratings during enhance and suppress conditions, respectively, from the average intensity during the view only condition. Zhu and Bonanno (2017) found that change in affective enhancement and suppression scores over the course of the study was associated with fewer symptoms of depression. In the VAMS, participants’ are asked to rate the intensity of their affective experience before and after negative and positive mood inductions (Beshai et al., 2018). Emotional flexibility is estimated as the differences in scores between mood inductions and between the negative mood induction and recovery, such that higher scores (i.e., greater differences) indicate that an individual is able to change emotions according to context and to spontaneously recover from negative mood. Based on their results, Beshai and colleagues (2018) hypothesized that greater emotional flexibility would be associated with mindfulness, self-compassion, and resilience.

Granularity

Emotional granularity refers to individual differences in the tendency or ability to “represent emotional experiences with precision and specificity” (Tugade et al., 2004, p. 1168). Individuals with higher emotional granularity “make fine-grained distinctions between emotional experiences” (Aaron et al., 2018, p. 116) and describe and “label [their] emotions in a nuanced and specific manner” (Lee et al., 2017b, p. 1). In contrast, individuals with lower emotional granularity represent and describe their emotional experiences in a global manner, often using broad affective terms such as “good” or “bad” that primarily capture pleasure or displeasure (Barrett, 2004). The term “emotional granularity” was first coined by Barrett in 2004 (Barrett, 2004; Tugade et al., 2004), although the construct is based on her older work examining the emphasis that individuals place on valence or arousal when reporting their experiences (i.e., valence focus and arousal focus; Barrett, 1998, 2004; Feldman, 1995a, 1995b)¹¹. In this regard, emotional granularity captures “the ability to distinguish between distinct emotions of similar valence” (Dixon-Gordon et al., 2014, p. 617), such that individuals higher in granularity represent their experiences using more than a single pleasant-unpleasant dimension (e.g., they exhibit more arousal focus). Emotionally granularity is synonymous, in most cases, with emotion(al) differentiation (e.g., as defined by Barrett et al., 2001; for contrasting definitions, see Goldston et al., 1992; Plonsker et al., 2017).

Work on emotional granularity has been predominantly anchored in a constructionist approach to emotion (Barrett, 2006, 2017b, 2017a). Broadly, this approach proposes that the experience of emotion occurs when the brain uses concepts for emotion (i.e., prior experiences and accrued knowledge) to make meaning of current affect (i.e., feelings of valence and arousal derived from interoceptive signals from the body) in a context-specific manner. From this perspective, it follows that higher emotional granularity is the ability to create instances of emotion that are tailored to the situation at hand, and effective at facilitating goal-relevant and culturally-congruent outcomes.

Emotional granularity is typically measured using data collected from momentary self-reports repeated over time. These data are most often gathered using experience sampling methods (ESM; Barrett

¹¹ Work on valence focus has also continued in parallel with work on emotional granularity (Barrett & Niedenthal, 2004; Pietromonaco & Barrett, 2009; Suvak et al., 2011).

& Barrett, 2001; Csikszentmihalyi & Larson, 1987) or ecological momentary assessment (EMA; Shiffman & Stone, 1998; Stone & Shiffman, 1994). These studies ask participants to respond to a series of prompts throughout their day, at each point rating the intensity of their current experience on a set of emotion words (e.g., Barrett, 2004; Boden et al., 2013, Study 2; Dixon-Gordon et al., 2014; Erbas et al., 2014, Study 1; Sheets et al., 2015; Trull et al., 2015; Tugade et al., 2004). Repeated emotion intensity ratings have also been collected retrospectively, using daily diary methods (e.g., Barrett et al., 2001; Lee et al., 2017b). Alternatively, these data have been collected in the lab, by having participants provide emotion intensity ratings to a series of emotionally-evocative photographs (e.g., Barrett, 2004, Study 2; Erbas et al., 2013, 2014, Study 3, 2019; Lee et al., 2017b; Plonsker et al., 2017; Suvak et al., 2011), film clips (e.g., Aaron et al., 2018; Barrett, 2004, Study 3), scenarios (e.g., Boden et al., 2013, Study 1; Cameron et al., 2013), or other types of emotion inductions (e.g., Barrett, 2004, Study 3; E. R. Edwards & Wupperman, 2017). In a few studies, emotion intensity ratings have been gathered using a social perception task, in which participants are asked to rate people in their lives (e.g., partner, best friend, parents) on a set of emotion words (e.g., Erbas et al., 2014, Study 2; Goldston et al., 1992).

Estimates of emotional granularity are derived from repeated emotion intensity ratings in several, related ways. Most commonly, intraclass correlations (ICCs; Shrout & Fleiss, 1979) are calculated across ratings for positively- and negatively-valenced emotion words, respectively (e.g., Boden et al., 2013; Cameron et al., 2013; Kashdan et al., 2010; Pond et al., 2012; Tugade et al., 2004)¹². ICCs can be calculated using either absolute agreement across ‘raters’ (here, emotion words; e.g., Dixon-Gordon et al., 2014; Tugade et al., 2004) or consistency (e.g., Erbas et al., 2013, 2014, 2019), although in practice these estimates are highly correlated (Erbas et al., 2014). ICCs for positive and negative emotions can be averaged to achieve an overall estimate of granularity (e.g., E. R. Edwards & Wupperman, 2017)¹³, and can also be calculated separately for each measurement occasion or day of experience sampling (e.g., Tomko et al., 2015). Less commonly, emotional granularity has been estimated as the average bivariate correlation between all pairs of similarly-valenced words (e.g., Barrett et al., 2001; Zaki et al., 2013), or *P*-correlation matrices (Cattell et al., 1947) are computed for use in further analyses (e.g., Barrett, 2004; Feldman, 1995a; Suvak et al., 2011). In a few studies, emotion differentiation has been estimated by examining person-specific clustering of emotion intensity ratings (Goldston et al., 1992), or the average sum of similarly-valenced emotions endorsed across measurement occasions (Plonsker et al., 2017) – however, it should be noted that these studies followed theoretical approaches (e.g., basic emotion approaches such as differential emotions theory; Dougherty et al., 1996; Izard, 1971, 2013; Malatesta & Wilson, 1988; Tomkins, 1962, 1963) in which there is a specified set of emotions that participants ‘should’ be able to differentiate.

Emotional granularity has also been measured using alternative paradigms to those that generate repeated emotion intensity ratings. For example, Barrett (2004) asked participants to rate the pairwise similarity of a set of emotion words, and then subjected these ratings to group- and participant-level multidimensional scaling (MDS) analyses to identify to what extent each individual’s ratings were captured by the group-level dimensions of valence and arousal (a similar procedure was also used by Suvak et al., 2011). Erbas and colleagues (2013) used a free-sort task in which participants were asked to group emotion words into piles based on their semantic similarity, and counted the number of piles as an index of emotional granularity. Kang and Shaver (2004) introduced a global self-report measure as a subscale of their Range and Differentiation of Emotional Experiences Scale (RDEES). The first to use physiological data to investigate emotional granularity, Lee and colleagues (2017b) recorded

¹² ICCs can also be calculated within-valence, to examine the relationships between superordinate emotion categories (e.g., ‘anger’, ‘sadness’, ‘fear’) or the relationships between specific emotions within these superordinate categories (e.g., ‘frustration’ vs. ‘rage’ vs. ‘annoyance’ within the category of ‘anger’). See Erbas et al. (2019) for details.

¹³ This procedure avoids interpretation issues that arise from including ratings for all emotion words in a single ICC; because ratings for pleasant and unpleasant emotion words are typically negatively correlated, including all emotion words in the same analysis can result in negative ICC values.

electroencephalography (EEG) while emotionally-evocative photographs were presented to participants, and examined patterns of event-related potentials (ERPs) and de/synchronization (ERD/ERS) in individuals with lower versus higher granularity.

Across all these measurement methods, higher emotional granularity has been associated with a wide variety of positive mental and physical health outcomes (Kashdan et al., 2015), such as improved self-regulation (Barrett et al., 2001; Kalokerinos et al., 2019), reduced depression (Erbaş et al., 2019), and healthier recovery from cancer (Stanton, Danoff-Burg, et al., 2002). In contrast, lower granularity is associated with greater symptoms of anxiety (Mennin et al., 2005) and depression (Erbaş et al., 2014; Starr et al., 2017), and poorer behavioral indices of coping (for reviews, see Barrett, 2017a; Kashdan et al., 2015; Smidt & Suvak, 2015).

The construct of affect(ive) differentiation has also been put forward by several groups of researchers. Some of these definitions and measurement approaches closely resemble those outlined for emotional granularity and emotion differentiation. For example, Terracciano and colleagues (2003) examined “[individual] differences in the ability to differentiate feelings in terms of arousal within the categories of pleasant and unpleasant affect” (p. 673) using a covariance structural modeling approach (CIRCUM; Browne, 1992) to evaluate the fit of a circumplex structure. Other definitions, such as theoretical proposals by Labouvie-Vief and González (2004), have understood affect differentiation as the developmental elaboration (Lane & Schwartz, 1987; Piaget, 1937) of a set of primary or basic emotions (Izard, 1971; Tomkins, 1962, 1963) to achieve conceptual and emotional complexity. Lastly, following the Dynamic Model of Affect (e.g., Zautra et al., 2000, 2001, 2005), researchers have defined affect(ive) differentiation as “the extent to which [positive and negative affect] operate independently or in a dependent, inverse manner” (Dasch et al., 2010, p. 441). In this line of research, affect(ive) differentiation is measured as the correlation between repeated intensity ratings for positively- versus negatively-valenced emotion words (e.g., Dasch et al., 2010; M. C. Davis et al., 2004). Because this operationalization is ultimately about the relationship between positive and negative affect, rather than specific emotion categories, it has not been discussed further.

Intelligence

Emotional intelligence is a multi-faceted, multiply-defined construct that has received extensive research attention in the past 30 years. For the purposes of the present review, we have adopted the first definition of emotional intelligence, posited by Salovey and Mayer (1990b): “the ability to monitor one's own and others' feelings and emotions, to discriminate among them and to use this information to guide one's thinking and actions” (p. 189). This definition is generally the most widely-used and psychometrically-validated (Cherniss, 2010; Livingstone & Day, 2005; but see Maul, 2012; Roberts et al., 2010). It encompasses four facets: *emotion perception*, *emotion understanding*, *emotion regulation* (i.e., emotion management), and *emotion facilitation* (i.e., using emotion to facilitate thought; e.g., Mayer, Roberts, et al., 2008). Salovey and Mayer's (1990b) model (sometimes called the Four-Branch Ability model; Mayer, Roberts, et al., 2008) sought to situate emotional intelligence as a research-based bridge between prevailing emotion theories of the time (mainly basic emotion and appraisal theories, e.g., Arnold, 1960; Izard, 1971; Tomkins, 1962, 1963) and theories of intelligence (broadly construed as abstract reasoning, e.g., Sternberg, 1997; see Mayer et al., 2000; Mayer & Salovey, 1993).

In 1995, journalist Daniel Goleman published his book *Emotional Intelligence*, which built upon Salovey and Mayer's initial work, but included broader social competencies in the construct and made substantive claims about the importance of emotional intelligence to personal and workplace success. Goleman's (1995) book generated public interest in emotional intelligence and spurred academic debate. Mayer and colleagues (2000) opposed this broadening, while other researchers such as Bar-On (1997, 2000) embraced it, defining emotional intelligence as “a multifactorial array of interrelated emotional, personal, and social abilities that influence our overall ability to actively and effectively cope with daily demands and pressures” (Bar-On, 2000, p. 384). This multi-faceted definition for emotional intelligence, which combines abilities with social and personality traits, is one example of a *mixed model*, in contrast to the purely *ability model* of Salovey and Mayer (Salovey & Mayer, 1990b; see also Mayer et al., 2000) or

a *trait model* (e.g., Petrides & Furnham, 2000). These models of emotional intelligence have been extensively reviewed in past articles (see Elfenbein & MacCann, 2017; Mayer et al., 2000; Mayer, Roberts, et al., 2008; Mayer, Salovey, et al., 2008; Palmer et al., 2008; Petrides & Furnham, 2000; Roberts et al., 2010; Salovey & Grewal, 2005; Siegling et al., 2015). Many mixed models and measures have been proposed in the industrial and organizational psychology literature (e.g., Petrides, 2010); however, due to the extensive nature of that literature and its divergence from traditional basic science research, we have excluded these models from our overview.

Measures have been created for both ability and mixed models of emotional intelligence (for reviews, see Brackett & Mayer, 2003; Conte, 2005; Livingstone & Day, 2005; Roberts et al., 2010; Siegling et al., 2015). For example, Mayer and colleagues developed a performance-based measure of emotional intelligence ability, first as the Multifactor Emotional Intelligence Scale (MEIS; Mayer et al., 2000), later revised to the Mayer-Salovey-Caruso Emotional Intelligence Test (MSCEIT; Mayer et al., 2002, 2003). The MSCEIT consists of eight tasks, two for each of the four facets: for example, selecting an emotion word that corresponds to faces and photographs (emotion perception), reasoning about the relationships between emotion words (emotion understanding), and choosing between various courses of action or feeling in hypothetical scenarios (emotion regulation; Mayer et al., 2002, 2003). Responses can be scored in comparison to ‘correct’ answers as determined by consensus of the authors, or as determined by a normative sample (Mayer et al., 2003). Self-report measures of emotional intelligence are also used, especially in the mixed model literature. Common measures include the Bar-On Emotional Quotient Inventory (EQ-i; Bar-On, 1997; Dawda & Hart, 2000), the Schutte Emotional Intelligence Scale (SEIS; also called the Assessing Emotions Scale; Schutte et al., 1998) and the Trait Emotional Intelligence Questionnaires (TEIQue; Petrides et al., 2007).

Emotional intelligence has been associated with many other psychological constructs and real-world outcomes (for reviews, see e.g., Mayer, Roberts, et al., 2008; Mayer, Salovey, et al., 2008; Salovey et al., 2002). Briefly, both ability and mixed model measures of emotional intelligence have been positively correlated with self-reported empathy (Mayer & Geher, 1996), optimism (Schutte et al., 1998), subjective well-being (Brackett & Mayer, 2003; Saklofske et al., 2003), life satisfaction and relationship quality (Ciarrochi et al., 2000). These measures have been negatively correlated with self-reported symptoms of depression (Bar-On, 2000; Dawda & Hart, 2000; Schutte et al., 1998), as well as anxiety and schizophrenia (Bar-On, 2000). There is also evidence that emotional intelligence is related to real-world outcomes such as higher self-reported scores on standardized tests such as the ACT and Verbal SAT (Brackett & Mayer, 2003), lower self-reported risky behavior such as substance use and criminal activity (Salovey et al., 2002; Salovey & Grewal, 2005), and lower self-reported physical health symptoms (reviewed in Bar-On, 2005).

Chapter 2: A Multidimensional, Time-Varying Approach to Measuring Emotional Granularity

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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 multidimensional, time-varying measures. Using a network approach, we generated person-specific networks using experience sampling ratings of emotional experience. Individuals with higher granularity were characterized by less dense networks 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 efficacy 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 reference 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, Danoff-Burg, 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 times 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; M. D. 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 estimated emotional granularity in the typical fashion, using ICCs, and compared these to multidimensional, time-varying measures provided by network analyses (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). 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. 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 strong, 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 2-2, 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 2-1). 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 2-1. 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 traditional 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; 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 ($M = 19.39$ years, $SD = 1.58$ years; 46% female). The study was approved by the Northeastern University Institutional Review Board; 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 traditional measures of emotional granularity (Barrett, 1998, 2004; Barrett et al., 2001; Feldman, 1995a). *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 $(1-\beta) > .80$ (J. 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 2-1; descriptions and equations for these measures are provided in Table 2-2, 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 2-2 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., E. R. 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, Mestdagh, 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, Mestdagh, et al., 2019), with greater emotional instability associated with depression (e.g., R. J. 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 2-2. 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 links¹⁴. (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 $k_i^w = \sum_{j \in N} w_{ij}$.

¹⁴ Without any thresholding or edge-pruning procedure applied, the network is fully connected: each node is connected to every other node, such that $l = n(n-1)/2$.

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. 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.	Newman (2004)
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 :	Lohse et al. (2014)

	$R_u = \frac{1}{n_u} \left(\sum_{i \in u} r_i^2 - \sum_{i \in u} r_i^2 \right)^{\frac{1}{2}}$ 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: $\rho_N = \frac{1}{n} \sqrt{\left(\sum_{i=1}^n \ r_i\ ^2 - \left\ \sum_{i=1}^n r_i \right\ ^2 \right)}$	
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: $SD_{NA} = \sqrt{\frac{\sum_{t=1}^T (NA_t - M_{NA})^2}{T-1}}$	Dejonckheere et al. (2019); 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 2-1). 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: $M = 34.64$, $SD = 4.48$).

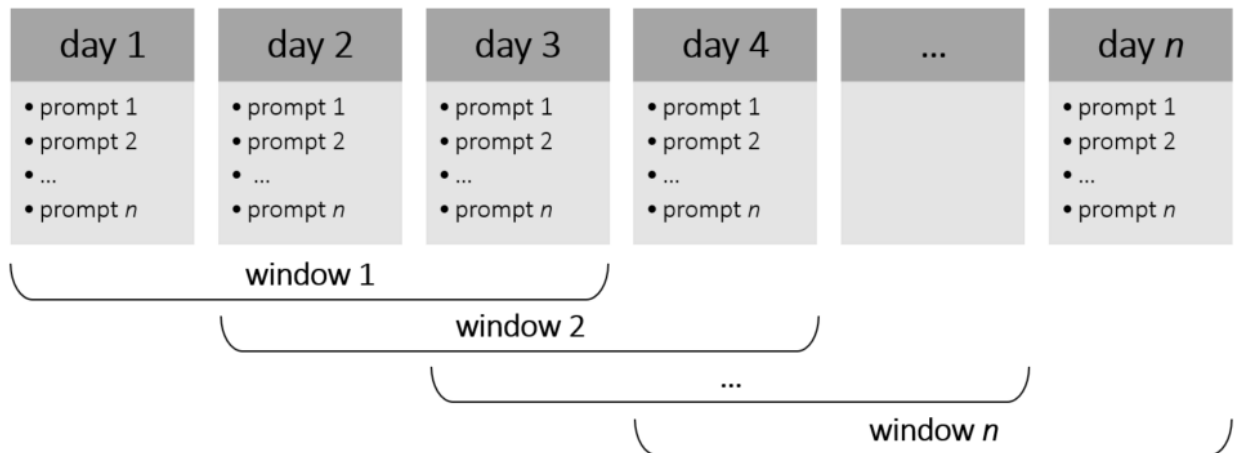


Figure 2-1. Schematic diagram of three-day overlapping sliding windows used to construct time-varying emotion networks.

Measure derivation. For each network, we computed seven network measures (Tables 2-1 and 2-2) 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). 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 2-1 and 2-2, 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 2-2) directly from participants' experience sampling data. All measures were inspected to verify their ranges were suitable for use as individual difference measures.

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 traditional 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)¹⁵. 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 from the regression, and

¹⁵ 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.

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 2-3.

Table 2-3. 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 (*-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 2-2 below; window-level network snapshots from the corresponding time-varying networks are presented in Figures S2-21 and S2-22. Overall and time-varying network visualizations for example participants in sample 2 are presented in Figures S2-23, S2-24, and S2-25¹⁶.

As can be seen in Figure 2, individuals with lower ICCs (e.g., Figure 2-2, 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 2-2, right panel) tend to have denser

¹⁶ 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 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.

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).

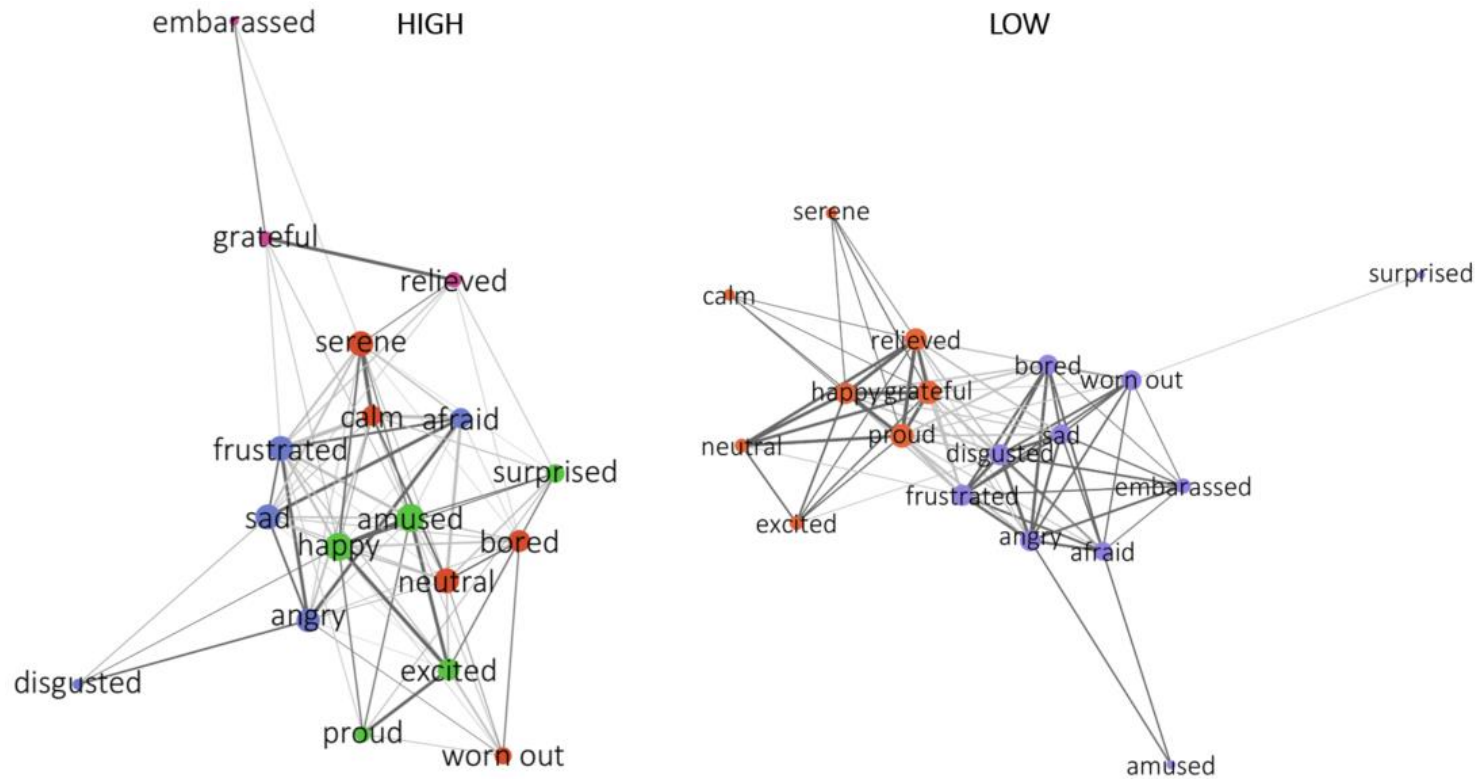


Figure 2-2. Overall emotion networks for example participants in sample 1 with higher emotional granularity (i.e., a lower ICC; left panel) and lower emotional granularity (i.e., a higher ICC; right panel). Node color represents community assignment; node size represents degree (i.e., number of edges). 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 ($r \leq .3$); orthogonal rotation (varimax) was used to establish the final solution (Table 2-4; see also Table S2-4).

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 2-3, left panel). This was true even when controlling for measures of negative affect and mean DIF/DDF alexithymia score (Table 2-5).

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 2-4). This solution is broadly similar to that identified for sample 1.

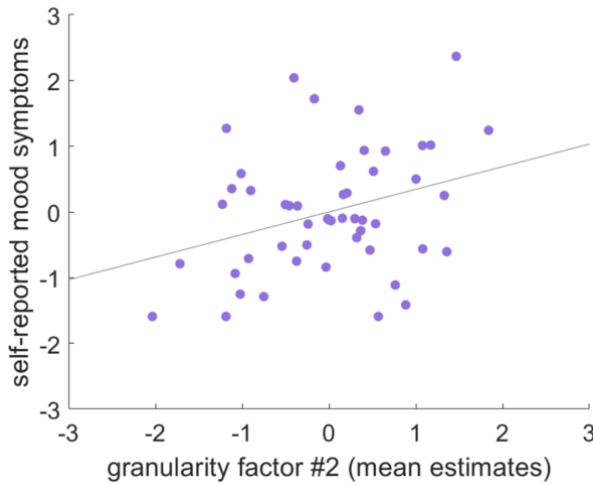
A multiple regression revealed that participants with higher ICCs, whose networks had fewer communities (numCom [reversed]) and lower diversity of negative edges (nDiv [reversed]) between those communities, reported more mood symptoms (Figure 2-3, right panel). Although this granularity factor's contribution to the model did not reach conventional levels of significance, it was a better predictor of anxiety than measures of negative affect and mean DIF/DDF alexithymia score (Table 2-5).

Table 2-4. 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.

sample 1



sample 2

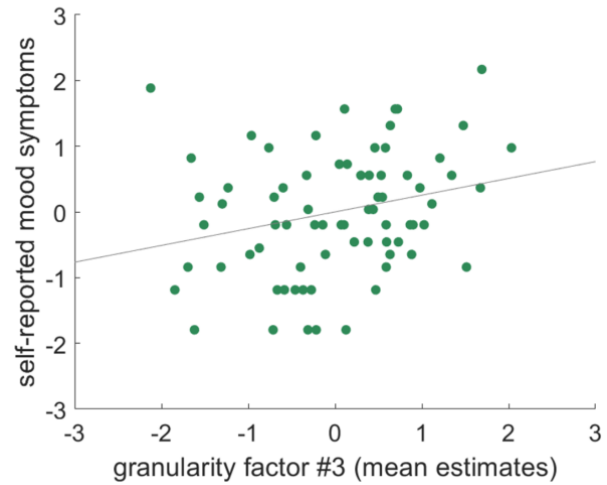


Figure 2-3. Scatter plots of zero-order correlations between significant granularity factors for time-varying network mean estimates, and self-reported mood symptoms, for sample 1 (left panel) and sample 2 (right panel). Mood symptom measures were standardized prior to analysis and so are presented in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

Table 2-5. 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
	<i>M</i> _{NA}	.27	.15	.29	1.81	.04	-.03, .57
	<i>SD</i> _{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
	<i>M</i> _{NA}	.28	.32	.28	.89	.19	-.35, .91
	<i>SD</i> _{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 communality. We retained two orthogonally-rotated factors (Table 2-6).

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 2-4, 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 2-7).

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 2-6). However, this granularity factor did not predict mood symptoms (Table 2-7; Figure 2-4, right panel).

Table 2-6. 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.

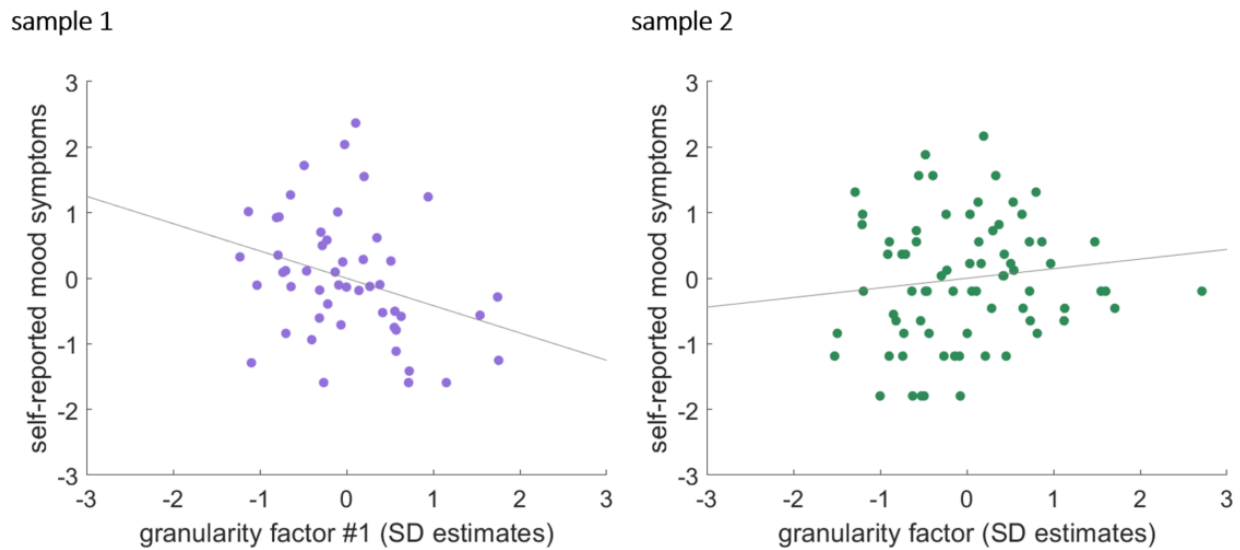


Figure 2-4. Scatter plots of zero-order correlations between granularity factor for time-varying network standard deviation estimates, and self-reported mood symptoms, for sample 1 (left panel) and sample 2 (right panel). Mood symptom measures were standardized prior to analysis and so are presented in z-score units.

Table 2-7. 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	.10	-.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 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 traditional measure of emotional granularity (ICC) as well as a set of seven network measures (Table 2-1), 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 efficacy 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, low emotional granularity (Barrett, 1998, 2004; Feldman, 1995a), 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 measures 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, Mestdagh, 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 analysis 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 inter-connected, 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

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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.

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All data analyzed in this paper, along with the accompanying analysis code, are available via a repository hosted by the Center for Open Science at <https://osf.io/nmja4/>.

Chapter 2 Supplemental Materials

Methods

Sample 1

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; K. 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 S2-1. 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 S2-1. 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; K. Kirby et al., 1999). After the third trial, blood pressure cuffs were removed and participants again completed another version of the anagrams task (Beverdort 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 S2-2 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 S2-3, according to the schedule noted on their experience sampling calendar (see Table S2-2 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 S2-3. 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 S2-3.

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 S2-1. 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 S2-2. 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 S2-3. 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.

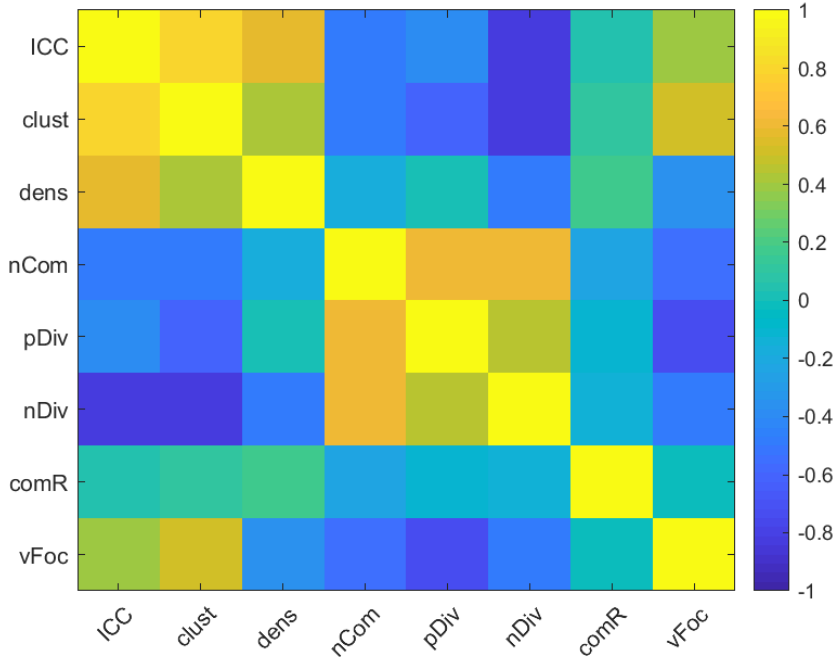


Figure S2-1. Heat map of correlation matrix between granularity measures estimated from overall networks for sample 1.

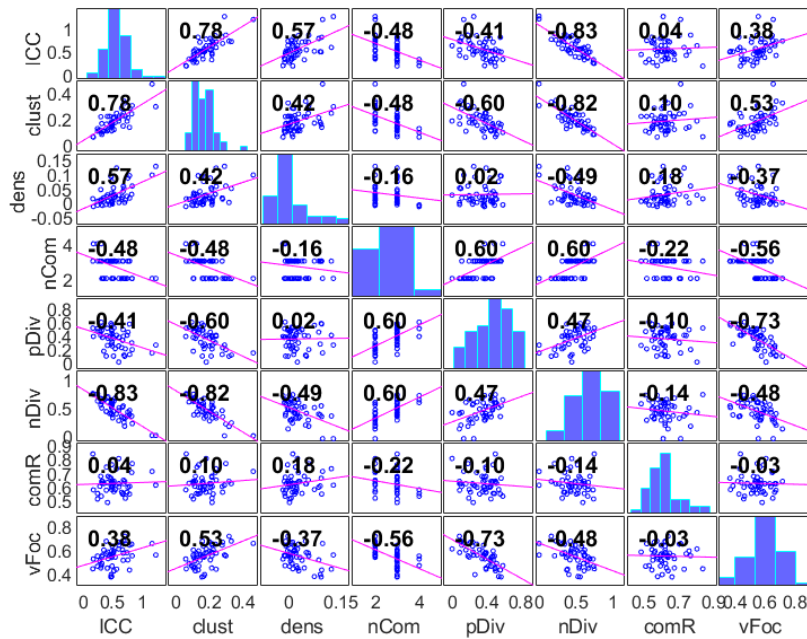


Figure S2-2. Scatter plots of the correlations between granularity measures estimated from overall networks (off-diagonals) and histograms of individual measures (diagonal) for sample 1.

Time-varying emotion networks: mean estimates.

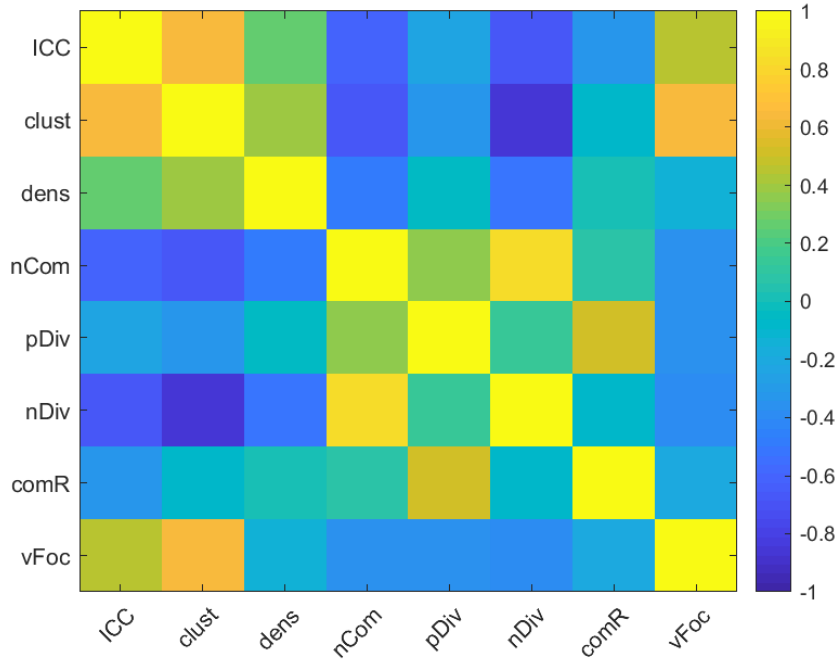


Figure S2-3. Heat map of correlation matrix between granularity measures estimated from time-varying means for sample 1.

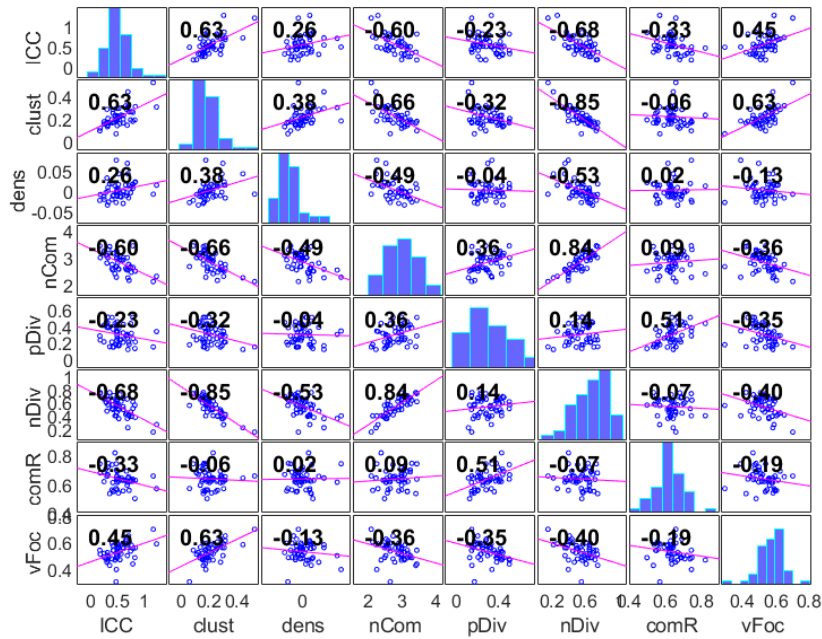


Figure S2-4. Scatter plots of the correlations between granularity measures estimated from time-varying means (off-diagonals) and histograms of individual measures (diagonal) for sample 1.

Time-varying emotion networks: standard deviation estimates.

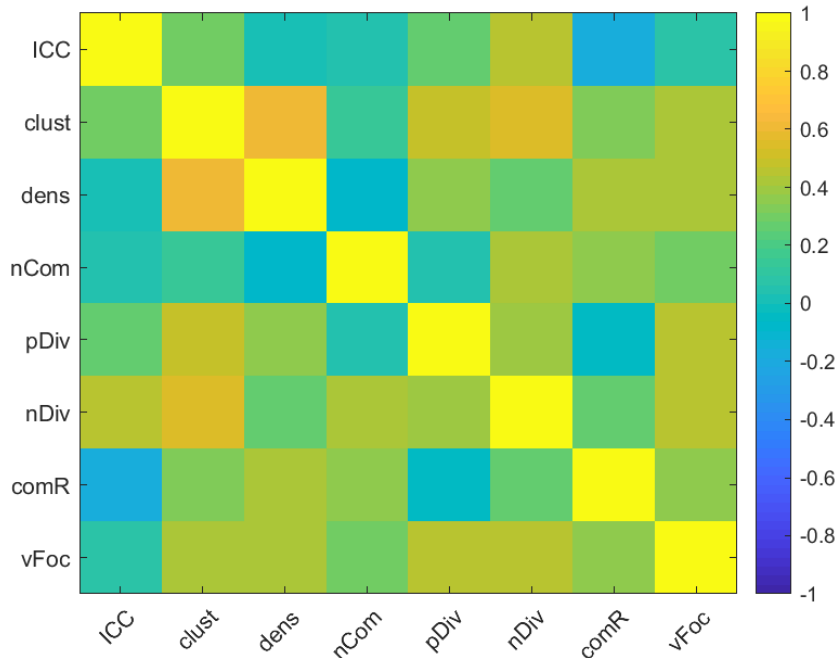


Figure S2-5. Heat map of correlation matrix between granularity measures estimated from time-varying standard deviations for sample 1.

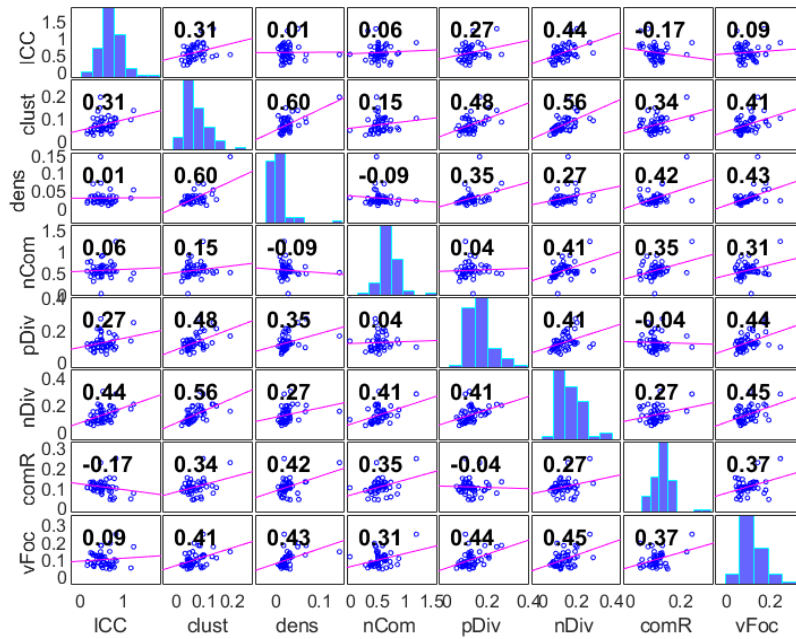


Figure S2-6. Scatter plots of the correlations between granularity measures estimated from time-varying standard deviations (off-diagonals) and histograms of individual measures (diagonal) for sample 1.

Measures derived from experience sampling data.
Overall estimates.

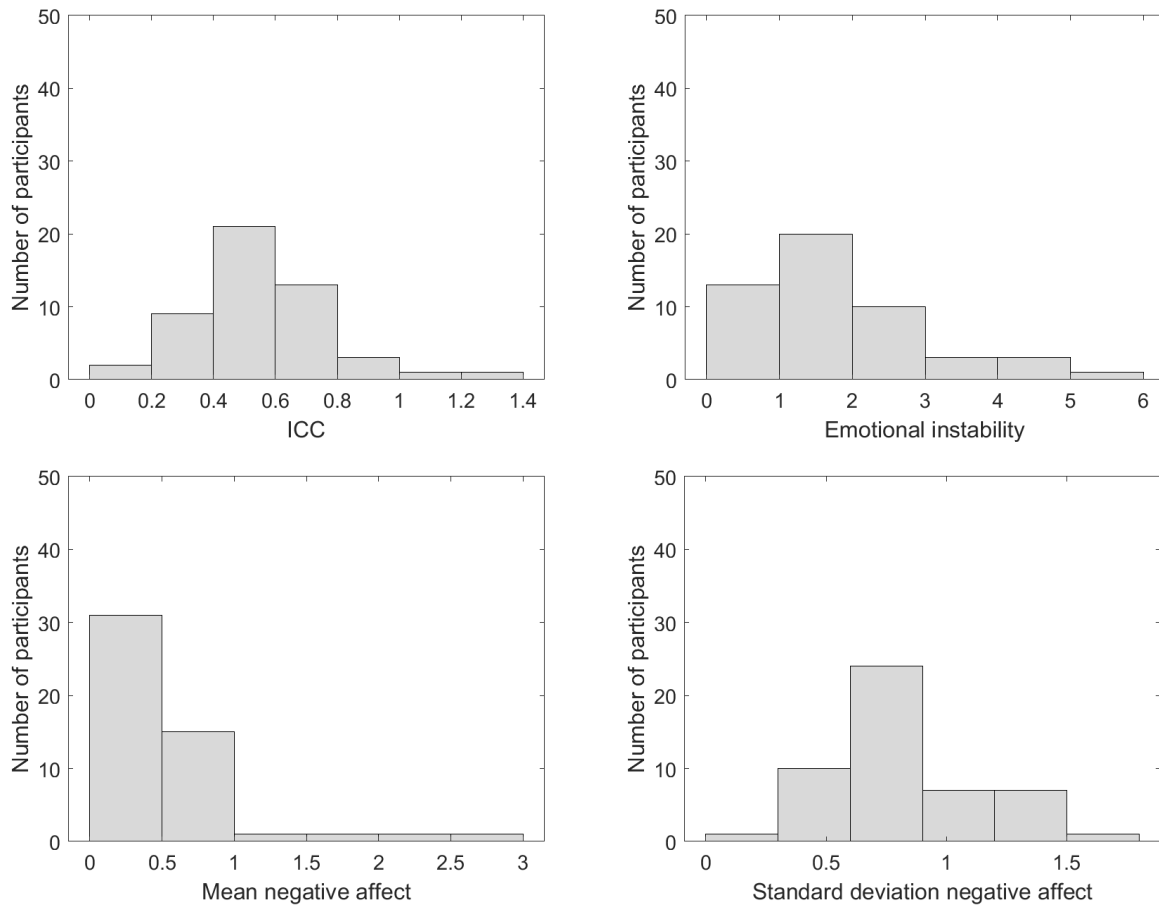
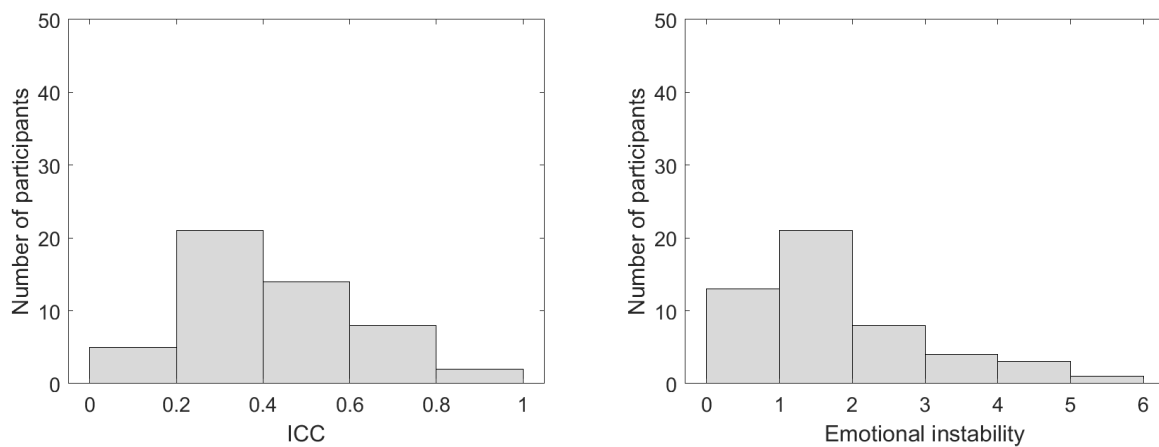


Figure S2-7. Histograms of measures derived as overall estimates of experience sampling data from sample 1: ICC (upper left), emotional instability (upper right), mean negative affect (lower left), standard deviation negative affect (lower right).

Mean estimates.



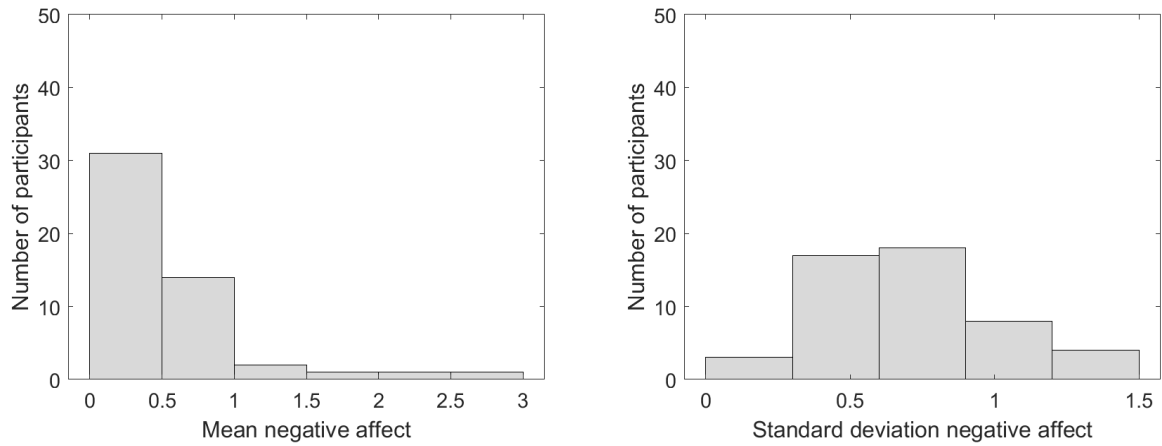


Figure S2-8. Histograms of measures derived as time-varying mean estimates from experience sampling data from sample 1: ICC (upper left), emotional instability (upper right), mean negative affect (lower left), standard deviation negative affect (lower right).

Standard deviation estimates.

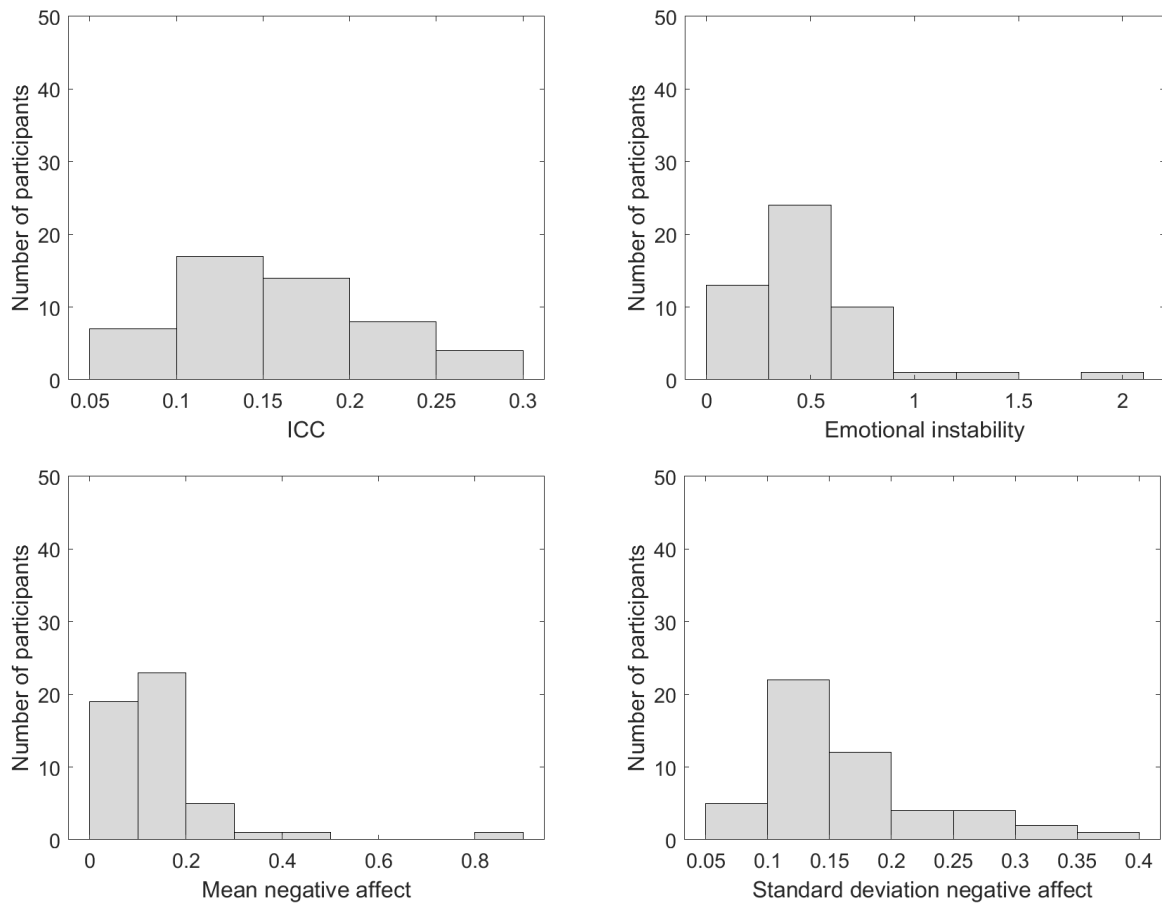


Figure S2-9. Histograms of measures derived as time-varying standard deviation estimates from experience sampling data from sample 1: ICC (upper left), emotional instability (upper right), mean negative affect (lower left), standard deviation negative affect (lower right).

Self-report questionnaires.

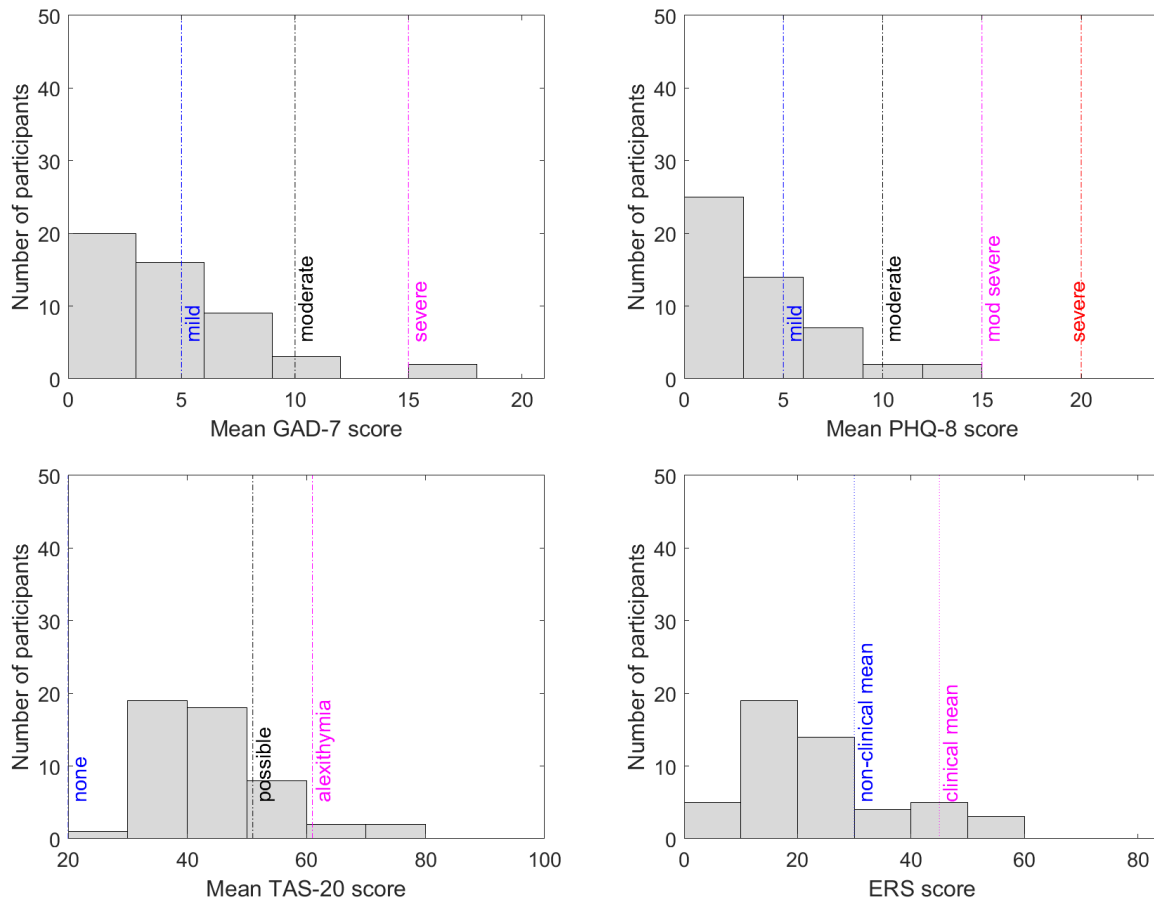


Figure S2-10. Histograms of self-report questionnaire scores from sample 1: anxiety (GAD-7; upper left), depression (PHQ-8; upper right), alexithymia (TAS-20; lower left), emotion reactivity (ERS; lower right).

Sample 2

Measures derived from emotion networks.

Overall emotion networks.

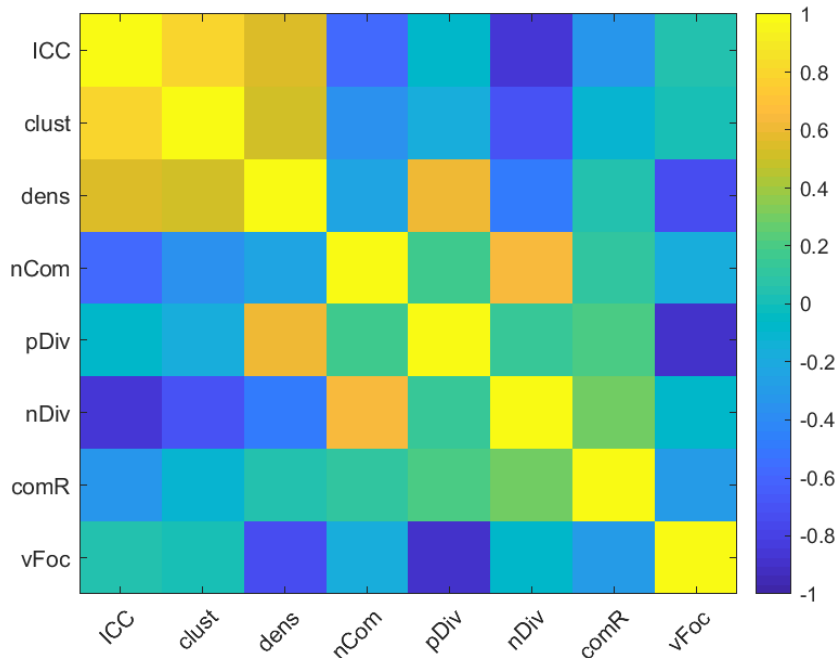


Figure S2-11. Heat map of correlation matrix between granularity measures estimated from overall networks for sample 2.

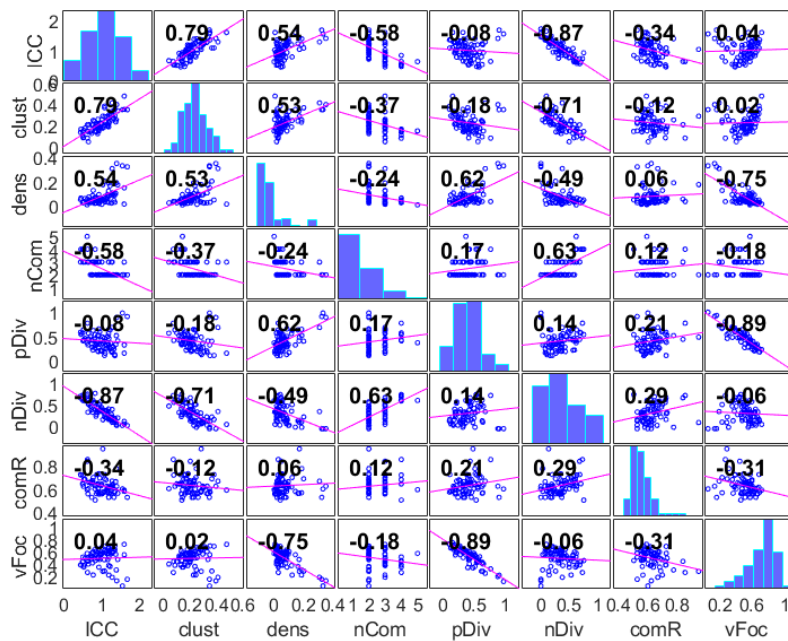


Figure S2-12. Scatter plots of the correlations between granularity measures estimated from overall networks (off-diagonals) and histograms of individual measures (diagonal) for sample 2.

Time-varying emotion networks: mean estimates.

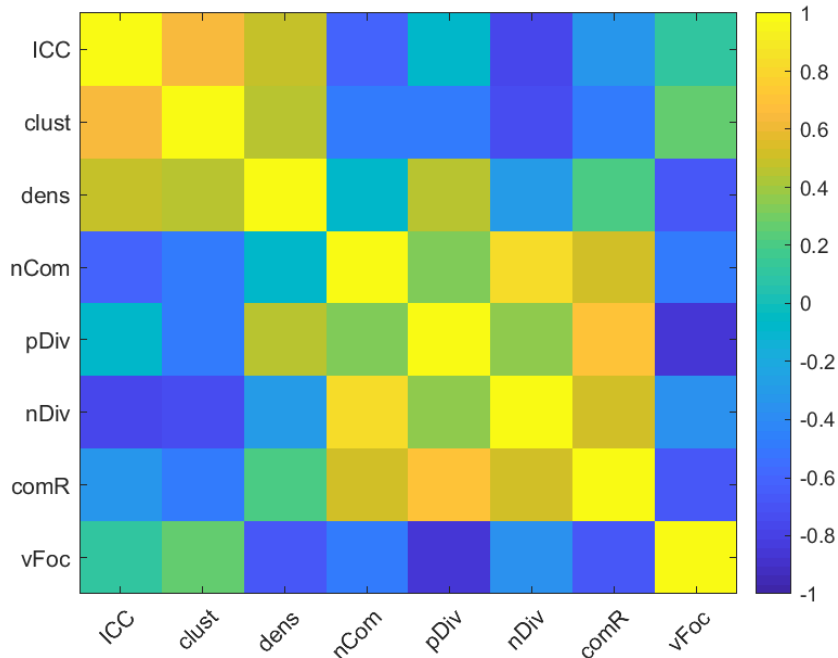


Figure S2-13. Heat map of correlation matrix between granularity measures estimated from time-varying means for sample 2.

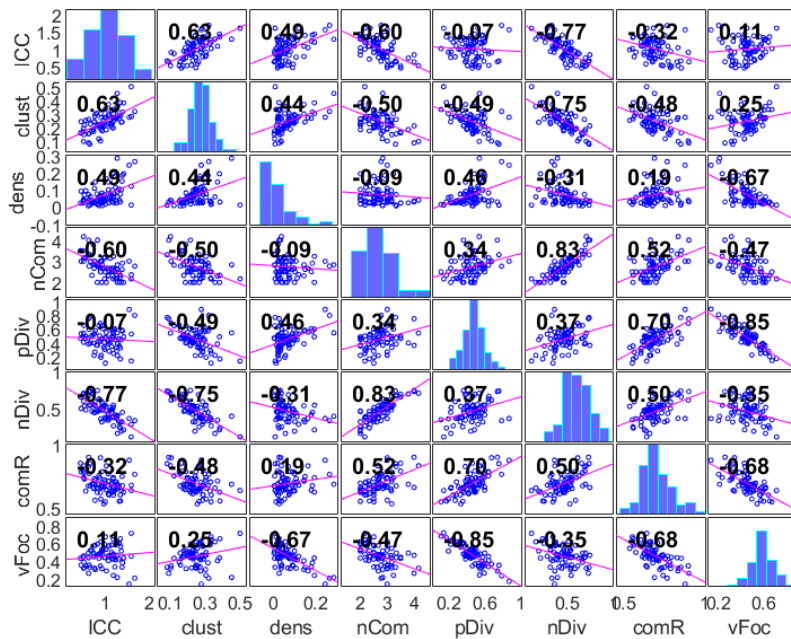


Figure S2-14. Scatter plots of the correlations between granularity measures estimated from time-varying means (off-diagonals) and histograms of individual measures (diagonal) for sample 2.

Time-varying emotion networks: standard deviation estimates.

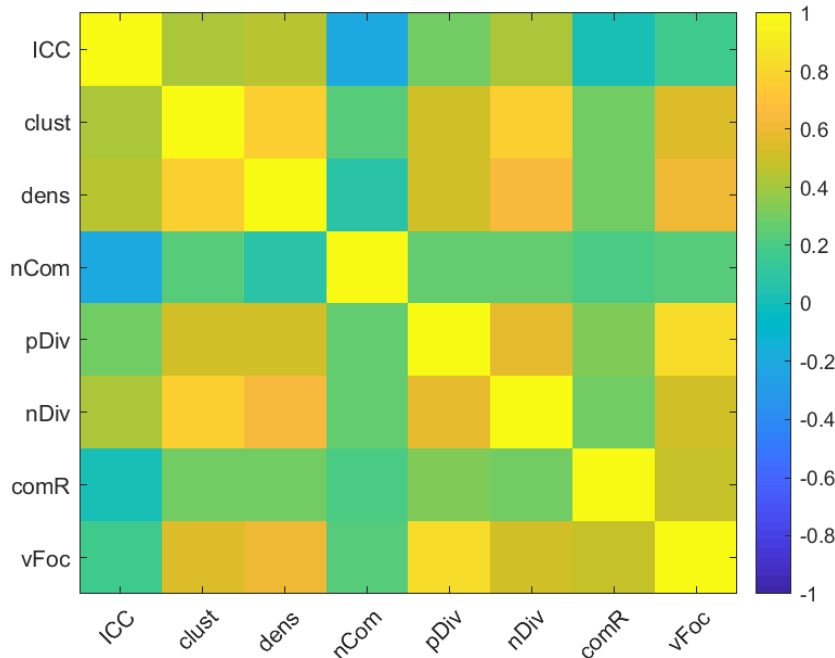


Figure S2-15. Heat map of correlation matrix between granularity measures estimated from time-varying standard deviations for sample 2.

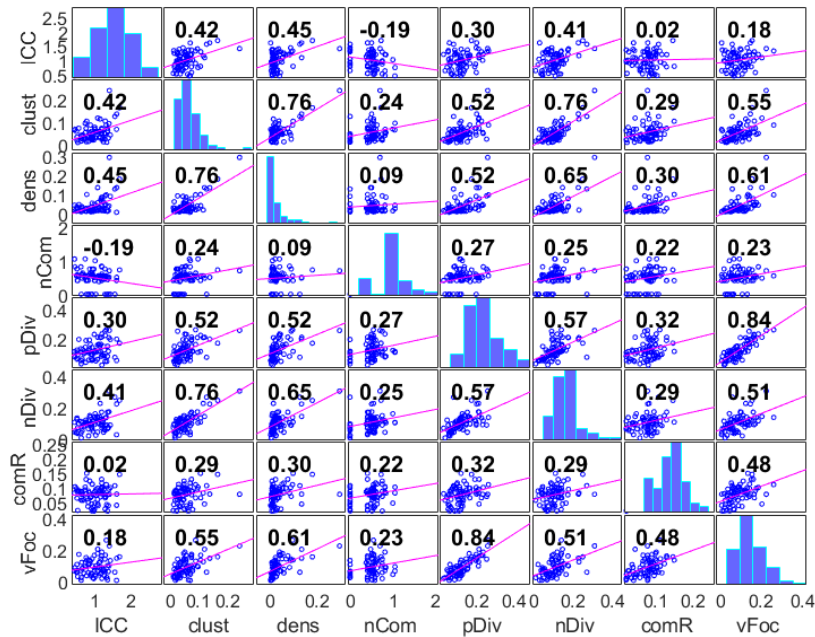


Figure S2-16. Scatter plots of the correlations between granularity measures estimated from time-varying standard deviations (off-diagonals) and histograms of individual measures (diagonal) for sample 2.

Measures derived from experience sampling data.
Overall estimates.

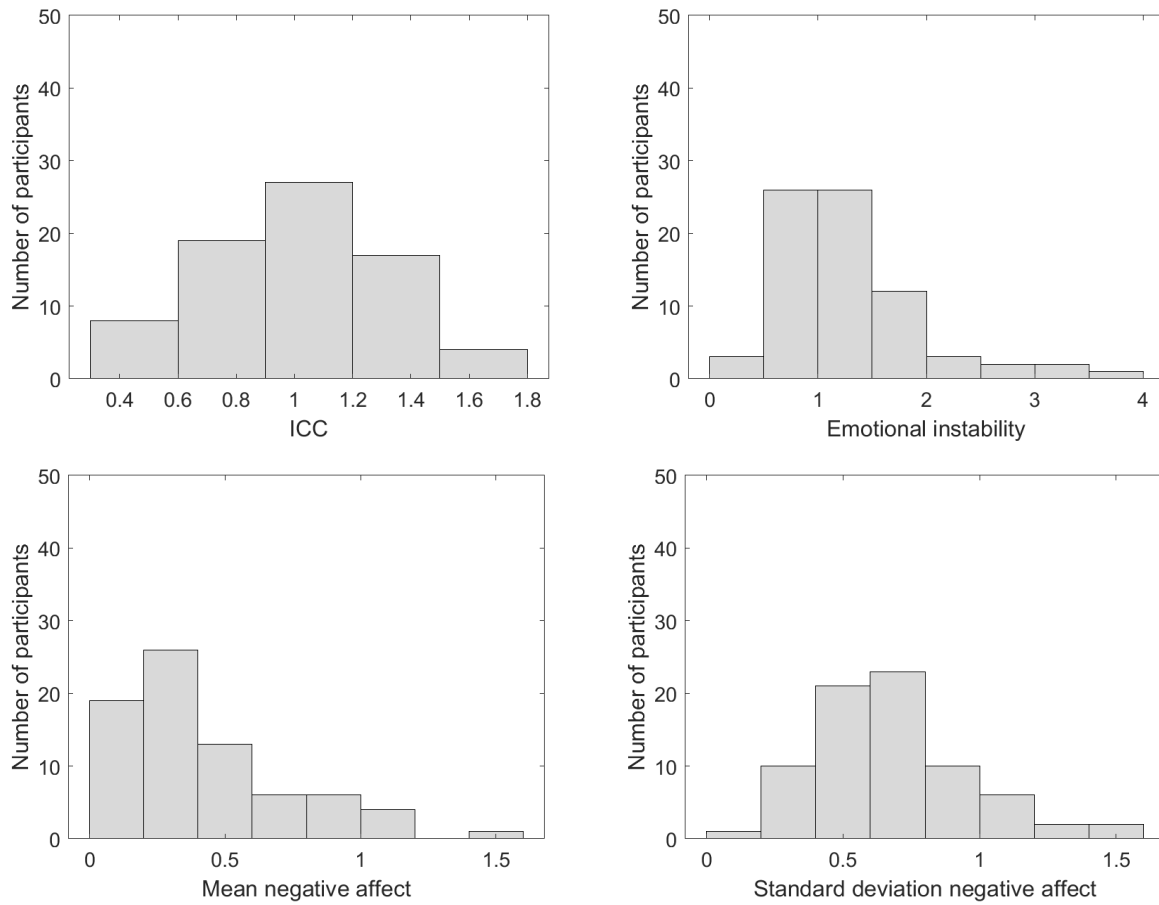
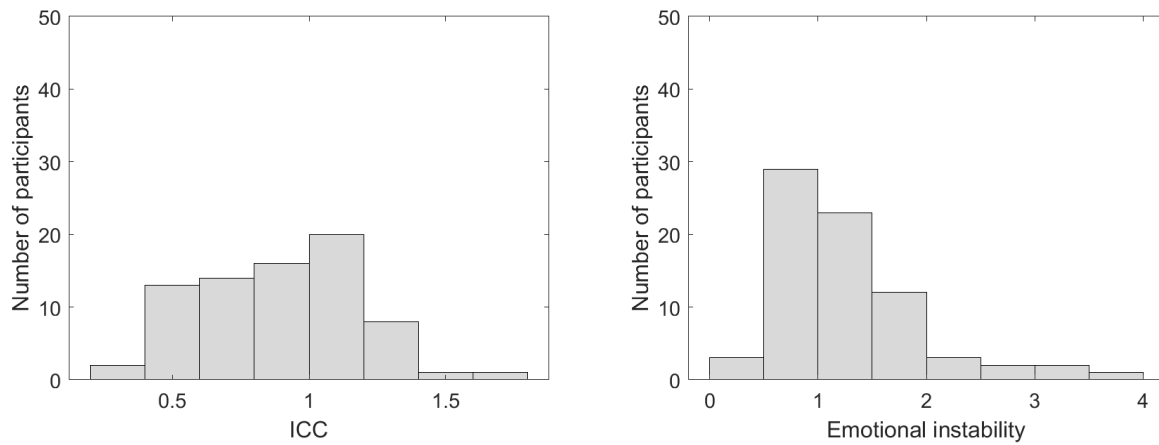


Figure S2-17. Histograms of measures derived as overall estimates of experience sampling data from sample 2: ICC (upper left), emotional instability (upper right), mean negative affect (lower left), standard deviation negative affect (lower right).

Mean estimates.



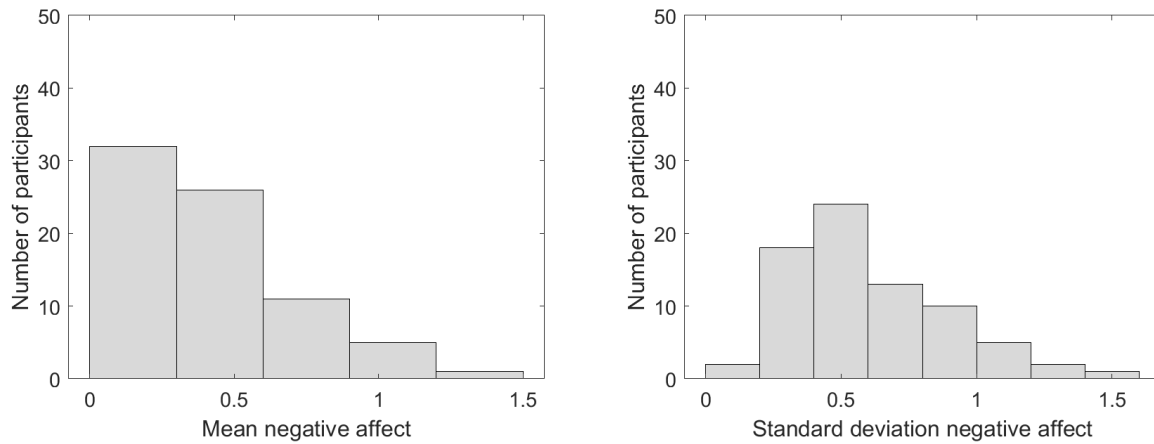


Figure S2-18. Histograms of measures derived as time-varying mean estimates from experience sampling data from sample 2: ICC (upper left), emotional instability (upper right), mean negative affect (lower left), standard deviation negative affect (lower right).

Standard deviation estimates.

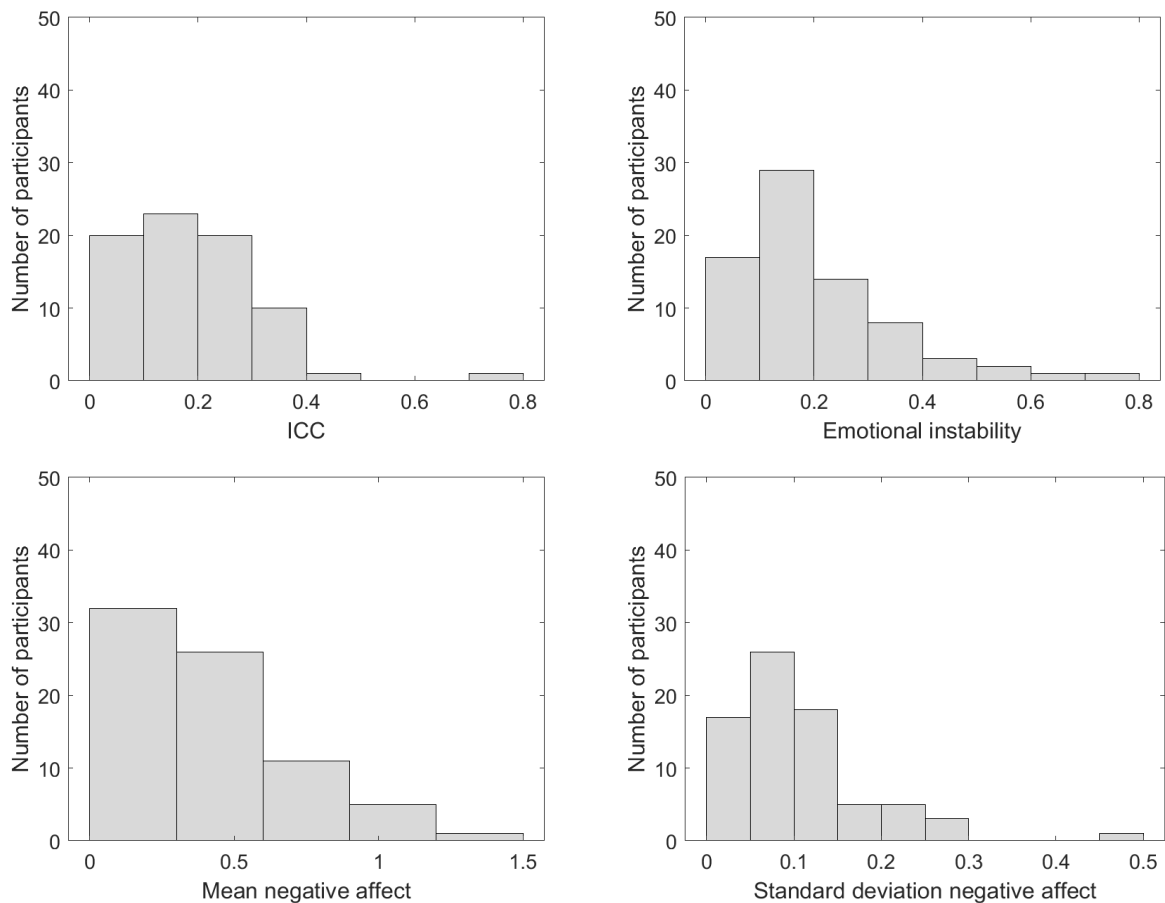


Figure S2-19. Histograms of measures derived as time-varying standard deviation estimates from experience sampling data from sample 2: ICC (upper left), emotional instability (upper right), mean negative affect (lower left), standard deviation negative affect (lower right).

Self-report questionnaires.

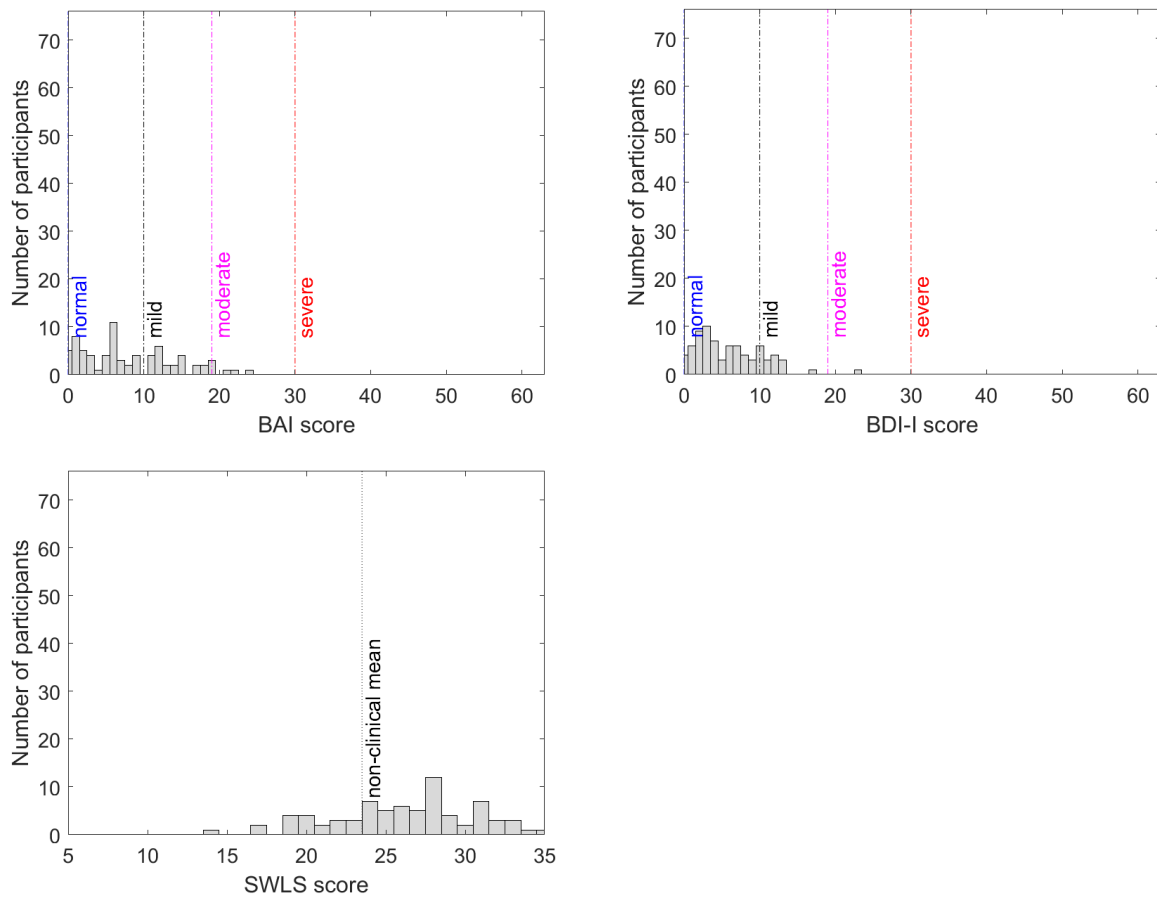


Figure S2-20. Histograms of self-report questionnaire scores from sample 2: anxiety (BAI; upper left), depression (BDI-I; upper right), alexithymia (TAS-20; lower left).

Supplemental Results

Network Visualizations

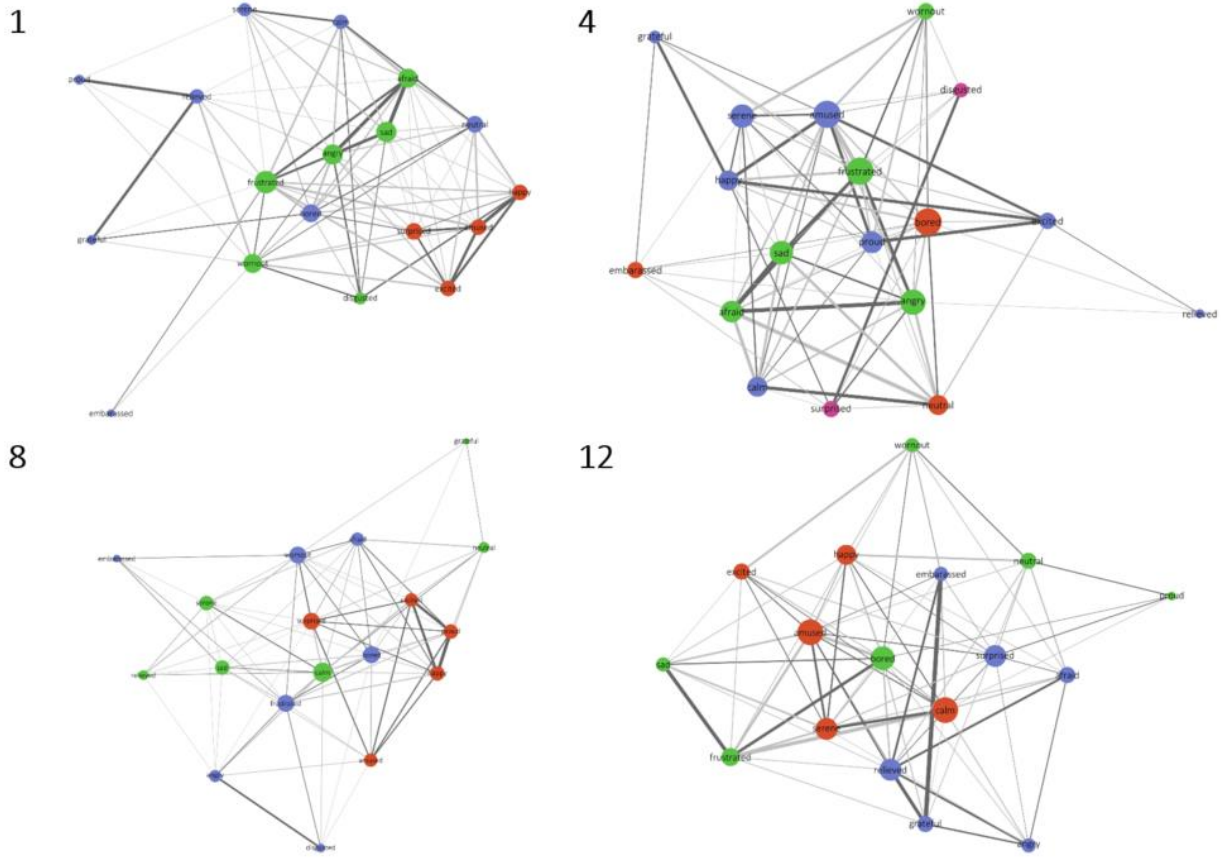


Figure S2-21. Time-varying emotion network for the example participant in sample 1 with higher granularity (i.e., a lower ICC): snapshots at window 1 (upper left panel), window 4 (upper right panel), window 8 (lower left panel) and window 12 (lower right panel). Node color represents community assignment; 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.,

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

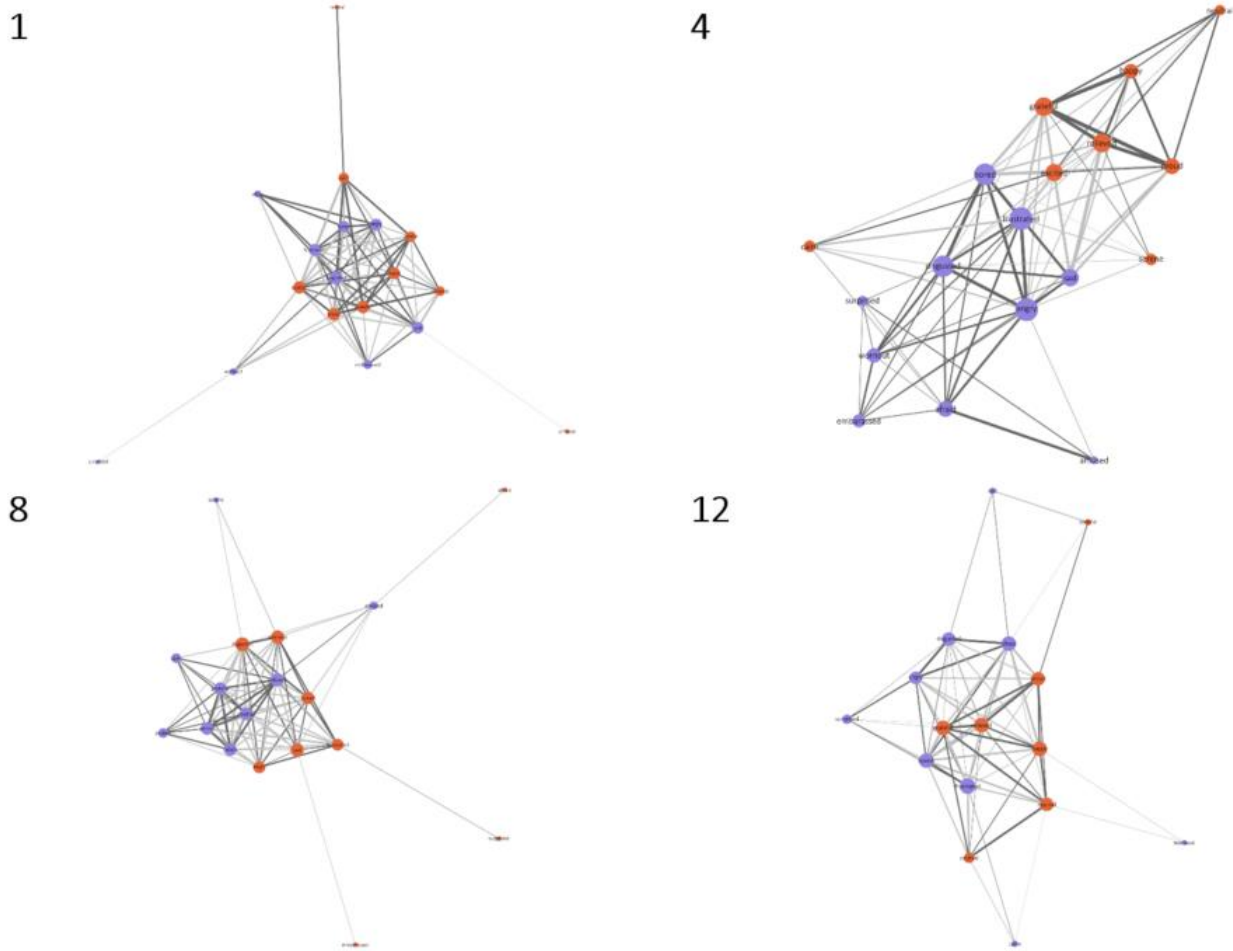


Figure S2-22. Time-varying emotion network for the example participant in sample 1 with lower granularity (i.e., a higher ICC): snapshots at window 1 (upper left panel), window 4 (upper right panel), window 8 (lower left panel) and window 12 (lower right panel). Node color represents community assignment; 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.,

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

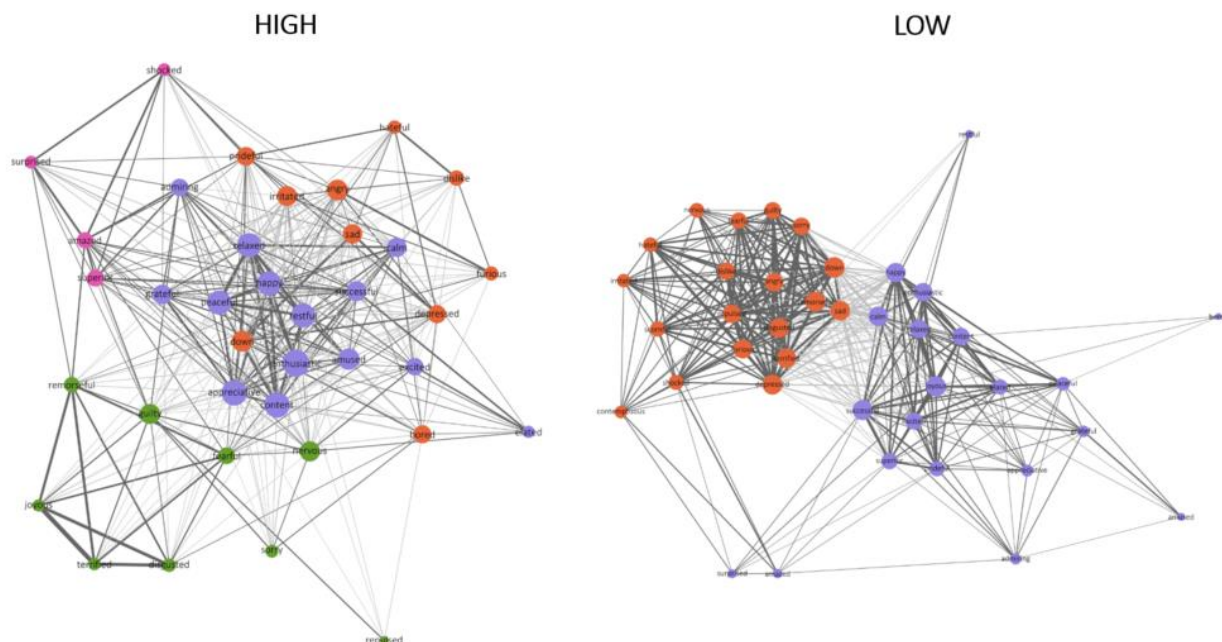


Figure S2-23. Overall emotion networks for example participants in sample 2 with higher granularity (i.e., a lower ICC; left panel) and lower granularity (i.e., a higher ICC; right panel). Node color represents community assignment; node size represents degree (i.e., number of edges). Edge thickness 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.,

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

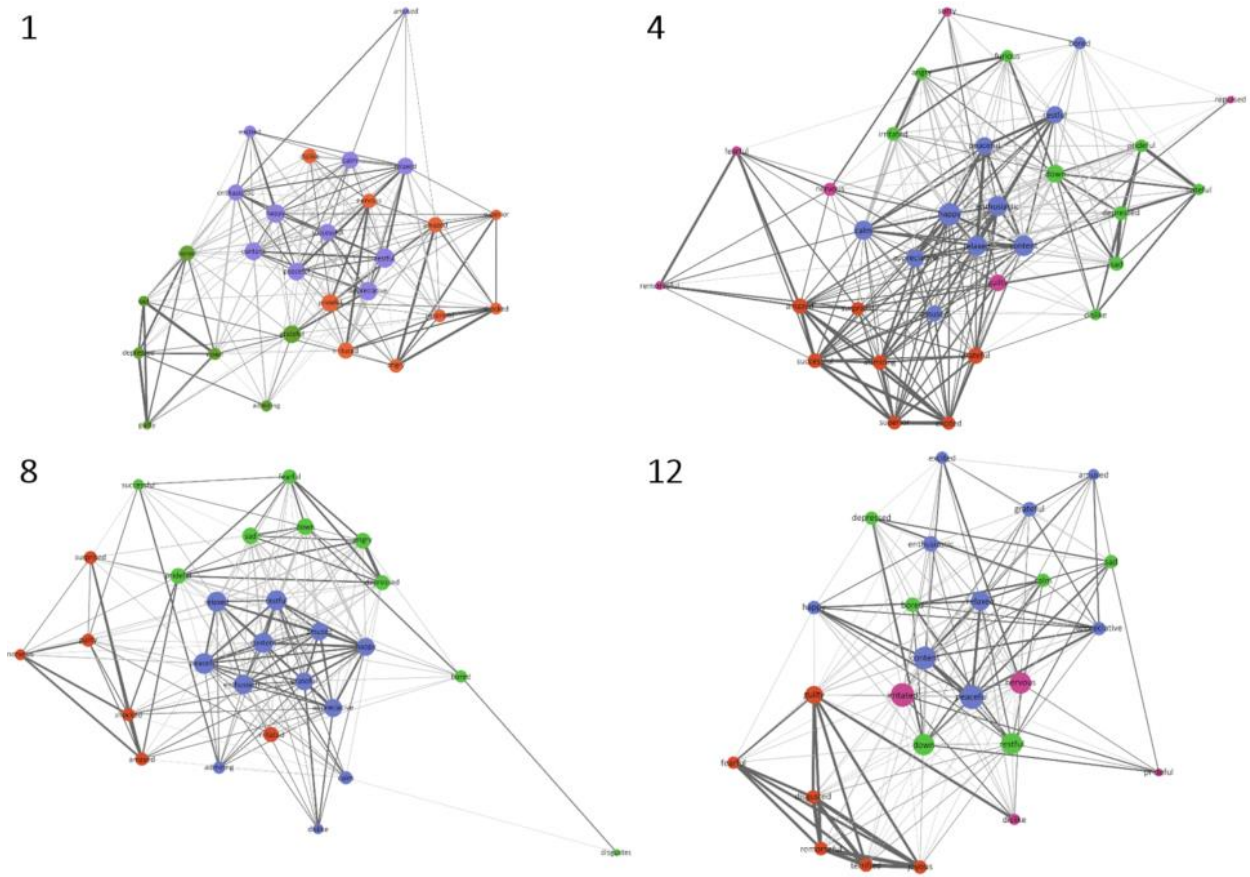


Figure S2-24. Time-varying emotion network for the example participant in sample 2 with higher emotional granularity (i.e., a lower ICC): snapshots at window 1 (upper left panel), window 4 (upper right panel), window 8 (lower left panel) and window 12 (lower right panel). Node color represents community 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).

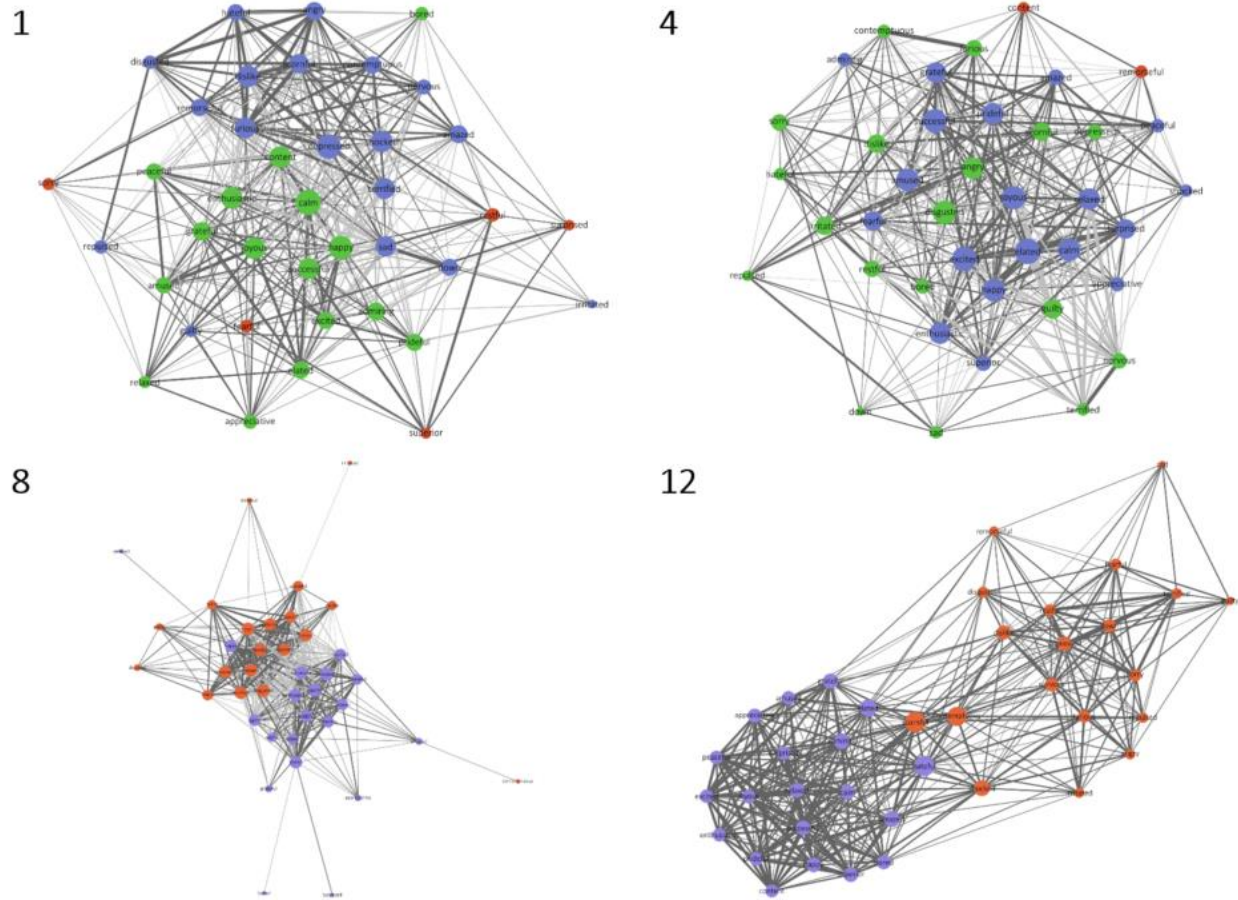


Figure S2-25. Time-varying emotion network for the example participant in sample 2 with lower emotional granularity (i.e., a higher ICC): snapshots at window 1 (upper left panel), window 4 (upper right panel), window 8 (lower left panel) and window 12 (lower right panel). Node color represents community 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 S2-4. Summary of Exploratory Factor Analyses for Networks using Pearson Correlations

Sample	Variables with Low Communalities ($h^2 < .4$)	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.

Chapter 3: Investigating the Relationship between Emotional Granularity and Cardiovascular Physiological Activity in Daily Life

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To be submitted for review at Health Psychology or Annals of Behavioral Medicine

Abstract

Objective: Emotional granularity describes the ability to create emotional experiences that are precise and detailed. Granularity's relationship to physical health has been under-investigated, especially given the link between depression and cardiovascular disease (CVD). This study explored the relationship between granularity and cardiovascular physiological activity in everyday life, with particular reference to the role of respiratory sinus arrhythmia (RSA), an index of vagal influence on the heart associated with positive mental and physical health outcomes.

Methods: Fifty participants (54% female), aged 18-36 years, completed approximately 14 days of experience sampling including ambulatory recording of electrocardiogram (ECG), impedance cardiogram (ICG), movement, and posture. Using physiologically-triggered experience sampling, participants documented a daily average of 8.80 ($SD = 1.22$) emotional events. Estimates of emotional granularity were compared with RSA during seated rest, with the number of patterns of physiological activity discovered in seated rest data, and with the performance of classifiers trained on event-related changes in physiological activity.

Results: Emotional granularity was positively but non-significantly correlated with resting RSA ($r = .18$, $p = .11$), positively correlated with the number of clusters discovered in seated rest data ($r = .26$, $p = .037$), and positively correlated with classifier performance ($r = .29$, $p = .049$).

Conclusions: Individuals with higher granularity exhibited more, and more specific, patterns of physiological activity during seated rest as well as during emotional events. These findings are consistent with accounts that propose concepts as a key mechanism underlying individual differences in emotional experience and physical health.

Keywords: ambulatory assessment, emotion differentiation, experience sampling, heart rate variability, psychophysiology

Emotional granularity, also known as emotion differentiation, describes an individual's ability to create experiences of emotion that are precise and detailed (Barrett, 2013, 2017a), and is associated with more specific action planning and better self-regulation (Barrett et al., 2001; Kalokerinos et al., 2019). Individuals with lower granularity are unable to distinguish rage from frustration, or even anger from sadness (e.g., they just say they feel 'bad'). By contrast, individuals with higher granularity are able to make finer distinctions, which they mark with specific words. Emotional granularity is typically measured using data from experience sampling studies, in which individuals are prompted to report their experiences multiple times per day, across multiple days, allowing experimenters to examine their pattern of responses over time in natural settings. There is growing evidence of a link between emotional granularity and mental health in both clinical and non-clinical samples. However, the relationship between granularity and physical health has been under-investigated. Understanding granularity's relationship with cardiovascular physiological activity in everyday life is especially relevant given the well-established association between cardiovascular disease (CVD) and depression (e.g., Carney et al., 2005; Stein et al., 2000; Vaccarino et al., 2008). With the present study, we begin to fill this gap, highlighting in particular the relationship between granularity and respiratory sinus arrhythmia (RSA), an index of vagal influence on the heart that is associated with positive mental and physical health outcomes (e.g., Beauchaine, 2015; Curtis & O'Keefe, 2002).

Emotional Granularity and Health

Recent findings strongly indicate that lower emotional granularity is a transdiagnostic feature of mental disorders (for reviews, see Barrett, 2017a; Kashdan et al., 2015; Smidt & Suvak, 2015) and a likely risk factor for mental illness. Lower granularity occurs across a range of mental disorders, including schizophrenia (Kimhy et al., 2014), depression (Demiralp et al., 2012), social anxiety disorder (Kashdan & Farmer, 2014), eating disorders (Selby et al., 2013), autism spectrum disorders (Erbas et al., 2013), and borderline personality disorder (Suvak et al., 2011). Lower granularity manifests as an inability to identify and describe emotional experiences, and so is closely related to the construct of alexithymia (Aaron et al., 2018; E. R. Edwards & Wupperman, 2017; Erbas et al., 2014, 2018). Measured as alexithymia, lower granularity is a negative predictor of psychotherapeutic success across a number of disorders (McCallum et al., 2003; Ogrodniczuk et al., 2011; for a review, see Rufer et al., 2010). In non-clinical samples, lower granularity is related to more symptoms associated with anxiety (Mennin et al., 2005; Seah et al., 2020) and depression (Erbas et al., 2014, 2018; Starr et al., 2017; Willroth et al., 2019). Further, lower granularity is linked to poorer behavioral indices of coping. Individuals with lower granularity report greater alcohol consumption during intense negative emotional experiences (Kashdan et al., 2010), more urges to binge eat (Dixon-Gordon et al., 2014), higher incidence of drug relapse (Anand et al., 2017), and increased urges to physically aggress when provoked (Pond et al., 2012).

Despite strong links between emotional granularity and mental health, relatively little work has been done to understand how granularity may be related to indices of physical health.¹⁷ In this domain, cardiovascular disease (CVD) and metabolic syndrome – a cluster of precipitating factors for CVD, including hypertension, high cholesterol, (pre)diabetes, and abdominal obesity (Alberti et al., 2005; Grundy et al., 2004) – stand out as primary candidates for research. Both CVD and metabolic syndrome are linked with depression (Carney et al., 2005; Grippo & Johnson, 2002; Sheps & Sheffield, 2001; Stein et al., 2000; Vaccarino et al., 2008), and depression is a risk factor for mortality and cardiovascular events in patients with coronary artery disease (Barth et al., 2004; Van Melle et al., 2004). Prior work has identified a number of emotion-related risk factors for CVD and metabolic syndrome (Krantz & McCeney, 2002; Rozanski, 2014), with more effective emotion regulation serving as a protective factor. Lower granularity (measured as alexithymia) predicts the hypertension and high triglyceride levels

¹⁷ There is extensive research on the relationship between alexithymia and physical health, especially in the context of psychosomatic disorders where it was first documented (e.g., Sifneos, 1973; Subic-Wrana et al., 2005; G. J. Taylor, 2000). For reviews, the interested reader is referred to Bermond et al. (2015), Kojima (2012), and Lumley et al. (2007).

indicative of metabolic syndrome (Lemche et al., 2010), even in healthy populations (Karukivi et al., 2016), and is associated with obesity (De Chouly et al., 2000; Elfhag & Lundh, 2007; Pinna et al., 2011). Higher granularity, on the other hand, is associated with decreased risk for cardiac events in patients with previous myocardial infarction (Beresnevaite, 2000), as well as fewer follow-up medical visits related to physical illness (e.g., cancer; Stanton, Danoff-Burg, et al., 2002). Indeed, better emotion regulation and coping strategies are directly associated with lower risk for metabolic syndrome (Kinnunen et al., 2005), even when experienced negative affect is taken into account (Yancura et al., 2006).

Lower emotional granularity may be linked with CVD and metabolic syndrome via a form of compromised and inefficient allostasis: the process by which body systems actively regulate or adjust to environmental perturbations, to prepare for expected metabolic needs (Sterling, 2012). Detrimental shifts in the contributions of the two branches of the autonomic nervous system (ANS) to visceral functions throughout the body, in particular a reduction in resting parasympathetic activity, are observed with both emotional dysregulation and disordered mood (Bleil et al., 2008; Carney et al., 2005; J. L. Hamilton & Alloy, 2017; Kapczinski et al., 2008), and may be a common, core vulnerability for CVD and metabolic syndrome (e.g., Buccelletti et al., 2009; Stein et al., 2007; Togo & Takahashi, 2009; Villareal et al., 2002). Substantial evidence demonstrates that autonomic dysregulation marked by decreased parasympathetic activation at rest is associated with a number of other cardiovascular risk factors (Thayer et al., 2010). The parasympathetic nervous system (PNS) influences the heart via the vagus nerve (Acharya et al., 2006; Berntson et al., 1993; Task Force, 1996). Vagal influence on the heart is typically quantified using respiratory sinus arrhythmia (RSA): heart rate variability (HRV) occurring within the typical respiratory frequency range (approximately .12-.40 Hz; Beauchaine, 2001) and driven almost exclusively by the PNS (Akselrod et al., 1985; Cacioppo et al., 1994; Pomeranz et al., 1985).

Research suggests that resting RSA levels and short-term changes in RSA (RSA reactivity) are related to individual differences in physical and mental health (Buccelletti et al., 2009; Stein et al., 2007; Togo & Takahashi, 2009; Villareal et al., 2002). Diminished HRV is independently predictive of negative cardiovascular outcomes (Curtis & O'Keefe, 2002) and broadly associated with cardiovascular disease processes (Stys & Stys, 1998).¹⁸ Lower resting RSA and blunted or excessive RSA reactivity is associated with poorer emotion regulation and higher incidence of psychopathology (e.g., Beauchaine, 2015). Lower resting RSA, in particular, is linked to negative affective states (Bleil et al., 2008), depression (Rechlin et al., 1994), anxiety (e.g., Thayer et al., 1996), and post-traumatic stress and panic disorders (H. Cohen et al., 2000). In contrast, higher resting RSA appears to permit more efficient regulation by promoting recovery and energy conservation, reducing allostatic load (McEwen, 1998). Higher resting RSA is associated with greater subjective well-being (e.g., Geisler et al., 2010), lower anxiety (Chalmers et al., 2014) and depression (Carnevali et al., 2018), and more effective emotion regulation (for a review, see Balzarotti et al., 2017). Emotion regulation may be further facilitated by RSA reactivity (Butler et al., 2006; Tiller et al., 1996), which is hypothesized to signal the availability of precise, context-specific emotions (Thayer et al., 2012).

The Present Study

In the present study, we investigated the relationship between emotional granularity and cardiovascular physiological activity with data collected using experience sampling with ambulatory peripheral physiological monitoring. This approach provided for enhanced ecological validity, and allowed us to characterize patterns within individuals, over time, in real-world situations (Quigley & Barrett, 2014; Wilhelm & Grossman, 2010). As part of a larger study on affective experience and decision making in daily life, 50 participants completed approximately 14, eight-hour days of monitoring. Each day, participants visited the lab and were outfitted with sensors and portable equipment to measure their

¹⁸ The relationship between HRV and risk for CVD varies according to demographic factors such as ethnicity (Hill et al., 2015) and sex (Koenig & Thayer, 2016). More broadly, factors such as socioeconomic status (SES) may be independent predictors of CVD morbidity and mortality (e.g., Blikman et al., 2014; Kaplan & Keil, 1993; Krueger & Chang, 2008).

electrocardiogram (ECG) and impedance cardiogram (ICG) as well as bodily movement and posture (via accelerometers). To enable efficient sampling of psychologically-salient moments, we used a novel, physiologically-triggered experience sampling approach. Specifically, a custom smartphone application 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. Prompts were not generated if participants had moved substantially or changed posture within the proceeding 30 seconds. In response to each experience sampling prompt, participants freely labeled their current state with emotion words. At the end of each day, participants completed a survey in which they provided additional information about what was going on at the time each prompt was received, and rated the intensity of their experienced emotion on a set of 18 emotion adjectives.

Using the ambulatory physiological data, we derived seven cardiovascular features for analysis (Table 3-1): interbeat interval (IBI), respiratory sinus arrhythmia (RSA), respiration rate (RR), pre-ejection period (PEP), left ventricular ejection time (LVET), stroke volume (SV), and cardiac output (CO). These features were chosen because of their importance in prior work on physiological changes associated with motivated performance tasks (Blascovich & Mendes, 2001; Seery, 2011; Tomaka et al., 1993; Wormwood et al., 2019). We derived these features for all periods of seated rest longer than 60 seconds when participants did not receive experience sampling prompts. We also computed change scores for each experience sampling event, as the difference in physiological activity before and after the IBI change that initiated the experience sampling prompt (Hoemann et al., 2020). Using the emotion intensity ratings from the end-of-day surveys, we computed estimates of emotional granularity for each participant.

Table 3-1. Cardiovascular Features Derived from Ambulatory Physiological Data

Feature	Definition	Interpretation
Interbeat interval (IBI)	Time (in ms) between heartbeats (inverse of heart rate)	IBI describes how fast the heart is beating; greater IBI values denote a slower heart rate
Respiratory sinus arrhythmia (RSA)	High frequency variability in IBI which occurs at the respiratory frequency	RSA is an estimate of parasympathetic (PNS) influence on the heart; greater RSA values typically indicate PNS activation
Respiration rate (RR)	Number of breaths (in cycles) per unit of time (min)	RR is the breathing rate
Pre-ejection period (PEP)	Time (in ms) between the beginning of electrical stimulation of the heart and the opening of the aortic valve	PEP is an inverse estimate of cardiac contractility and sympathetic (SNS) control of the heart; greater PEP values typically indicate reduced contractility and SNS withdrawal (when posture is held constant)
Left ventricular ejection time (LVET)	Time (in ms) between the opening and closing of the aortic valve	LVET describes how long it takes the heart to pump blood from the heart on each heartbeat; greater LVET values are associated with greater time to eject per heartbeat
Stroke volume (SV)	Volume (in mL) of blood ejected by the heart with each beat	SV describes the volume of blood ejected from the heart during each heartbeat; greater SV values indicate greater blood volume per heartbeat

Cardiac output (CO)	Volume (in L) of blood circulated in the body per unit of time (min)	CO describes blood flow over time; greater CO values indicate greater blood flow rate (in L/min)
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In a set of pre-registered analyses, we tested three hypotheses. First, in a set of correlational analyses, we tested the hypothesis that emotional granularity is positively related to resting RSA. Second, in a set of unsupervised clustering analyses, we tested the hypothesis that granularity is positively related to the number of patterns (i.e., clusters) in cardiovascular physiological activity during seated rest, as discovered using person-specific clustering algorithms. We predicted that more clusters would be discovered for individuals with higher granularity due to the need for more context-specific shifts in ANS activity. Third, in a set of supervised classification analyses, we tested the hypothesis that granularity is positively related how distinctly patterns in ANS activity map onto the words used to label emotional events. Here, we used the results of the person-specific supervised classification analyses reported in Azari et al. (2020). We predicted that granularity would be positively correlated with classifier performance, such that participants with higher granularity would have patterns of cardiovascular physiological activity during emotional events that could be more accurately classified.

Method

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

Participants

Sixty-seven participants ranging in age from 18-36 years (55% female; 38.8% White, 3.0% Black, 29.8% Asian, 28.4% other; $M_{age} = 22.8$ years, $SD_{age} = 4.4$ years) were recruited from the greater Boston area through posted advertisements, and Northeastern University classrooms and online portals. Eligible participants were non-smoking, fluent English-speakers, and were excluded if they had a history of cardiovascular illness or stroke, chronic medical conditions, mental illness, asthma, skin allergies, or sensitive skin. Eligible participants also confirmed they were not taking medications known to influence autonomic physiology including those for attentional disorders, insomnia, anxiety, hypertension, rheumatoid arthritis, epilepsy/seizures, cold/flu, or fever/allergies. Informed consent was obtained from all participants before beginning the study. Participants received \$490 as compensation for completing all parts of the study, plus up to \$55 in task incentives as detailed on page 1 of the supplemental materials.

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

Procedure

Overview. Each participant completed approximately 14 days ($M = 14.4$, $SD = 0.6$) of context-aware experience sampling distributed across a three- to four-week period ($M = 24.9$ days, $SD = 5.5$ days). On each day of experience sampling, participants came into the lab and were instrumented for peripheral physiological recording. Participants were instructed to continue physiological recording for eight hours each day, after which they were able to remove and recharge all equipment. Upon completing experience sampling each day, participants automatically received an end-of-day survey via SurveyMonkey (San Mateo, CA), which they used to provide additional details about the prompts they completed throughout the day. Before and after the two-week experience sampling protocol, participants completed two in-lab sessions. In each session, participants completed tasks and questionnaires that are not reported here (see pages 1-2 of supplemental materials for overview).

Physiological measurement. All ambulatory peripheral physiological measures were recorded at 500 Hz on a mobile impedance cardiograph from MindWare Technologies LTD, (Model # 50-2303-02, Westerville, OH), which participants wore clipped onto their clothing on the hip. ECG and ICG were obtained using pre-gelled ConMed (Westborough, MA) Cleartrace Ag/AgCl sensors, connected via wires to the cardiograph. Sensor sites were cleaned with alcohol and abraded lightly with gauze. ECG was obtained using a modified lead II configuration, with recording electrodes placed on the distal right collarbone and an inferior left rib, respectively, and a reference electrode placed on an inferior right rib. The ECG signal was acquired using a low cutoff of 0.5 Hz and a high cutoff of 45 Hz. ICG was obtained using a four-spot electrode configuration (Qu et al., 1986). Two inner recording electrodes were placed on the front of the torso: one at the base of the neck at the top of the sternum, and a second at the bottom of the sternum over the xiphisternal junction. Outer current electrodes were placed over the spine on the neck (at approximately C4) and at the vertical level that was 4-5 cm below the lower recording electrode on the ventrum. Basal impedance (Z_0) was acquired using a low frequency cutoff of 10 Hz. The first derivative, dZ/dt , was acquired using a low frequency cutoff of 0.5 Hz and a high cutoff of 45 Hz.

The mobile impedance cardiograph collected continuous three-axis accelerometry data that was used to assess movement. Additionally, participants wore two inertial measurement units (IMUs) purchased from LP-Research (Minato-ky, Tokyo, Japan) to derive measures of posture and changes in posture. One IMU was placed medially on the sternum beneath the top impedance recording electrode and affixed to the skin using a double-sided adhesive patch. The other IMU was placed on the front of the thigh using either a cloth holder attached to the clothing, or a second adhesive patch affixed to the skin.

Context-aware experience sampling. Peripheral physiological and accelerometric data were recorded continuously throughout the eight-hour sampling period and communicated via Bluetooth to a Motorola Moto G⁴ smartphone. A custom smartphone application, MESA, processed the continuous ECG and accelerometer data in real time, and initiated an experience sampling prompt anytime a substantial, sustained change in 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 an interbeat interval (IBI) change of more than ± 167 ms over an 8 s 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/s^2 within the preceding 30 s. Posture (standing, sitting, reclining) was determined by comparing the relative orientation of the two IMUs on a participant's torso and thigh. Absence of posture change was operationalized as any time when the relative orientation of the two IMUs did not change within the preceding 30 s.

Participants also received 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. 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 on page 1 of the supplemental materials.

At each sampling event, participants were prompted to respond to a series of questions presented in the MESA application. Participants first provided a brief free-text description of what was happening at the time they received the prompt. Participants then self-generated words to label their current affective experience. Participants were able to provide as many words as they felt necessary to describe their affective experience but were required to input at least one word. For each self-generated word, participants were asked to provide an intensity rating on a five-point Likert-style scale from 1 ("not at all") to 5 ("very much"). Participants also responded to additional questions that are not included in the present report (see page 1 of the supplemental materials for details).

At the end of each experience sampling day, participants received a modified day reconstruction survey (Kahneman et al., 2004; Stone et al., 2006), in which they were presented with the brief description of each prompt they completed during the day. After describing the event in more detail, participants were asked to rate the intensity of their emotional experience on a set of 18 emotion adjectives (“afraid”, “amused”, “angry”, “bored”, “calm”, “disgusted”, “embarrassed”, “excited”, “frustrated”, “grateful”, “happy”, “neutral”, “proud”, “relieved”, “sad”, “serene”, “surprised”, “worn out”) using a 7-point Likert-style scale from 0 (“not at all”) to 6 (“very much”). Participants also provided additional details about each experience sampling event that are not reported here (see page 3 of the supplemental materials).

Data Processing

Physiological signal processing and feature extraction. From the peripheral physiological data, we isolated periods of seated rest according to the following criteria: participant position is seated and not moving (i.e., no forward acceleration); participant maintains this position for at least 60 seconds; no experience sampling prompt was generated. We excluded data from the first 30 s of each period of seated rest to allow for signals to stabilize following movement. For each rest period, we derived the features of cardiovascular physiological activity listed in Table 3-1 using 30 s bins, and computed the mean and standard deviation of each feature across all bins. As reported in Hoemann et al. (2020), we also computed change scores for each experience sampling event, as the difference in each feature between the 30 s preceding the IBI change that initiated the experience sampling prompt and the 30 s following (Figure S3-1). Peripheral physiological signals were processed following previous work (Forouzanfar et al., 2018; Hoemann et al., 2020; Nabian et al., 2018) using an in-house pipeline coded in Python to accommodate the volume of physiological data collected (400+ hours), as well as the variability in signal morphologies and artifacts produced during long-term ambulatory monitoring.

Electrocardiogram (ECG). Raw ECG signal was passed through an elliptic bandpass filter to remove baseline and high frequency noise without affecting the waveform. Initial quality checks were then performed for each beat, checking for overall waveform shape, and acceptable minimum, maximum, and minimum-to-maximum values. Specific parameters are reported in Table S3-2.

R-peak detection for ECG was performed using established methods (P. Hamilton, 2002) and implemented using the BioSPPy package (Carreiras et al., 2018). Mean interbeat interval (IBI) was then derived as the average R-R interval. Additional quality checks (Table S3-2) were performed on each IBI series to ensure that values were within acceptable ranges (300-2000 ms), and that expected beat-to-beat differences were consistent with normal beats and unlikely to be artifacts (following established benchmarks; Berntson et al., 1990). ECG data failing any quality check were excluded from analysis.

Respiratory sinus arrhythmia (RSA) was derived from the IBI series. These calculations were coded to mimic the processing steps of standard HRV analysis software (MindWare Technologies LTD, Westerville, Ohio), including: cubic interpolation of beat-to-beat IBI, detrending to minimize non-stationarity, tapering using a Hamming window, and lastly, fast Fourier transformation (FFT). RSA was calculated as the log of the area under the power spectrogram that lies between .12 and .4 Hz.

Impedance cardiogram (ICG). The first derivative of the basal impedance (Z_0) signal, dZ/dt , was segmented into time windows corresponding to 250 ms before the ECG R-peak to 500 ms after; eight such segments (i.e., eight beats) were averaged together to form overlapping ensembles. B points were detected in each ensemble by taking the first and second derivatives of the dZ/dt signal and comparing them with thresholds based on signal frequency (Table S3-2). Forward and reverse autoregressive modeling was then used to perform detection and correction of B point outliers (Forouzanfar et al., 2018). X points were detected by examining the second derivative of the dZ/dt signal within each ensemble (Nabian et al., 2018). Segments of the ICG signal from which we could not detect B or X points and segments that corresponded with unusable ECG data were excluded from analysis.

Pre-ejection period (PEP) was calculated as the time (ms) between the ECG R peak and the ICG B point – also referred to as PEP_R (Berntson et al., 2004). Left ventricular ejection time (LVET) was calculated as the time (ms) between the ICG B point and X point. Quality checks (Table S3-2) were

performed; only values that occurred within an acceptable range (30-200 ms for PEP, 100-500 ms for LVET), and that did not result in changes in the gradient greater than 30 ms from one ensemble to the next were retained. Stroke volume (SV) was calculated using Kubicek's equation (Kubicek et al., 1966). Cardiac output (CO) was calculated as the product of SV and heart rate (Sherwood et al., 1990).

Impedance pneumogram. Respiration rate (RR) feature detection was performed based on methods described in previous work (de Geus et al., 1995; Ernst et al., 1999). The basal impedance signal, Z_0 , was tapered using a Hamming window and an interpolated finite impulse response (IFIR) bandpass filter was applied using the defined RSA frequency band (.12-.40 Hz $\pm$ 20%) as the low/high cutoffs. The resulting waveform was then detrended and zero-averaged before being subjected to an FFT. The resulting frequency spectrum was used to identify the primary (i.e., highest-power) frequency above .17 Hz (approximately 10 cycles/min). This lower boundary was introduced to avoid potential influence from the Traub-Hering-Mayer (THM) peak related to baroreceptor activity (Berntson et al., 1993) and to reflect clinical guidelines of a 12 cycle/min minimum (Bleyer et al., 2011). As described on pages 1-2 of the supplemental materials, two five-minute resting baselines were recorded for participants in the lab. During these baselines, RR was recorded using a respiratory belt, such that these values represented criterion measures for participants' ambulatory RR. In-lab RR for each baseline was scored in 30 s bins, with maximum resting RR defined as $M_{RR} + 3*SD_{RR}$ and minimum resting RR defined as $M_{RR} - 3*SD_{RR}$. Maximum change in in-lab RR was defined as the greatest (absolute value) difference between subsequent 30 s bins. Segments of the ICG signal in which derived RR value(s) exceeded any of these thresholds, and segments that corresponded with unusable ECG data, were excluded from analysis.

Emotional granularity. The intensity ratings for the 18 emotion adjectives in the end-of-day surveys were used to compute estimates of emotional granularity for each participant. Following prior literature (e.g., Tugade et al., 2004), granularity was computed as an intraclass correlation (ICC) using agreement with averaged raters ('A-k' method; Shrout & Fleiss, 1979). Higher ICC values reflected lower emotional granularity (i.e., greater shared variance among adjectives' ratings). Negative values are outside the theoretical range for an ICC, and so were recoded as 0 (following e.g., Anand et al., 2017). Separate indices of granularity were computed for pleasant (positive) versus unpleasant (negative) emotions, with this distinction based on normative ratings (Warriner et al., 2013). These indices were averaged to create an overall estimate of granularity (e.g., E. R. Edwards & Wupperman, 2017). ICCs were Fisher r -to- z transformed to fit the variable to a normal probability distribution. These transformed values were multiplied by -1 to yield an estimate of granularity that scaled intuitively, such that lower (more negative) values reflect lower granularity, and higher (less negative) values reflect higher granularity. Data for a given experience sampling day were excluded from analysis if the participant did not complete at least six prompts or if the participant completed the corresponding end-of-day survey late (i.e., the following day). Participants completed an average of 8.80 prompts ($SD = 1.22$) per day.

Analyses

Correlational analyses. We entered emotional granularity as a predictor in a multiple regression with resting RSA as the dependent variable, and controlling for resting RR (e.g., Grossman et al., 1991). We also fitted a model with IBI to control for differences in heart rate, which is known to have a negative relationship with HRV (de Geus et al., 2019). Recent studies have shown that RSA is non-linearly related to indices of mental and physical health (with extreme values of RSA linked to maladaptive psychological and physiological processes; Kogan et al., 2013, 2014; Stein et al., 2005). Accordingly, we examined the nature of the relationship between resting RSA and granularity and, if necessary, fitted regressions using a quadratic term for RSA. In all analyses, we used the R^2 for the granularity term as a measure of variance explained. Because we had a directional prediction, we used a one-tailed test of significance at $\alpha < .05$.

Clustering analyses. We submitted all periods of seated rest from each participant to a separate Dirichlet Process-Gaussian Mixture Model (DP-GMM) with Variational Inference (Bishop, 2006; Blei & Jordan, 2006). DP-GMM is a specialized variant of Gaussian Mixture Modeling (GMM) that allowed us to discover the number of clusters in the data, as well as each cluster's location (i.e., mean), shape (i.e., covariance), and relative size (i.e., mixture proportion or prior probabilities of a point belonging to that

cluster relative to others; see Table S3-3 for specific parameter values). Data points were four-dimensional vectors of resting period means for RSA, RR, IBI, and PEP, standardized prior to clustering. These features were selected to further investigate the role of RSA (and thereby PNS activity) during seated rest: RR and IBI are directly related to RSA, while PEP provides an inverse estimate of SNS activity. An average of 112.18 ($SD = 69.07$) seated rest periods were submitted to clustering per participant. Two participants were excluded because they had fewer than seven days of sufficient seated rest data. We assessed the cross-participant correlation between number of clusters and granularity using a one-tailed test of significance at $\alpha < .05$.

Classification analyses. As reported by Azari et al. (2020), event-specific change scores from each participant were submitted to separate supervised classification analyses. Four participants were excluded because they had fewer than 70 experience sampling events devoid of major physiological artifact. Only experience sampling events that corresponded with each participant's top three most frequently-generated emotion labels were used; the data point for each event was a six-dimensional vector of the change scores for IBI, RSA, PEP, LVET, SV, and CO. RR was not included in this analysis because breathing rates are typically too low-frequency to capture meaningful changes from one 30-s period to another. An average of 72.73 ($SD = 28.46$) events were used for classification per participant. For each participant, a fully-connected neural network was trained and tuned using five-fold cross-validation: the data were divided into five groups, and the network iterated across all combinations of training on four-fifths and testing on the left-out fifth. Details of neural network configuration are reported on page 5 of the supplemental materials. For each fold, accuracy was measured as the proportion of events for which vectors of changes scores were classified as belonging to their respective emotion labels. We assessed the cross-participant correlation between mean classification accuracy against granularity using a two-tailed test of significance at $\alpha < .05$.

Results

Correlational Analyses

Consistent with our predictions, a multiple regression across participants revealed a positive association between emotional granularity and resting RSA. This relationship held when controlling for RR, but was not significant ($r = .18$, $p = .11$; $b = .61$, 95% CI $[-.42, 1.63]$, $\beta = .17$, $R^2 = .03$, $F(1,47) = 1.43$, $p = .12$, one-tailed). These results did not change when controlling for IBI in addition to RR ($b = .48$, 95% CI $[-.33, 1.30]$, $\beta = .14$, $R^2 = .02$, $F(1,46) = 1.43$, $p = .12$, one-tailed). An examination of the scatter plots of both raw and residualized variables suggested a linear relationship, so we did not fit regressions using a quadratic term for RSA (Figure 3-1). See page 5 of the supplemental materials for exploratory within-participants correlational analyses.

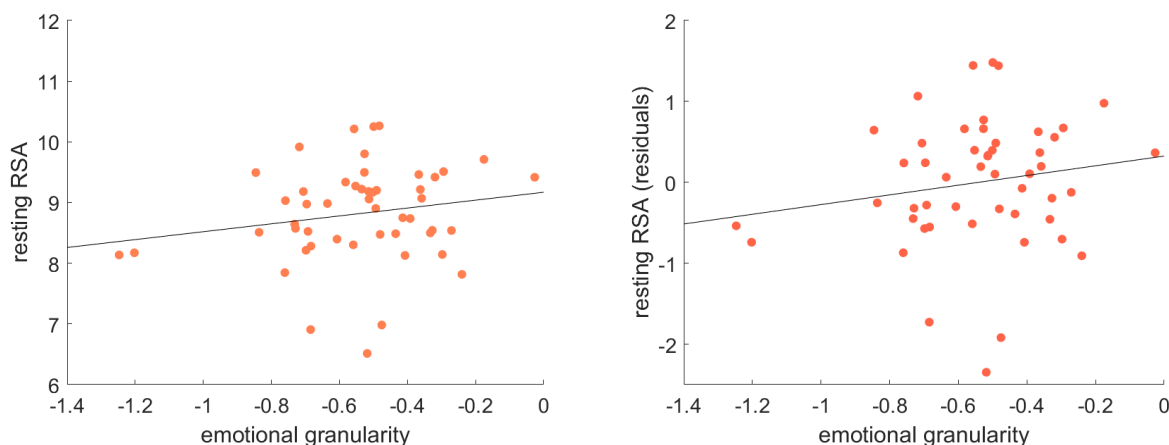


Figure 3-1. Scatter plot of the relationship between emotional granularity (x-axis) and mean RSA measured during periods of seated rest in everyday life (y-axis). *Left panel:* raw RSA scores. *Right panel:* residualized RSA scores after controlling for RR.

Clustering Analyses

Consistent with our predictions, emotional granularity correlated positively with the number of clusters discovered, such that individuals with higher granularity exhibited a greater number of patterns of physiological activity during seated rest, $r = .33$, $p = .012$, one-tailed (Figure 3-2, left panel). It is possible that these results can be partially accounted for by individual differences in the amount of seated rest data. Because a DP-GMM discovers the number of clusters in each participant's data, in principle a greater number of data points (here, periods of seated rest) allows for the discovery of a greater number of clusters. In the present analyses, we observed that the number of clusters discovered indeed had a significant positive correlation with the number of seated rest periods, $r = .58$, $p < .001$, two-tailed. Notwithstanding, the relationship between granularity and the number of discovered clusters held after controlling for the number of seated rest periods, $b = 2.55$, 95% CI $[-.34, 5.45]$, $\beta = .21$, $R^2 = .04$, $F(1,45) = 3.16$, $p = .041$, one-tailed (Figure 3-2, right panel). See pages 5-11 of the supplemental materials for exploratory between-participants clustering analyses.

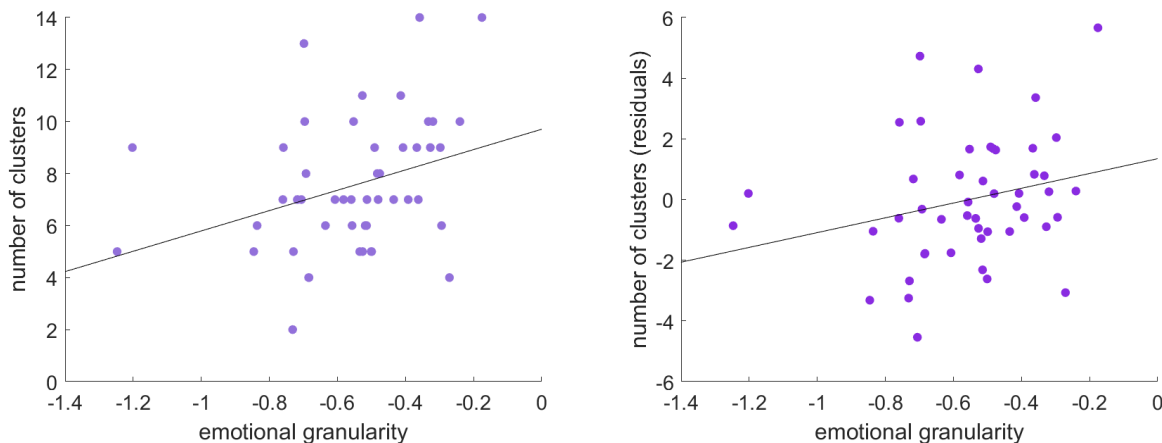


Figure 3-2. Scatter plot of the relationship between emotional granularity (x-axis) and number of clusters discovered in cardiovascular physiological activity during periods of seated rest in everyday life (y-axis). *Left panel:* raw number of clusters. *Right panel:* residualized number of clusters after controlling for number of seated rest periods.

Classification Analyses

Consistent with our predictions, emotional granularity correlated positively with mean classifier performance, such that individuals with higher granularity exhibited patterns of cardiovascular physiological activity during emotional events that were more accurately matched to their corresponding emotion label (i.e., based on participants' own ground truth), $r = .29$, $p = .049$, two-tailed (Figure 3-3, left panel). The relationship with classification accuracy was particularly strong for granularity for positive (i.e., pleasant) emotions (e.g., amusement, calm, excitement), $r = .35$, $p = .018$, two-tailed (Figure 3-3, right panel).

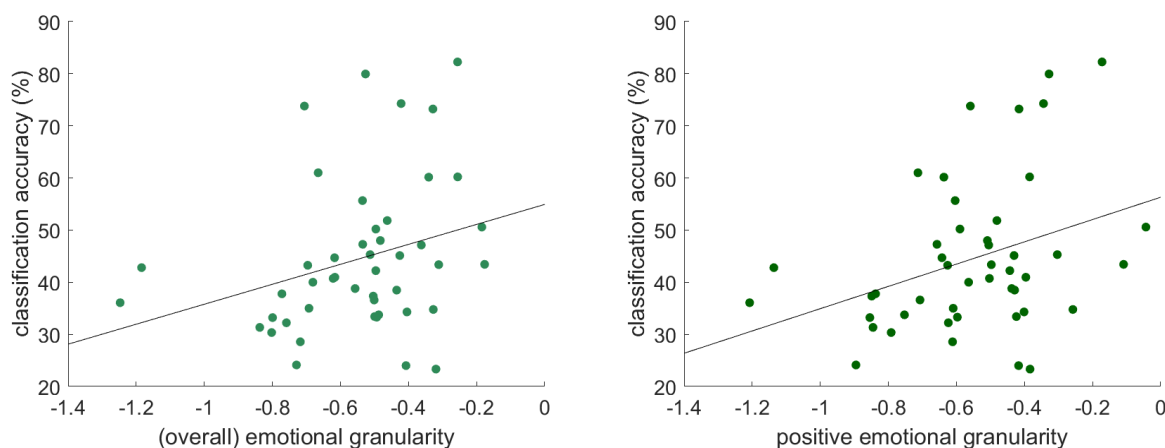


Figure 3-3. Scatter plot of the relationship between emotional granularity (x-axis) and classification accuracy for patterns of change in cardiovascular physiological activity during emotional events in everyday life (y-axis). *Left panel:* overall emotional granularity scores. *Right panel:* granularity scores for positive (i.e., pleasant) emotions.

Discussion

Despite strong evidence of a link between emotional granularity and mental health (e.g., Kashdan et al., 2015; Smidt & Suvak, 2015), the relationship between granularity and physical health has been under-investigated. Filling this gap is particularly critical given ties between CVD and depression (e.g., Carney et al., 2005; Stein et al., 2000; Vaccarino et al., 2008). In the present study, we used data from an experience sampling study with ambulatory physiological monitoring to test hypotheses about the relationship between granularity and cardiovascular physiological activity in daily life. We found that individuals with higher granularity tended to exhibit higher RSA during periods of seated rest, although this relationship did not reach statistical significance in our sample. We also found that individuals with higher granularity exhibited more patterns of physiological activity (as discovered during seated rest), and that these patterns were more distinctive (as assessed during emotional events). These findings join a growing number of studies linking granularity to more specific action planning, as manifested via better self-regulation (e.g., Barrett et al., 2001; Kalokerinos et al., 2019) and adaptive coping strategies (e.g., Kashdan et al., 2010; Starr et al., 2017). In linking granularity with physiological diversity and specificity, these findings provide the first evidence of how granular action planning may be manifested in the body and brain (see also Lee et al., 2017b).

Emotion Concepts as an Underlying Mechanism

Better self-regulation and adaptive coping strategies are also observed in individuals with higher resting RSA (e.g., Appelhans & Luecken, 2006; Geisler et al., 2010), suggesting a common mechanism underlying both (dys)regulated psychological and physiological processes. As reviewed previously, lower emotional granularity may be linked with CVD via a form of compromised and inefficient allostasis (Sterling, 2012). This hypothesis is consistent with constructionist accounts of emotion, which propose that concepts are the mechanism by which the brain makes meaning of the current situation, and proactively tailors the body's responses accordingly (i.e., accomplishes allostasis; Barrett, 2017b; Hoemann et al., 2017). In particular, the theory of constructed emotion (TCE; Barrett, 2006, 2012, 2013, 2017b, 2017a) offers a biologically-principled model of how the brain constructs emotional experiences using concepts in the service of allostasis. Concepts are principles of categorization (Rosch, 2002) – the accrued knowledge and experience by which the brain determines how to best categorize incoming sensory input. The TCE proposes that the brain is an internal model of its body in the world, which uses concepts (i.e., prior experience) as predictions to regulate the body's autonomic, immune, and neuroendocrine systems to prepare for the metabolic demands of situated behavior and anticipate viscerosensory inputs (Barrett, 2006, 2012, 2013; Garfinkel et al., 2015). When a prediction is confirmed

by incoming sensory inputs, it has explained them (by categorizing sensations) and guided action (by identifying causes and consequences; Barrett, 2017a; Barrett & Simmons, 2015; Chanes & Barrett, 2016; Hohwy, 2013).

This mechanistic, brain-based approach explains how a potential vulnerability factor, insufficiently distinct emotion concepts, relates lower emotional granularity to less effective physiological regulation (Barrett, 2017b; Barrett et al., 2014, 2015; Kashdan et al., 2015). Following from the TCE, individual variation in the experience of emotion and its associated patterns of physiological activity is the norm (Hoemann et al., 2020), and is tied to individual differences in the granularity of emotion concepts. Indeed, meta-analyses of cross-sectional laboratory studies indicate that emotion categories like anger and fear do not show consistent, specific patterns of ANS activity (Siegel et al., 2018). Rather, each category evidences tremendous ANS heterogeneity, such that pattern classifiers from one study do not replicate in subsequent studies (Kragel & LaBar, 2013; Stephens et al., 2010; for discussion, see Quigley & Barrett, 2014). The TCE posits that precise emotional experiences and associated patterns of physiological activity come from precise emotion concepts, which the brain uses to create situation-specific predictions to guide physiological regulation and situated action (e.g., Barrett, 2006, 2013). Recent neuroimaging studies have shown that emotional experiences are constructed by brain networks involved in implementing emotion concepts (Lindquist et al., 2012; Wilson-Mendenhall et al., 2011, 2014), and these same networks contain the majority of the visceromotor (limbic) circuitry that regulates the systems of the body (Kleckner et al., 2017). This evidence supports the hypothesis that a person with fewer emotion concepts, or little diversity in the exemplars of concepts, will regulate their ANS less effectively and may be experientially blind to their highly variable physiological sensations, experiencing instead general feelings pleasantness and activation (Barrett, 2017a, 2017b).¹⁹

Constructionist accounts of emotion such as the TCE are further consistent with neurobiological perspectives on psychological stress and CVD, such as that proposed by Gianaros and Jennings (2018). From this perspective, maladaptive patterns of cardiovascular physiological activity are the result of visceral prediction errors, in which the brain issues predictions (i.e., visceral motor commands) for metabolic support that are disproportionate or mismatched to actual demands. In turn, afferent neural pathways convey visceral sensory information from the body to the brain, and this information shapes future predictions. Visceral prediction errors may also have psychological consequences, as metabolic burdens (e.g., inflammatory responses) are associated with changes in affect (e.g., unpleasant mood, fatigue) and with depression (Harrison, Brydon, Walker, Gray, Steptoe, & Critchley, 2009; Harrison, Brydon, Walker, Gray, Steptoe, Dolan, et al., 2009).²⁰ In this way, dysregulated psychological and physiological processes are linked through a maladaptive brain-body loop (Gianaros & Jennings, 2018). This emphasis on feedback and feedforward processes in cardiovascular psychophysiology is also present in Obrist's (1981) model of cardio-somatic uncoupling. Similarly, Thayer and Lane (2000) present a dynamical systems approach to neurovisceral integration in their model of emotion (dys)regulation and its relationship to cardiovascular health (see also Lane et al., 2009; Thayer et al., 2012; Thayer & Lane, 2009). The present findings cannot be fully accounted for by these frameworks, however, as they do not provide a role for both diversity and specificity of predictions (e.g., via emotion concepts) in efficient allostasis. In this regard, the TCE offers unique insight into the relationship between emotional and physical health.

Alternative Explanations and Limitations

¹⁹ For example, individuals with lower emotional granularity (measured as alexithymia) have impoverished emotion concepts and restricted emotion vocabulary (Lecours et al., 2009; Meganck et al., 2009; Roedema & Simons, 1999), and report physical symptoms and feelings of affect, but do not consistently experience them as emotional (Lane et al., 1997; Lane & Garfield, 2005).

²⁰ More generally, evidence suggests that prediction errors are encoded in the anterior cingulate cortex (ACC; e.g., Hyman et al., 2017) and periaqueductal gray (PAG; e.g., Roy et al., 2014) – areas associated with the experience of negative and aversive affect (Buhle et al., 2013; Hajcak et al., 2004; Satpute et al., 2013; Shackman et al., 2011).

The hypotheses of the TCE notwithstanding, there are alternative explanations that may account for the present findings. For example, the relationship between emotional granularity and the number of patterns in physiological activity during seated rest may be due to individual differences in the proportion of time spent in various situational contexts (e.g., work vs. home) or engaged in various activities (e.g., socializing vs. watching TV). It could be that individuals whose days are distributed across a greater diversity of situations and activities also exhibit a greater diversity of accompanying patterns of physiological activity. This hypothesis remains to be tested in future research, which should also account for the time-dynamic nature of both physiological and psychological data. Relatedly, the relationship between granularity and the physiological specificity of emotional events may be attributable to individual differences in conscientiousness: perhaps individuals with higher granularity provided higher-quality data that were easier to classify (e.g., by being more intentional with their selection of in-the-moment emotion words). We consider this possibility unlikely. Individuals can control which emotions they self-report, but cannot directly control their physiological activity. However, it is possible that individual differences in interoceptive ability (e.g., Garfinkel et al., 2015) may partially account for these findings, as individuals with higher granularity may be better able to differentiate between the bodily states underlying emotional experience (Barrett et al., 2004; Herbert et al., 2011). Measures of interoceptive ability (e.g., Schandry, 1981; Whitehead et al., 1977) were not collected in the present study, and should be added by future extensions of this work. Finally, it is possible that the present findings can be partially accounted for by covariates such as age, sex, ethnicity, and socioeconomic status (SES). In the present sample, participants covered a limited range of demographic variables, suggesting that these factors are not likely to contribute greatly to the observed effects. Future replications of this experimental paradigm will provide us with sufficient statistical power to confirm these hypotheses in a larger sample.

The present study also has limitations. This was the first study to employ a physiologically-triggered experience sampling paradigm, and so served as a proof of concept. The sample size was set accordingly, and was not adequately powered to detect smaller effect sizes – such as that observed for the relationship between emotional granularity and resting RSA. Granularity and resting RSA are both indirect indices (i.e., proxies) for the efficiency of prediction and allostasis, so it makes sense that the effect size is small. As a non-clinical sample, participants with chronic health conditions or a current mental health diagnosis were excluded. This decision restricted the range of values that could be observed for both physiological and psychological measures. Likewise, the use of ambulatory data may have decreased our signal-to-noise ratio, obscuring relationships that we may have been able to discern in the lab. However, we view the use of ambulatory measures as a strength rather than a weakness. By providing support for our hypotheses in the world, we have established a lower bound on the possible effect size of granularity's relationship with cardiovascular physiological activity. We have also demonstrated generalizability of these effects to everyday life.

Implications for Future Research

The present study is the first to demonstrate a relationship between emotional granularity and peripheral physiological measures with impact for health. Interpreted within the framework of the TCE, these findings raise the possibility that interventions that improve granularity will also decrease risk for physical (i.e., cardiovascular) illness by increasing the efficiency of allostasis and encouraging adaptive coping mechanisms. In particular, concept training methods may be an avenue for improving granularity. Improvements in emotion concept knowledge have been trained in children and adolescents and result in better self-regulation, social functioning, and academic performance (Hagelskamp et al., 2013; Rivers et al., 2013). In adults, simply cueing participants to focus on the subtlety and variety of their experiences improves their ability to make nuanced distinctions between different emotions, and helps them to better understand how emotions impact judgments (Cameron et al., 2013). However, researchers have yet to identify how emotion concepts can be trained most efficiently, or test the relative efficacy of different training methods for improving granularity. Evidence from the concept acquisition literature indicates that language plays a special role in concept acquisition due to its capacity to direct attention, communicate

intentionality, and organize shared experience (Chen & Waxman, 2013; Ferry et al., 2010; Gelman, 2009). Words provide context to make meaning from perceptual cues, encouraging integration across multiple sensory channels (Goldstone et al., 2001). More importantly: language creates a context for prediction, in which words minimize prediction error by fine-tuning top-down influences on lower-level processes (Lupyan & Clark, 2015). Future research could test the hypothesis that words are integral to emotion concept training, in the service of enhancing granularity and efficient allostasis.

Emotion concept training could likewise be assessed for its potential to produce changes in the ANS activity associated with emotional experience, including changes in RSA. For example, in-lab training protocols could measure pre- and post-training physiological reactivity to tasks that are emotionally-evocative (e.g., scenario immersion protocols; Wilson-Mendenhall et al., 2011, 2013, 2014) or stress-inducing (e.g., serial subtraction; Kirschbaum et al., 1993), to determine if there are corresponding changes in RSA reactivity. If in-lab training were to have the predicted effects on both behavioral and physiological measures, these findings would set the stage for work testing whether longer-term training mitigates declines in resting RSA in a community sample. These general population studies could include additional metabolic measures, such as blood pressure, lipids, or hair cortisol, to assess how markers of CVD risk are impacted by training in a naturalistic setting over the course of months. Future work of this nature would extend the current line of research into direct, clinical tests of the causal relationship between granularity and cardiovascular health, with the prospect of transforming our understanding of how the mind and body are integrated.

Author Notes

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K.H., L.F.B., and K.S.Q. designed the study. K.H. assisted with data collection. All authors developed the data pre-processing and analysis plan; Z.K., K.H., and N.K. analyzed the data. K.H. wrote the manuscript. All authors reviewed and revised the manuscript.

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

Methods

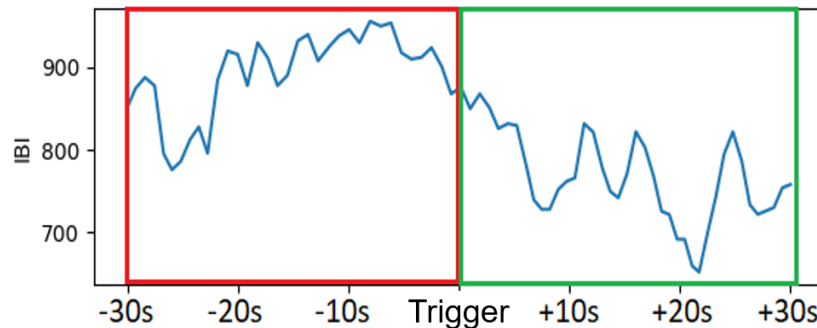


Figure S3-1. Example interbeat interval (IBI) series taken from ECG signal 30 seconds preceding and following an event trigger, or the start of the period of heart rate change preceding an experience sampling prompt. All physiological measures are calculated as change scores, in which the mean of the 30 seconds preceding the trigger is subtracted from the mean of the 30 seconds following the trigger.

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.

Payment

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.

In-Lab Tasks and Questionnaires

Participants completed in-lab sessions before and after experience sampling, each two-three 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 the initial in-lab session, 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 five-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; K. 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 S3-1. Upon completion of the session, participants were disconnected from the physiological equipment, instructed about the scheduling of their experience sampling days, and paid.

In the second and final in-lab session, participants were first instrumented for physiological monitoring and then asked to complete the Session 2 questionnaires listed in Table S3-1. Participants were then instrumented with blood pressure cuffs and finger PPG and sat quietly for a five-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; K. 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.

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”). Second, participants were asked to provide a brief description of what was happening as they received the prompt. 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).

Table S3-1. 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 & McRae (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

Physiological Signal Processing

Table S3-2. Hyperparameters for Physiological Signal Processing

Signal	Hyperparameter	Value	Reference Value	Reference Publication
Electrocardiogram (ECG)	Length of signal for flatness check	1.2*sampling frequency	0.8*sampling frequency	Nabian et al. (2018)
	Minimum standard deviation for flatness check	1.00E-05	1.00E-05	
	Length for minimum-maximum check	1.2*sampling frequency	1.2*sampling frequency	
	Minimum/maximum for max/min check	-.005/.005	-.005/.005	
	Length of signal for skewness check	1.2*sampling frequency	1.2*sampling frequency	
	Length of sub-chunks for skewness check	.064*sampling frequency	.032*sampling frequency	
	Minimum skewness	.45	.45	
Impedance cardiogram (ICG)	Window for point detection around R-peak	-250ms to +500ms	-250 ms to +500 ms	Nabian et al. (2018)
	Number of cycles for ensemble averaging	8	8	Forouzanfar et al. (2018)
	Maximum dZ/dt slope (d^2Z/dt^2) for d^3Z/dt^3 zero-crossings over first third of detected most prominent monotonically-increasing segment	Start threshold at 2*H/fs, increase in steps of 2 until > 1 zero-crossing; max 10*H/fs	10*H/fs	
	Minimum d^3Z/dt^3 value for local maxima over first third of most prominent monotonically-increasing segment	7*H/fs	4*H/fs	

Note: Default parameters, originally selected based on data collected in laboratory settings, were found to be too aggressive for this ambulatory data set, so we relaxed these thresholds based on manual review of the results by experts (e.g., K.S.Q.) for a random subset of the data.

Unsupervised Clustering Analyses

Table S3-3. Hyperparameters for Dirichlet Process-Gaussian Mixture Modeling (DP-GMM)

Hyperparameter	Value
Initial number of components	Number of events
Number of random restarts	100
Covariance type	Full
Initialization	K-means
Weight concentration prior	Dirichlet Process
Mean prior	Mean of data

Supervised Classification Analyses

Neural networks were multilayer perceptrons (Baum, 1988) trained and tuned per participant. The analyses were implemented in MATLAB's Deep Learning Toolbox (MathWorks, Natick, MA). Networks consisted of three fully-connected layers of size 5, 4, and 3. After each fully-connected layer, a batch normalization layer was used to speed up training and reduce sensitivity to initialization (Ioffe & Szegedy, 2015). A rectified linear unit (ReLU) activation layer was applied after batch normalization (Nair & Hinton, 2010). Finally, a soft max layer generated the classification probabilities. The batch size was 10, the maximum epoch was set to 50, and the learning rate was chosen as a hyperparameter to be equal to .001. ADAM optimization algorithm (Kingma & Ba, 2014) was used to iteratively update network weights in the training procedure.

Supplemental Results

Within-Participants Correlational Analyses

We tested the hypothesis that emotional granularity is positively related to resting RSA within participants in our sample, to examine possible correlations in day-to-day variation in emotional experience and cardiovascular physiology. Using person-specific linear multiple regressions, we compared mean RSA from all periods of seated rest per day with day-level estimates of emotional granularity. Because we had directional predictions, we used one-tailed tests of significance at $\alpha < .05$.

These analyses revealed that the direction of the relationship between granularity and resting RSA varied by participant. Only 52% of participants evidenced a positive relationship between granularity and resting RSA (defined as a positive regression coefficient for the granularity term) when controlling for RR; this relationship was significant ($p < .05$, one-tailed) for 18% of participants, and trending toward significance ($p < .10$, one-tailed) for 30% of participants. These results did not change when controlling for IBI in addition to RR (50% positive coefficients; 18% significant). An examination of the scatter plots of both raw and residualized variables suggested only linear relationships, so we did not fit regressions using a quadratic term for RSA.

Between-Participants Clustering Analyses

We tested the hypothesis that estimates of emotional granularity and/or resting RSA will drive participants' patterns of overall ANS activity, rather than PEP or other cardiovascular features. We predicted that participants will cluster together based on similar levels of granularity and/or resting RSA (an index of PNS activity), and that PEP (an index of SNS activity) would play a weaker role in clustering. To test this hypothesis, we submitted all participant-level data to four clustering analyses using Dirichlet Process-Gaussian Mixture Modeling (DP-GMM) with Variational Inference (Bishop, 2006; Blei & Jordan, 2006). Data points submitted to clustering varied by analysis. In clustering analysis 1a, we clustered participants using four-dimensional vectors of participant-level means for RSA, RR, IBI, and PEP. In analysis 1b, we added participant-level estimates of granularity to cluster on five-dimensional vectors. In analysis 2a, we included both participant-level means and standard deviations for the

cardiovascular features only, to create eight-dimensional vectors. In analysis 2b, we again added participant-level estimates of granularity to cluster on nine-dimensional vectors. Due to the larger number of features submitted in analyses 2a and 2b, we reduced the number of parameters estimated by the model by restricting the covariance matrices to only estimate the diagonals. In all analyses, data points were standardized prior to clustering by subtracting the grand mean and dividing by the standard deviation of each feature. Specific parameter values are reported in Table S3-3.

For each clustering analysis, we examined the mutual information (MI) between cluster assignments and features (following Wormwood et al., 2019). MI reflects the extent to which knowledge of one random variable (here, one feature) reduces the uncertainty of another random variable (here, the cluster assignments). Higher MI values include greater reduction in uncertainty, such that features with higher values can be understood as driving the clustering solution. Because MI is unbounded, we standardized this measure so that values ranged between 0 and 1 (Darbellay & Wuertz, 2000). For analyses where granularity was not included as a feature (i.e., analyses 1a and 2a), we used a one-way ANOVA to determine whether there were significant differences in granularity between clusters. Because these analyses were more exploratory in nature, we used a two-tailed test of significance at $\alpha < .05$.

An initial DP-GMM over participant-level means for RSA, RR, IBI, and PEP discovered six clusters in participants' cardiovascular activity during seated rest in everyday life; five of these clusters included more than one participant (see Figure S3-3 for feature correlation matrices per cluster). Contrary to our predictions, MI values were roughly equivalent across features (Figure S3-2, upper left panel), suggesting that participant-level differences in resting RSA were not a main driver. Further, a one-way ANOVA revealed that participant clusters did not vary in level of emotional granularity, $F(4,42) = .30$, $p = .88$, two-tailed. A second DP-GMM over participant-level means, including granularity, discovered 10 clusters of participants, seven of which included more than one participant (see Figure S3-4 for feature correlation matrices). MI values suggested that neither RSA nor granularity was a main driver of the solution (Figure S3-2, upper right panel).

A third and fourth DP-GMM were used to explore the contribution of variability in cardiovascular activity to group-level clustering. These models included participant-level standard deviations in addition to the means for RSA, RR, IBI, and PEP. The third DP-GMM, over participant-level means and standard deviations, discovered six clusters of participants, four of which included more than one participant (see Figure S3-5 for feature correlation matrices). These participant clusters did not vary in level of emotional granularity, $F(3,42) = .17$, $p = .91$, two-tailed. The fourth DP-GMM, which also included granularity, discovered 29 clusters of participants, five of which included more than one participant (see Figure S3-6 for feature correlation matrices). Feature comparisons using MI again suggested that RSA and granularity did not exert a larger amount of influence on the clustering solutions than other included features (Figure S3-2, lower panels).

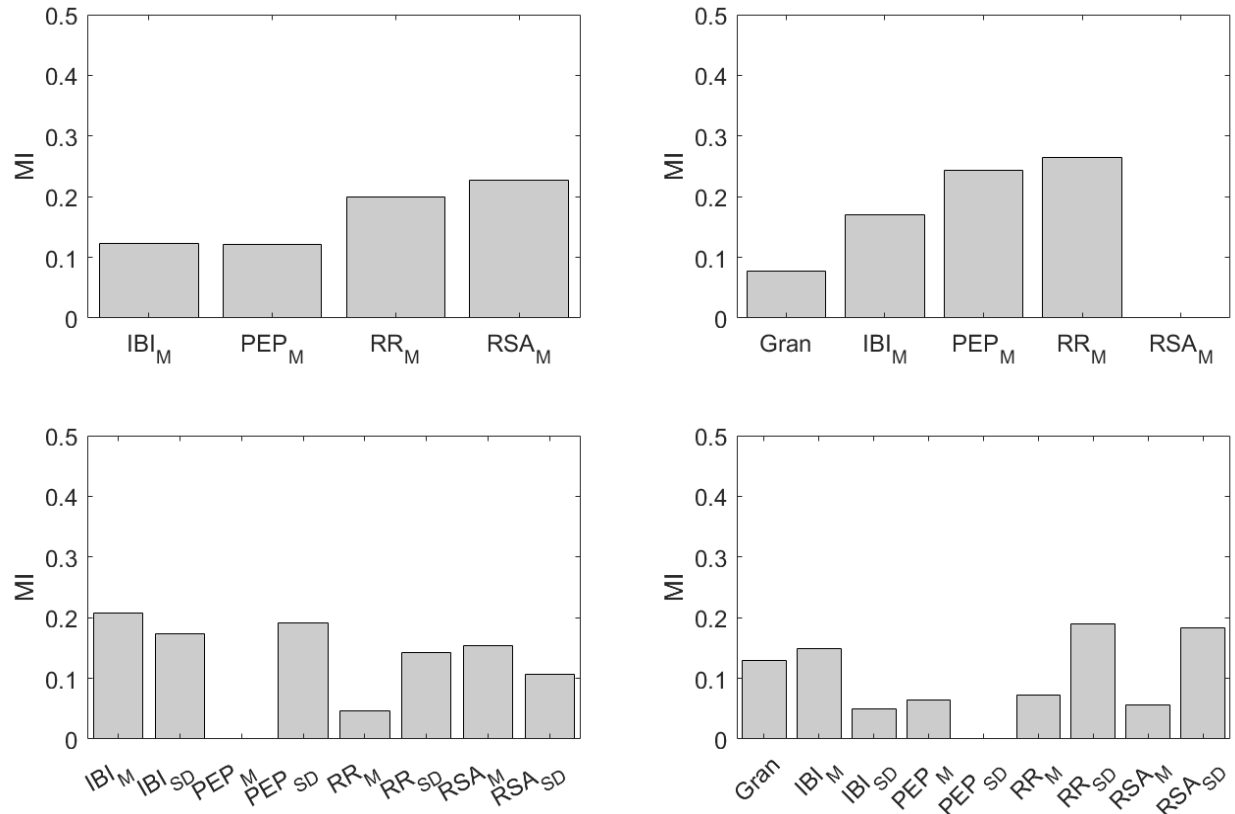


Figure S3-2. Bar graphs of the mutual information (MI) between each physiological feature and participants' group-level clustering assignments. *Upper left panel:* clustering analysis including mean IBI, PEP, RR, and RSA per participant. *Upper right panel:* clustering analysis including emotional granularity in addition to mean IBI, PEP, RR, and RSA per participant. *Lower left panel:* clustering analysis including mean and standard deviation IBI, PEP, RR, and RSA per participant. *Lower right panel:* clustering analysis including emotional granularity in addition to mean and standard deviation IBI, PEP, RR, and RSA per participant.

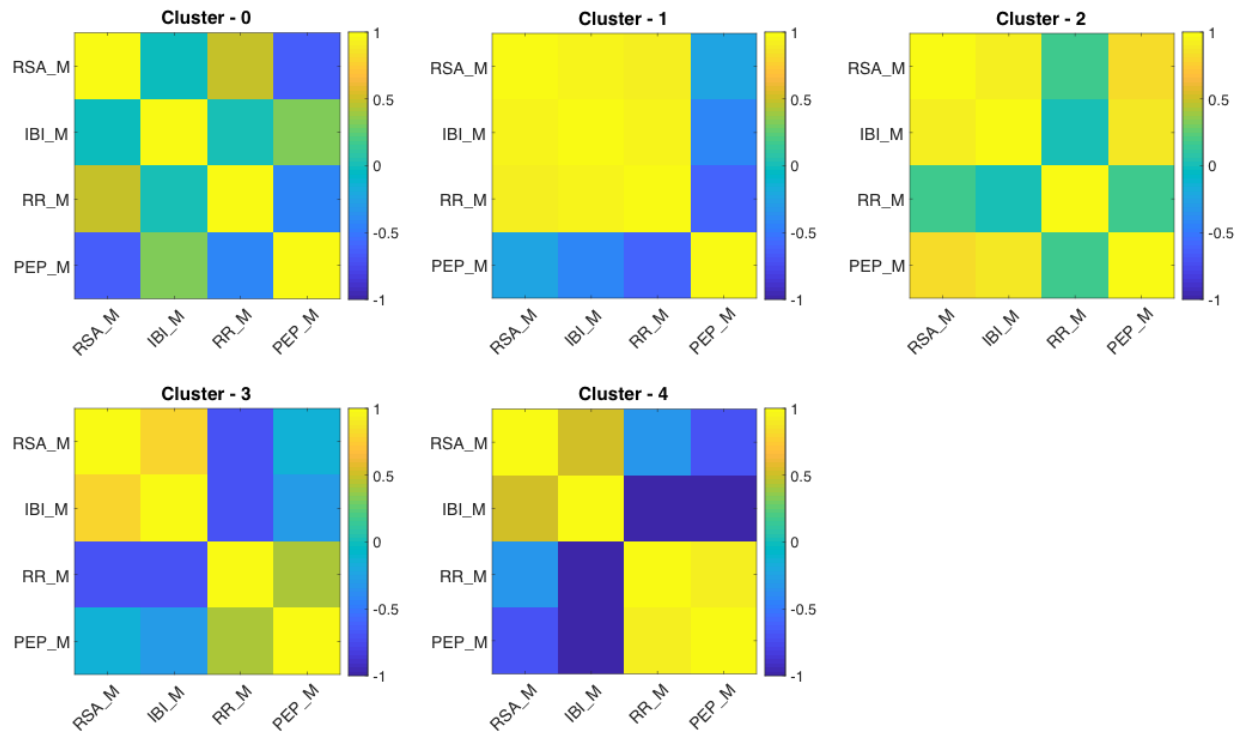


Figure S3-3. Feature correlation matrices per cluster discovered in between-participants clustering analysis 1a. A DP-GMM over participant-level means for RSA, RR, IBI, and PEP discovered six clusters of participants. Feature correlation matrices are provided for the five clusters that included more than one participant.

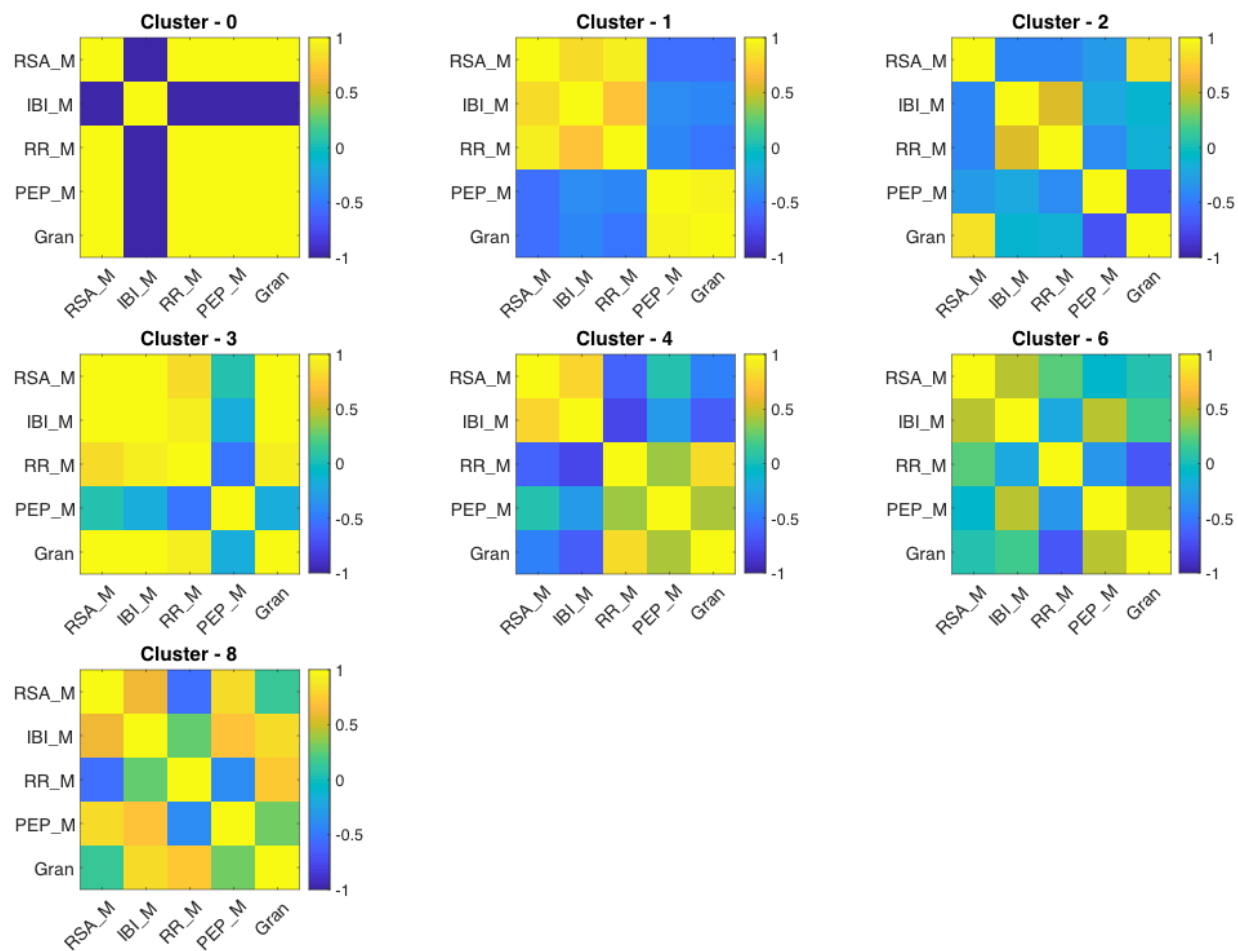


Figure S3-4. Feature correlation matrices per cluster discovered in between-participants clustering analysis 1b. A DP-GMM over participant-level means for RSA, IBI, RR, and PEP, and including granularity, discovered 10 clusters of participants. Feature correlation matrices are provided for the seven clusters that included more than one participant.

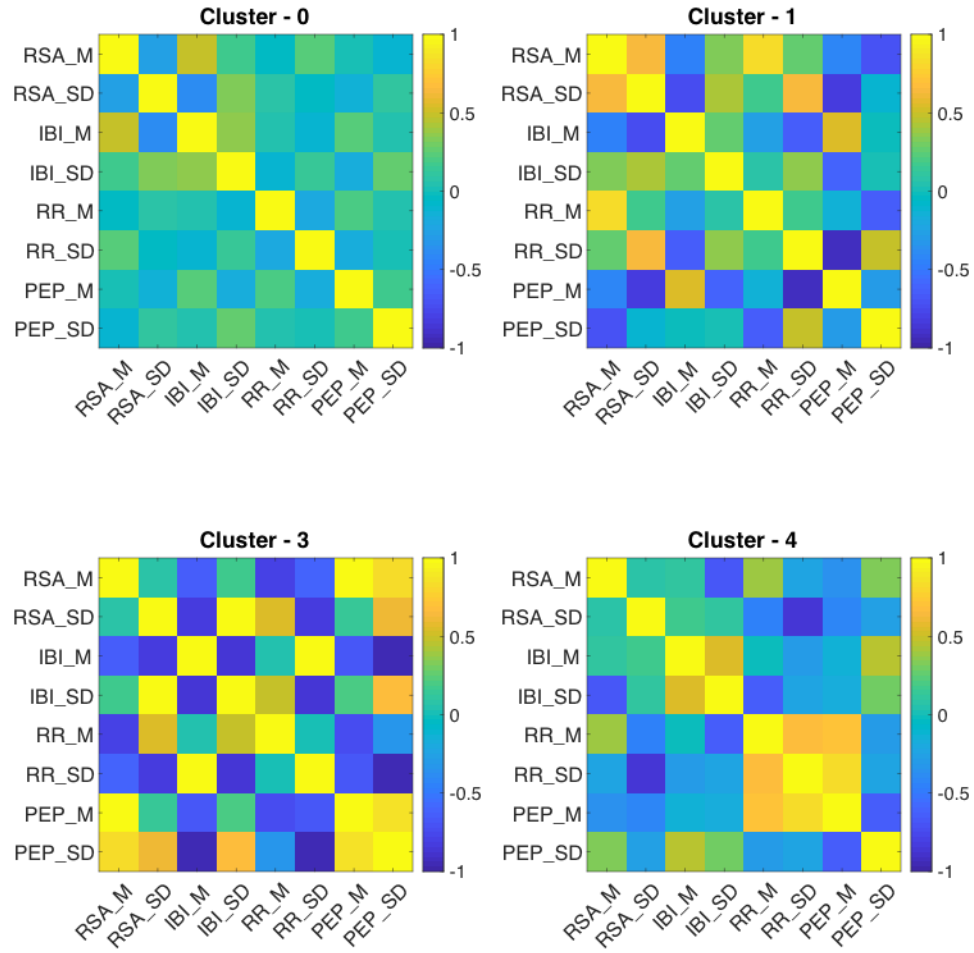


Figure S3-5. Feature correlation matrices per cluster discovered in between-participants clustering analysis 2a. A DP-GMM over participant-level means and standard deviations for RSA, IBI, RR, and PEP discovered six clusters of participants. Feature correlation matrices are provided for the four clusters that included more than one participant.

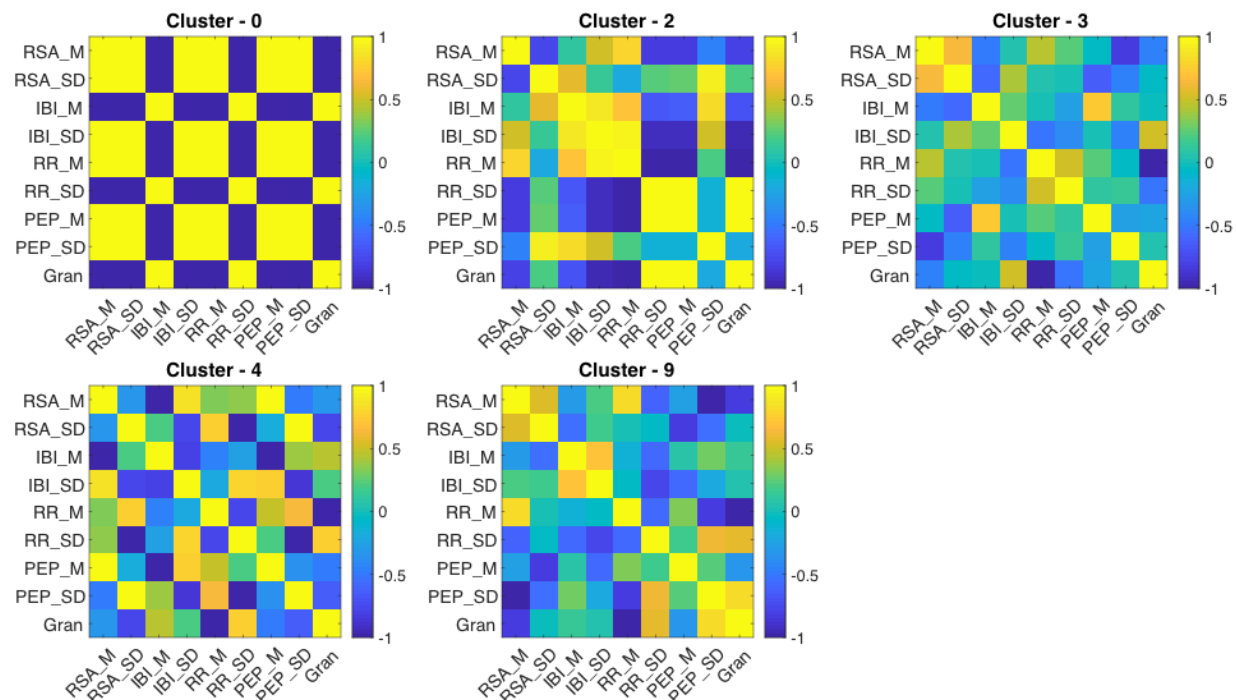


Figure S3-6. Feature correlation matrices per cluster discovered in between-participants clustering analysis 2b. A DP-GMM over participant-level means and standard deviations for RSA, IBI, RR, and PEP, and including granularity, discovered 29 clusters of participants. Feature correlation matrices are provided for the five clusters that included more than one participant.

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