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Graphical Networks of Freely Generated Affective Labels in Individuals with High and Low Emotional Granularity

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Abstract

Emotional granularity, or the ability to make fine-grained distinctions among emotional states, has been linked to adaptive psychological functioning. However, summary measures of granularity quantify the extent to which individuals differentiate emotions without revealing *how* they organize emotion concepts. The present study employed a network-analytic approach applied to self-generated affective labels to explore how affective space is structured in individuals with high and low granularity. Given that affective space is organized around both mental and somatic representations, we focused on chronic pain as a prototypical context where these dimensions are especially intertwined. Seventy-one participants experiencing chronic pain completed a one-month event-contingent experience sampling protocol, reporting on their affective experience during pain episodes using both fixed negative emotion labels and self-generated descriptors. Dispositional negative emotional granularity was indexed via intraclass correlation and used to classify participants into high- and low-granularity groups. For each group, between-person graphical emotion networks were constructed based on participants' self-generated affective labels. Results revealed a sparser and more semantically coherent network in the high-granularity group, with differentiated and meaningfully organized clusters. By contrast, the low-granularity group generated a larger and denser affective network, with more heterogeneous affective communities and uncertainty- and need-related terms as central hubs. Despite these differences, both groups produced affective labels spanning emotional, cognitive, bodily, and relational domains, and shared a substantial subset of affective descriptors. Although exploratory and descriptive in nature, these findings offer a novel characterization of how granularity is reflected in the structural organization of affective space. Implications for adaptive psychological functioning, particularly in the chronic pain context, and granularity measurement are discussed.

1. Introduction

While different emotions are traditionally thought of as discrete and distinct mental states, modern Bayesian predictive coding theories argue that emotions are ad hoc constructions arising from the categorization of a continuous underlying affective space (Barrett, 2006; Barrett et al., 2025). Such "constructivist" theories are supported by research showing that self-reported experiences of emotion do not map neatly onto distinct patterns of physiological change (Hoemann et al., 2020; Siegel et al., 2018), nor do they have clear-cut and distinct neural correlates (Lindquist et al., 2012) or unique facial expressions (Barrett et al., 2019). That is, the physical, neural, and biological processes implicated in a given emotion may vary, despite people describing them as the same emotion, reflecting "populations" rather than a "fingerprints" view of emotion (Siegel et al., 2018). From this perspective, the act of categorizing an affective state as a particular emotion is thus a constructive process shaped both by embodied experience and semantic knowledge, wherein mental and bodily processes are conceived of as integrated, rather than through the lens of a classical Cartesian mind–body dualism (Barrett et al., 2025).

Constructivist theories provide a framework for thinking about individual differences in emotion (Barrett, 2009), foregrounding variation in emotion knowledge and competence as an object of study. One of the most well-studied of these individual differences is emotional granularity, which refers to the ability to use conceptual knowledge and language to make fine-grained distinctions within one's affective experience (Tugade et al., 2004; also referred to as emotion differentiation, Barrett et al., 2001). Individuals low in emotional granularity tend to describe their emotional experience using emotion labels interchangeably (Barrett et al., 2001; Tugade et al., 2004) or broad, less context-dependent terms (Barrett, 2004, 2006). In contrast, those higher in granularity treat emotion concepts as distinct categories and use more nuanced emotion labeling. Granularity has shown relationships with adaptive functioning across multiple domains, presumably because more fine-grained emotion concepts function as context-sensitive guides to action (Barrett et al., 2001). While lower emotional granularity is observed in a range of mental health conditions (Ozomaro et al., 2025), higher granularity is associated with better coping behaviors (Emery et al., 2014; Kashdan et al., 2010; Racine et al., 2024; Sheets et al., 2015; Walters et al., 2023), as well as with interpersonal processes (Erbas et al., 2016; Sels et al., 2024). Granularity of negative emotions is considered particularly adaptive, as individuals who can better conceptually distinguish negative emotions may be better able to recognize how to respond to the emotional situation (e.g., distinguishing whether to seek support or confront an individual; Barrett et al., 2001). Meta-analyses generally find significant associations of granularity with adaptive functioning across clinical and non-clinical samples, but only for differentiation of negative emotions and with small effect sizes (r = 0.15, O'Toole et al., 2020; r = -0.15, Seah & Coifman, 2022), suggesting unresolved heterogeneity.

While emotional granularity is reliably associated with adaptive outcomes, we lack a clear characterization of the organization of affective space associated with high or low granularity. From a constructivist perspective, "affective space" refers to both which emotion concepts individuals draw upon and how these concepts are applied to, and structured across, potentially overlapping populations of affective states (Barrett, 2017). Importantly, language plays a key role in shaping this space by organizing and systematizing emotion concepts, thereby integrating diverse, context-dependent experiences of feeling into abstract emotion categories (Barrett et al., 2025; Hoemann, 2024; Hoemann, Lee, et al., 2025). Emotion words mirror specific emotion concepts, yet the relationship between lexical labels and conceptual representations is neither fixed nor perfectly isomorphic (Barrett, 2004). The same word can map onto conceptually distinct experiences (e.g., the "sadness" experienced at the conclusion of a vacation differs from the "sadness" encountered in response to a bereavement), reflecting the brain's tendency to group diverse instances of emotion under a single conceptual category despite considerable experiential variability (Hoemann et al., 2019; Lindquist, MacCormack, et al., 2015). This points to two theoretically distinct components of emotional granularity, both relevant for characterizing its underlying affective space (Hoemann, Nielson, et al., 2021). The first refers to the structure, quality and breadth of conceptual knowledge, requiring nuanced and non-overlapping concepts. The second concerns the verbal representation of emotional experiences, encompassing the identification, labeling, and description of emotions and implying a normatively appropriate use of language.

Typically, in granularity research, experimenters supply a common set of affective mentalistic labels for all participants to use to rate their experiences (Thompson, Springstein, et al., 2021); granularity is indexed as the within-person variability (e.g., intra-class correlation) of participant ratings of these labels across multiple time points. While this standardization is advantageous for data analysis, it ignores important variation and other nuances in how participants naturally construct affective concepts and apply related language. First, the breadth and nature of affective vocabulary have been identified as an important individual difference, with paradoxically larger vocabularies for negative words being associated with impaired health and psychosocial functioning in both non-clinical and clinical samples (DeLap et al., 2024; Entwistle et al., 2023; Vine et al., 2020). Second, affective language in everyday life often spans both mentalistic and bodily descriptors (Ip et al., 2024): while some affective terms are readily categorized as non-emotional (e.g., *hungry*) and others as clearly emotional (e.g., *furious*), many terms lie on a more ambiguous boundary (e.g., *relaxed*). A full characterization of the affective space associated with emotional granularity thus addresses both the extent to which affective concepts span mentalistic and somatic domains and to the breadth and nature of the emotion lexicon individuals use.

On the one hand, investigating the somatic–mentalistic dimension can be facilitated by a context in which the inherent grounding of emotional experience in bodily processes is particularly salient and phenomenologically evident. A prototypical instance of such an intertwining is provided by pain (Barrett, 2017), defined as “an unpleasant *sensory and emotional* experience” (International Association for the Study of Pain, 2012) in which the boundary between somatic and mentalistic dimensions is especially blurred (Craig, 2003). As a result, in the immediate experience of pain, the organization of affective concepts is likely to be both especially complex and theoretically informative (Borelli et al., 2018). On the other hand, capturing the nature and breadth of emotion lexicons requires methods that do not constrain participants to a predetermined set of affective labels, allowing instead for the full range of naturalistic affective language to emerge. Only a few studies have used individuals’ own self-generated labels to explore emotional granularity.Ottenstein and Lischetzke (2020) andWilliams and Uliaszek (2022) both calculated granularity using human coders to rate the specificity of emotion words spontaneously generated by participants (e.g., *scared* or *sad*, vs. *bad* or *unpleasant*). However, this hand-coded approach was not found to be associated with classical measures of emotional granularity, despite similar relationships with adaptive functioning. Similarly, in an experience sampling context,Hoemann, Warfel, et al. (2025) found that the number of unique emotion words generated was related to the range and diversity of daily emotional experience, but not to emotional granularity.

Importantly, neither traditional correlation-based measures of granularity nor hand-coded approaches to freely generated emotional language capture *how* affective space is qualitatively structured across different levels of granularity. Affective space is also defined not only by the emotion concepts people recruit, but also by the relationships among them, which can be understood revealing the structure of the emotional experience itself (Niedenthal, 2008). Graphical network-based approaches (Boccaletti et al., 2006) provide a principled framework for modeling this structure, allowing emotion words to be represented as nodes and their semantic or experiential associations as edges (Ip et al., 2024). From this perspective, emotion concepts that share affective referents are more closely connected than those

that do not, and network-level properties (e.g., density, clustering, and centrality) can be used to descriptively quantify how differentiated, integrated, or hierarchically organized these affective referents are. This approach thus provides a novel lens on the semantic and experiential architecture of the affective space, allowing its representation across different granularity levels.

Previous research has examined these networks within individuals in the context of mixed emotions, finding high rates of co-occurrence between positive and negative emotions (Moeller et al., 2018). Longitudinal emotion networks have also been examined in depression, with denser emotion networks observed in depressed individuals (Pe et al., 2015). Additionally, network approaches have been applied to examine the similarity structure of emotion concepts in language (Toivonen et al., 2012) and to characterize emotional experience in everyday life (Trampe et al., 2015). To date, however, no study appears to have directly investigated how affective experience is organized in individuals with different levels of emotional granularity. The study that comes closest to this descriptive aim is Hoemann et al. (2020), who constructed person-specific networks to examine how affective space is structured as a function of dispositional differences in emotional granularity. They found that individuals lower in emotional granularity exhibited more dense emotion networks with higher clustering. However, because this study used experimenter-generated emotion labels, it does not capture differences in which words individuals use, and how these might differently organize people's affective experience.

2. The Present Study

The present study examines the organization of affective space, conceptualized as an associative network of participant-generated affective labels across mentalistic and bodily domains, in high- versus low-granularity individuals with chronic pain. This objective builds on two recent calls to advance research on emotional granularity (Ip et al., 2024). First, applying network-analytic approaches to the investigation of granularity offers a promising framework for examining the structure of affective concepts: rather than focusing solely on how interchangeably emotion terms are used over time (e.g., via ICC-based indices), this perspective emphasizes *which* terms are used and *how* they are structurally organized. Second, although granularity has traditionally been assessed through predominantly mentalistic emotion terms, affective space is organized around both mental and somatic representations that contribute directly to the meaning of emotional experience; a more comprehensive account of affective space should therefore incorporate both these interconnected domains, and chronic pain provides a prototypical context of such intertwining.

Building on these premises, we focused on pain as a paradigmatic context for investigating the structure of affective space across bodily and mental domains. To this end, we conducted a one-month event-contingent experience sampling study in which individuals with chronic pain reported on their affective experience during naturally occurring pain episodes. At each pain episode, the participants were instructed to rate a fixed set of negative emotion labels and to freely label their affective experience during each pain episode. The fixed emotion labels were used to compute granularity indices via classical variance-based methods, allowing us to classify participants into high- and low-granularity

subgroups. Given the substantial emotional burden associated with chronic pelvic pain (Niedenfuehr et al., 2023; Shallcross et al., 2018), our study focused specifically on negative emotional granularity (i.e., granularity in relation to negative emotions). To descriptively characterize the affective space of the two groups, we constructed graphical networks based on participants' freely generated affective labels.

Drawing on constructivist theories, we expected the group with high granularity to show a different characterization of affective experience compared to those with low granularity (Hoemann et al., 2020), by virtue of their putative more fine-grained conceptual and lexical emotional knowledge. While our study was primarily exploratory, we formulated two primary expectations regarding how high- and low-granularity individuals would differ. First, we anticipated that individuals with high granularity would demonstrate a more nuanced affective lexicon. This expectation follows from theoretical accounts linking granularity to the quality of conceptual emotion knowledge (Barrett, 2006; Hoemann, Nielson, et al., 2021), according to which individuals with finer-grained emotion concepts draw on a more differentiated repertoire of affective categories, reflected in more specific labeling of their experiences. Beyond this theoretically motivated expectation, and consistent with the exploratory nature of the study, no specific hypotheses were formulated regarding the domain membership of the generated labels (for instance, in terms of the somatic–mentalistic interrelation). Second, we expected the affective space of high-granularity individuals to be characterized by a larger number of affective labels, reflecting greater diversity in emotion knowledge and vocabulary (Hoemann, 2024). Within this same group, drawing on prior empirical work (Hoemann et al., 2020), we further anticipated sparser overall connectivity, reflecting greater semantic constraint. Finally, we expected affective communities (i.e., groupings of affective descriptors) to be more coherently organized, with bridging labels connecting conceptually related clusters – reflecting a differentiated yet integrated conceptual architecture (Hoemann, Nielson, et al., 2021).

3. Method

The data used in the present study were collected as part of a larger study on affective experience and chronic pelvic pain. All procedures described below received ethical approval by Università Cattolica di Milano (protocol number 58–23). Data and codes are available on the Open Science Framework (OSF) at https://osf.io/j65em/overview.

3.1. Participants

The participants were women diagnosed with neuropathic and nociplastic chronic pelvic pain (CPP). The exclusion criteria encompassed ongoing treatment for more than two years, recent (within the last two weeks) initiation or change in hormone treatment, recent (within the last two months) pelvic or abdominal surgery, scheduled pelvic or abdominal surgery during the study period, current pregnancy, or childbirth within the previous two months (Norman et al., 2004).

The initial sample consisted of 84 participants. Two participants dropped out after the baseline assessment. During data analysis, one participant was excluded as an outlier, and ten participants were excluded because granularity indices could not be computed (see Measures section). The final sample therefore comprised 71 participants. A detailed description of the sample characteristics is provided in Table 1. Additional information about participants' medical conditions is available in Table S1 in the Supplemental Material.

Participation in the study was voluntary and without monetary compensation.

Table 1
Sample characteristics.

Age		**Total Sample (n = 71)**	**High EG (n = 35)**	**Low EG (n = 36)**
	Mean	**27.70**	**28.50**	**26.90**
	Standard Deviation	6.10	5.81	6.35
	Range	18–44	20–42	18–44
Education	Middle School	1.40	0.00	2.90
	High School (5 Years)	30.40	29.40	34.30
	Bachelor's Degree	23.20	23.50	20.00
	Master's Degree	31.90	32.40	31.40
	Advanced Postgraduate Education	13.00	14.70	11.40
Occupation	Working	52.90	57.10	48.60
	Studying	31.40	25.70	37.10
	Studying And Woking	14.30	14.30	14.30
	Unemployed / Looking for a Job	1.40	2.90	0.00
Civil Status	Unmarried	81.40	80.00	82.90
	Married	15.70	20.00	11.40
	Divorced	2.90	0.00	5.70
Number of Children	Zero	91.40	91.40	91.40
	One	7.10	8.60	5.70
	Two	1.40	0.00	2.90

Note: EG = Emotional Granularity. Columns *High EG* and *Low EG* show descriptive statistics for the subsamples identified with high and low levels of emotional granularity, respectively. Education, Occupation, Civil Status, and Number of Children are reported as percentages. Advanced postgraduate education includes professional specialization programs and doctoral studies.

3.2. Procedure

Participants were recruited through healthcare professionals (e.g., gynecologists, midwives, physiotherapists) working in hospitals or specialized clinics for CPP. Recruitment was also facilitated through patient advocacy associations and online services dedicated to individuals with CPP.

The study employed a repeated measures design with three assessment points spaced one month apart. Additionally, between the first and second assessments, participants completed a one-month experience sampling protocol using an event-contingent design. The primary focus of the present study is on data collected during the one-month experience sampling assessment. The overall procedure is described in full in the Supplemental Material to ensure transparency regarding study design and implementation.

During the one-month experience sampling period, participants were instructed to complete an online diary each time they experienced a pain episode. For each episode, they freely generated one or more affective adjectives describing their current affective experience, and they provided ratings for each of these descriptors and for a fixed set of fourteen emotion labels (see *Measures*, below). Participants also reported their current pain intensity, completed standardized measures of their affective state, and provided an open-ended narrative describing the pain episode (including physical sensations, emotions and feelings, contextual factors, and personal reflections); however, these additional measures were not included in the present analyses.

To conclude the study, participants were invited to a debriefing session during which the research team shared preliminary findings and offered further explanations about the study's aims and design.

3.3. Measures

Dispositional Negative Emotional Granularity Groups. At each pain episode, participants provided ratings of their current emotional state on a 7-point Likert scale, ranging from 0 (*not at all*) to 6 (*extremely*) across fourteen negative emotion words (*embarrassed, worn out, sad, depressed, lonely, demoralized, frightened, anxious, anguished, worried, angry, frustrated, fed up, nervous*). Based on the circumplex model of affect (Russell, 1980), these emotional labels were chosen to represent both low-arousal and high-arousal negative affect across multiple emotional families. The selection of these emotion labels was further informed by empirical evidence highlighting their relevance to the experience of CPP (Niedenfuehr et al., 2023; Toye et al., 2014). An index of dispositional emotional granularity was obtained by calculating the intraclass correlation (ICC) of emotion items across measurement occasions for each participant (Eckland et al., 2021; Erbas et al., 2015). Following recent literature (Erbas et al., 2018; Hoemann et al., 2023; Kalokerinos et al., 2019), we conducted an ICC for consistency with averaged raters. Since ICCs do not typically have a normal distribution, in line with previous research (Barrett et al., 2001), resulting ICCs were Fisher *r*-to-*z* transformed. Finally, the indices were reverse-coded by multiplying by − 1, so that higher values reflect higher levels of granularity. Granularity indices could not be computed for six participants due to insufficient variance (i.e., only a single entry was completed), and for an additional four participants as they had negative ICCs. Consequently, these participants were excluded from further analyses. Participants were classified into high- and low-granularity groups using the sample median of dispositional emotional granularity scores (median = -1.22) as the cutoff.

Momentary Self-generated Affective Labels. For each pain episode, participants were asked to provide one or more freely generated words describing how they felt at that moment and to rate the intensity of the feeling on a 7-point Likert scale ranging from 0 (*not at all*) to 6 (*extremely*). Preprocessing of the affective adjectives included manual screening to correct spelling errors and to convert non-adjectival entries (e.g., *anger*) into their adjectival form (e.g., *angry*). We then constructed a dictionary containing all affective terms produced by participants and translated them into English using a back-translation procedure. For each participant, multiple occurrences of the same affective label were collapsed into a single mean score, yielding one intensity value per self-generated label per participant.

3.4. Statistical Analysis

All analyses were conducted in *R v.4.4.1* (R Core Team, 2021). The *igraph* (Csàrdi, 2013) and *ggraph* (Pedersen et al., 2017) R packages were used for network analysis and visualization. Pairwise correlations between all label pairs were computed and were tested for statistical significance; only significant associations ($p < .05$) were retained for subsequent network construction. This filtered correlation matrix was represented into an undirected weighted network where nodes corresponded to affective labels and edges represented significant co-occurrence patterns. Edge weights were defined as the absolute value of correlation coefficients, with directionality (positive/negative) preserved for interpretation. Network properties were quantified using standard centrality indices, including degree (number of connections), strength (sum of absolute edge weights), and betweenness (frequency of appearing on shortest paths between other nodes). Network visualization was performed using a Fruchterman–Reingold force-directed algorithm (Fruchterman & Reingold, 1991), which produces layouts in which strongly connected nodes are positioned closer together. Nodes were sized proportionally to betweenness centrality and colored by degree centrality. Edges were weighted by correlation strength and colored by direction (red for positive, blue for negative associations).

4. Results

Across the experience sampling period, participants generated a total of 191 distinct affective words, including 149 negatively valenced labels (e.g., *anxious*), 28 positively valenced labels (e.g., *happy*), and 14 labels whose valence may vary depending on contextual use (e.g., *incredulous*). These affective descriptors encompassed a wide range of experiential domains, spanning words with an intrinsic and specific emotional connotation (e.g., *sad*), words reflecting cognitive or attentional states (e.g., *deconcentrated*), and words primarily referring to bodily or somatic experiences (e.g., *painful*). The most frequently reported affective labels were *tired* (154 occurrences), *frustrated* (74 occurrences), *sick and tired* (61 occurrences), *angry* (56 occurrences), *painful* (48 occurrences), *sad* (45 occurrences), *bothered* (39 occurrences), and *worried* (34 occurrences). A comprehensive list of all freely generated affective labels along with their frequency of occurrence and average intensity is provided in Table S2 in the Supplemental Material.

Descriptive statistics for each group, including the number of diary entries, the number of self-generated affective labels per entry, ratings of self-generated affective labels, and dispositional negative emotional

granularity scores, are reported in Table 2.

Table 2
Descriptive statistics.

		Total Sample (n = 71)	High EG (n = 35)	Low EG (n = 36)
Number of Entries	*M*	6.70	6.46	6.94
	SD_{within}	–	–	–
	$SD_{between}$	3.37	2.86	3.82
	Min	2	2	2
	Max	20	17	20
Number of Self-generated Affective Labels per Entry	*M*	2.55	2.50	2.59
	SD_{within}	0.31	0.33	0.30
	$SD_{between}$	0.59	0.60	0.58
	Min	1	1	1
	Max	3	3	3
Ratings for Self-generated Affective Labels	*M*	4.70	4.79	4.61
	SD_{within}	0.89	0.84	0.94
	$SD_{between}$	0.68	0.78	0.57
	Min	1	1	1
	Max	6	6	6
Dispositional Negative Emotional Granularity	*M*	-1.23	-0.81	-1.65
	SD_{within}	–	–	–
	$SD_{between}$	0.53	0.29	0.36
	Min	-2.48	-1.16	-2.48
	Max	-0.04	-0.04	-1.22

Note: EG = Emotional Granularity. Columns *High EG* and *Low EG* show descriptive statistics for the subsamples identified with high and low levels of emotional granularity, respectively. The number of entries reflects the number of pain episodes reported by participants throughout the study period, which employed an event-contingent design.

Figures 1 and 2 depict the affective networks for participants with high and low emotional granularity, respectively. Networks were constructed by retaining only statistically significant correlations among affective labels, and centrality indices were incorporated into the layout. The high-granularity group generated a total of 120 distinct affective labels (98 negative, 15 positive, and 7 context-dependent) and exhibited 920 significant correlations (i.e., edges) among these labels (i.e., nodes). In contrast, the low-granularity group generated 138 affective labels (107 negative, 20 positive, and 11 context-dependent) and showed 1,658 significant correlations. The two groups shared 67 affective labels in common (56 negative, 7 positive, and 4 context-dependent). Table 3 presents the list of affective labels generated by each group, categorized according to whether they were shared across groups and further stratified by valence. Additional information regarding the correlation estimates between pairs of affective labels is reported in Tables S3 and S4 in the Supplemental Material.

Centrality indices revealed marked differences between the high- and low-granularity networks. With respect to degree centrality (which reflects the number of connections each node has within the network), in the high-granularity group, the nodes with the highest degree (degree range: 2–36) were *demotivated* (36 connections), followed by *deconcentrated*, *embarrassed*, *suffering*, and *torn down* (30 connections); *anguished*, *confused*, *embittered*, *empty*, and *without hope* (28 connections); and *content*, *defeated*, *tense*, and *tranquil* (24 connections). The lowest degree values in this group were observed for *broken*, *frustrated*, *reflective*, and *sick and tired* (2 connections), as well as *angry*, *astonished*, *calm*, *indifferent*, *influenced by the pain*, *knackered*, *reassured*, *stiff*, and *surrendered* (6 connections). In the low-granularity group (degree range: 2–62), the most highly connected nodes were *confused* (62 connections), *uncertain* (58 connections), *misunderstood* and *sleepy* (54 connections), *desperate* (50 connections), and *full* (48 connections), followed by *confident*, *lonely*, and *overwhelmed* (44 connections), and *alert*, *alive*, *attentive*, *awaiting*, *bad*, *doubtful*, *fed up*, *rigid*, *surrendered*, and *without faith* (42 connections). In contrast, the lowest degree values in this group were observed for *tired* and *sick and tired* (2 connections), *limp*, *normal*, *angry*, *different*, *envious*, *irritated*, and *thoughtful* (4 connections), as well as *without freedom*, *determined*, *impatient*, and *anxious* (6 connections).

Table 3
List of affective labels freely generated by participants accounting for valence and dispositional levels of negative emotional granularity.

Common to both High and Low EG Groups	**Negative Affective Labels**	**Positive Affective Labels**	**Affective Labels with Valence Depending on Context**
	Afflicted, Agitated, Angry, Anguished, Annoyed, Anxious, Bored, Bothered, Confused, Demoralized, Demotivated, Depressed, Desperate, Despondent, Disappointed, Discouraged, Disheartened, Disillusioned, Doubtful, Embarrassed, Embittered, Exhausted, Fearful, Fed up, Fractious, Frightened, Frustrated, Guilty, Helpless, Invisible, Irked, Irritated, Knackered, Lonely, Nauseous, Nervous, Out of energy, Overwhelmed, Painful, Pissed off, Regretful, Resigned, Sad, Sick and tired, Stressed, Surrendered, Tense, Tired, Unarmed, Unlucky, Upset, Weak, Without faith, Without hope, Worn out, Worried	***Calm, Confident, Content, Happy, Hopeful, Relieved, Tranquil***	***Accustomed to, Perplexed, Sleepy, Thoughtful***
Present in the High EG Group Only	*Astonished, Arid, Awkward, Braked, Broken, Burning, Dead, Consumed, Debilitated, Deconcentrated, Defeated, Defective, Destabilized, Destroyed, Disconcerted, Disconsolate, Drained, Empty, Exasperated, Exposed, Fragile, Grim, Influenced by the pain, Insecure, Listless, Loser, Lost, Melancholy, Miffed, Misunderstood, Ridiculous, Run-down, Sadden, Stiff, Suffering, Taken unawares, Tormented, Torn down, Uncomfortable, Unstable, Vulnerable, Weighted*	*At ease, Light, Reassured, Relaxed, Safe, Satiated, Satisfied, Serene*	*Incredulous, Indifferent, Reflective*
Present in the Low EG Group Only	*Abnormal, Alert, Apathetic, Bad, Blocked, Crazy, Darken, Dazed, Different, Disabled, Disoriented, Envious, Extenuated, Failed, Far apart, Full, Heavy, Huffy, Impatient, In a panic, In apnea, In danger, Incapable, Incurable, In difficulty, Irritable, Lifeless, Limp, Loaded, Miffed, Misunderstood, Naïve, Overcome, Passive, Pessimistic, Pounding, Rigid, Sick, Stressed out, Stupid, Terrified, Trapped, Turned nasty, Uncertain, Uneasy, Vexed, Victim, Weary, With no future, Without freedom, Wrong*	*Alive, Determined, Enthusiastic, Free, Grateful, Patient, Positive, Proactive, Resilient, Satisfied, Serene, Strong, Supported*	*Attentive, Awaiting, Aware, Impressive, In the background, Normal, Touched*

Note: EG = Emotional Granularity.

Regarding strength centrality (which reflects the sum of the absolute weights of a node's connections), in the high-granularity group (strength range: 0.73–17.42), the highest strength values were observed for *demotivated* (17.42), *torn down* (16.56), *embittered* (16.34), *deconcentrated* (16.17), *tense* (15.87), *confused* (15.39), *embarrassed* (15.32), *content* (14.73), *destabilized*, *fragile*, *irked*, *lost*, *unstable*, *upset*, and *vulnerable* (14.66), *empty* (14.47), *saddened* (14.29), *unarmed* (14.11), and *anguished* (14.09).

Conversely, the lowest strength values in this group were observed for *reflective* (0.73), *frustrated* (0.74), *sick and tired* (0.80), *broken* (0.95), *angry* (2.29), *sad* (2.89), *influenced by the pain* (2.93), *tired* (3.29), *astonished* (3.32), *knackered* and *bothered* (3.36), *agitated* (3.64), *painful* (3.71), *afflicted* (3.74), *light* (3.80), and *surrendered* and *calm* (3.91). In the low-granularity group (strength range: 0.68–36.00), the highest strength values were observed for *uncertain* (36.00), *misunderstood* (32.02), *sleepy* (31.91), and a cluster of labels including *accustomed to*, *aware*, *dazed*, *far apart*, *in a panic*, *in danger*, *patient*, *resilient*, *stupid*, *unarmed*, *unlucky*, *vexed*, and *victim* (30.17), followed by *alert*, *alive*, *attentive*, *awaiting*, *bad*, *rigid*, and *surrendered* (28.42), *desperate* (28.38), and *full* (26.24). The lowest strength values in this group were observed for *sick and tired* (0.68), *tired* (0.80), *thoughtful* (1.48), *normal* (1.53), *angry* (1.72), *limp* (2.15), *anxious* (2.56), *irritated* (2.62), *sad* (2.83), *frustrated* (2.91), *without freedom* (3.12), *envious* and *different* (3.19), *positive* (3.33), and *impatient* and *determined* (3.87).

Finally, with respect to betweenness centrality (which reflects the extent to which a node lies on the shortest paths between other nodes), in the high-granularity network (betweenness range: 0–1,083), the highest values were observed for *demotivated* (1,083), *tranquil* (920), *suffering* (688), *embarrassed* (657), *fearful* (594), *tired* (560), *lonely* (487), *anguished* (472), *exhausted* (457), *without hope* (435), *misunderstood* (430), *anxious* and *hopeful* (397), *exposed* (359), *defeated* (358), *empty* (336), *helpless* (332), *confused* (322), *disheartened* (319), and *insecure* (304). In contrast, several labels showed zero betweenness in this group, including *accustomed to*, *fed up*, *loser*, *pissed off*, *unlucky*, *happy*, *safe*, *satiated*, *satisfied*, *serene*, *relieved*, *indifferent*, *reassured*, *stiff*, *melancholy*, *destabilized*, *fragile*, *irked*, *lost*, *unstable*, *upset*, *vulnerable*, *unarmed*, *awkward*, *defective*, *desperate*, *regretful*, *disillusioned*, *dead*, *burning*, *destroyed*, *drained*, *grim*, *broken*, *sick and tired*, *frustrated*, and *reflective*. In the low-granularity network (betweenness range: 0–1,587), the highest betweenness values were observed for *confused* (1,587), *doubtful* (826), *worried* (775), *despondent* (671), *knackered* (541), *regretful* (456), *demoralized* (410), *misunderstood* and *annoyed* (392), *tranquil* (374), *full* (367), *impressive* and *trapped* (361.33), *discouraged* (354), *confident* (350), *fed up* (341), *hopeful* (328), and *helpless* (324). Labels with zero betweenness in this group included *embittered*, *different*, *envious*, *irritated*, *anxious*, *in apnea*, *incapable*, *tense*, *thoughtful*, *tired*, and *sick and tired*. A comprehensive overview of all centrality indices for each affective label in both groups is provided in Table S5 in the Supplemental Material.

5. Discussion

The main objective of the present study was to descriptively examine the structure of affective space, operationalized as a network of freely generated affective labels, in individuals with high and low emotional granularity. We analyzed both the *type* of emotional lexicon used by the two groups and the *structural organization* of this lexicon within affective networks. We expected individuals with high granularity to exhibit a richer and more nuanced emotion vocabulary, as well as a more integrated and coherently organized affective space, characterized by greater community coherence and more differentiated interconnections. Overall, the results partially aligned with these expectations, revealing qualitatively distinct affective networks in the two groups.

As we discuss as more detail below, with respect to lexical content, consistent with our expectations, individuals in the low granularity group relied more heavily on broad, undifferentiated descriptors. Both groups, however, generated a mix of generic and specific affective labels, with a predominance of negatively valenced terms spanning cognitive, motivational, and relational domains. Individuals in the high granularity group additionally produced a substantial proportion of terms located at the intersection of bodily and mental states. Regarding network structure, contrary to expectations, the high-granularity group generated fewer unique affective labels and exhibited fewer connections. However, consistent with predictions, this group displayed a sparser yet more semantically coherent network structure, in contrast to the denser, more internally heterogeneous communities and ambiguity-indexing hub nodes observed in the low-granularity network. The following sections discuss these findings in turn, focusing on lexical and structural differences, before considering their implications for adaptive functioning and granularity measurement.

5.1. The Nature of Affective Labels

Focusing first on the type of affective words generated, participants with low emotional granularity predominantly reported generic descriptors of their affective states (e.g., *bad, in difficulty, passive, uneasy*). This finding aligns with our expectations, which were grounded in theoretical accounts of granularity according to which individuals who are less able to differentiate among their affective states tend to rely on broad, undifferentiated descriptors (Barrett, 2006). Such individuals are thought to conceptualize affect primarily along a general pleasantness–unpleasantness dimension rather than as discrete, context-sensitive emotion categories (Barrett, 1998; Barrett et al., 2001). This finding also speaks to previous work by Ottenstein and Lischetzke (2020) and Williams and Uliaszek (2022). Both studies operationalized emotional granularity in terms of a lexicon specificity-based index, computed as the ratio of specific to total emotion words used when describing situated affective experiences. Our findings tentatively extend this line of research by suggesting that individuals classified as having lower emotional granularity based on ICC-based measures tend to produce a greater proportion of generic affective descriptors. Taken together, these results raise the possibility that the prevalence of generic versus specific emotion words may indeed be related to emotional granularity levels. However, since our analyses are descriptive and exploratory in nature, this interpretation should be regarded as tentative and warranting further investigation.

Interestingly, non-generic emotion words (e.g., *afflicted, desperate, despondent, relieved, regretful*) were observed in both groups, suggesting that possessing a relatively rich and fine-grained emotional vocabulary is not, in itself, sufficient to confer high granularity. This distinction is well aligned with theoretical and empirical work indicating that emotional granularity reflects *how* emotion words are used, rather than simply which of them are available (see paragraph 5.2 for further discussion). By definition, granularity is not merely about having access to many emotion terms and concepts, but about the flexible and contextually appropriate application of those terms and concepts (Hoemann, 2024). This view is further supported by recent empirical evidence examining the relationship between vocabulary richness and granularity and suggesting that a greater diversity of one's emotional vocabulary is not

necessarily associated with a higher degree to which emotion concepts are differentially applied across contexts (DeLap et al., 2024; Kandala et al., 2026). Together, these previous findings, along with the present results, reinforce the view that granularity may represent a context-sensitive competence in emotion concept application rather than a static property of vocabulary specificity.

Turning to the domain membership of the generated labels, participants with higher emotional granularity generated a series of terms that often lay at the intersection of bodily and mental states (e.g., *broken, burning, dead, consumed, debilitated, defective, destroyed, empty*), suggesting that a bodily and somatic component is central (rather than peripheral) to the representation of affective experience. This pattern is consistent with contemporary constructionist accounts of emotion (Barrett et al., 2025), which conceptualize emotion as an embodied, holistic process rather than as a purely mental phenomenon separable from the body in Cartesian terms. Importantly, although our sample consisted of individuals with CPP and all reports were anchored to specific pain episodes, the bodily connotation of many words did not render them purely or exclusively somatic. Terms such as *broken* or *consumed* evoke corporeal imagery but simultaneously convey experiential mentalistic meaning. Thus, the lexical space of high-granularity individuals seems not to collapse into mere somatic (versus mentalistic) descriptors; rather, it appears to reflect an integrated affective vocabulary in which bodily and mental meanings are intertwined. This finding challenges earlier views suggesting that reliance on bodily language reflects a developmental failure to differentiate psychological states into distinct mental categories (Leff, 1988), to fully describe emotions (Sifneos, 1973), and to achieve emotional awareness (Lane & Smith, 2021). From a constructivist perspective, the use of affective terms that rely on the boundaries between the bodily and mentalistic dimension may instead index a richly embodied conceptualization of emotion rather than low granularity.

Notably, both groups reported words with strong cognitive and motivational connotations (e.g., *confused, demoralized, demotivated, disillusioned, doubtful, thoughtful*) as well as socially and relationally embedded terms (e.g., *embarrassed, grateful, misunderstood, reassured, supported*). This shared vocabulary underscores the inherently situated and relational nature of affective experience (Boiger & Mesquita, 2012), regardless of one's expertise in emotion differentiation. Our findings suggest that emotions, even when experienced in the context of pain, are not merely internal states but are embedded within interpersonal, cognitive, and motivational drives. Taken together, these results highlight that affective and emotional experience transcends a narrow emotional dimension and encompasses multiple domains (Hoemann et al., 2019).

Finally, an additional feature shared by both groups was the predominance of spontaneously generated negative affective terms. This pattern is unsurprising given the event-contingent design of the study, which anchored reports to pain episodes (that is, experiences that are inherently unpleasant; Baliki & Apkarian, 2015; Craig, 2003). Importantly, however, both groups also generated a subset of positive terms, as well as words whose valence may shift depending on contextual interpretation. This finding aligns with research demonstrating that even adverse or unpleasant experiences can co-occur with positive or mixed emotional states, reflecting the complexity and multidimensionality of affective life

(Moeller et al., 2018). From a constructionist perspective, affective valence is not a fixed property of a word but emerges from the situated categorization of bodily sensations within a given context (Lindquist et al., 2015). Thus, the presence of both positive and contextually ambiguous terms, even in reports anchored to negative events, underscores the flexibility of affective meaning-making and further supports the view that emotional experience cannot be reduced to a single valence dimension (Hoemann et al., 2017; Hoemann, Lee, et al., 2025; Moeller et al., 2018). As a consequence, the coexistence of predominantly negative, yet occasionally positive or valence-ambiguous terms in our data highlights that granularity does not imply rigid segregation of experiences into strictly positive or negative categories and further illustrates its multidimensional nature (Thompson, Springstein, et al., 2021).

5.2. The Conceptual Structure of Affective Labels Within the Affective Space

Beyond lexical content, the two groups differed in the structural organization of their affective networks. Contrary to our expectations, the low-granularity group generated a greater number of unique affective terms (nodes) and exhibited a larger number of connections among these terms (edges). Crucially, both one's understanding of emotions and the variety of emotion words a person actively uses can reflect the nature of the emotional experiences they are familiar with, frequently encounter, or perceive as particularly salient (Niedenthal et al., 2005; Pennebaker, 2011; Vine et al., 2020). However, possessing knowledge about emotions does not automatically confer the ability to differentiate them in practice, nor does having a large emotion vocabulary necessarily guarantee granular application (Hoemann, 2024; Hoemann, Nielson, et al., 2021). Prior work has shown that broader emotion-word usage is not consistently aligned with higher emotional granularity. Hoemann, Warfel, et al. (2025) have found that the sheer number of unique emotion words indexes experiential diversity but not granularity per se, while Kandala et al. (2026) and DeLap et al. (2025) reported valence-dependent and inconsistent associations between vocabulary breadth and emotional granularity. Taken together, these findings suggest that lexical richness in emotion may more reliably index a broader experiential repertoire than a fine-grained differentiation ability. Accordingly, in the present study, network size alone may not index differentiated emotion use; rather, it may be the patterning of connections among terms to appear theoretically informative.

Consistent with this distinction, the two groups exhibited substantial differences in network connectivity, in line with both our hypotheses and previous findings (Hoemann et al., 2020). Specifically, the low-granularity group displayed a denser network, indicating that emotion terms were more correlated; by contrast, the high-granularity group exhibited a sparser network structure. Importantly, these networks captured the extent to which emotion concepts exhibit similar patterns of covariance in average experienced intensity. In the low-granularity group, covariance in emotional intensity was broadly distributed across the network, such that the average intensity of any given emotion tended to covary with that of a wide range of other emotions, irrespective of their semantic similarity. In contrast, in the high-granularity group, strong covariance was largely confined to semantically proximal emotions,

indicating that intensity covariation was selectively organized around conceptually related affective states. These results corroborate the idea that the greater density observed in the low-granularity group reflect a conceptual organization characterized by broad, overlapping categories (Hoemann et al., 2020). From a constructivist perspective, this pattern is consistent with undifferentiated affect, whereby multiple emotion terms are applied to similar experiential states without clear conceptual boundaries (Barrett, 2006; Barrett et al., 2001; Tugade et al., 2004). Conversely, the sparser structure observed in the high-granularity group may reflect increased semantic constraint and less shared variance in emotion concepts, suggesting greater conceptual differentiation.

Moving beyond overall network connectivity to the internal organization of specific communities, the observed patterns were largely consistent with our expectations. Although both groups demonstrated the presence of identifiable communities (i.e., clusters of nodes more strongly connected to one another than to the rest of the network), these communities appeared qualitatively distinct across groups. In the low-granularity group, communities were more densely populated but also more heterogeneous and, at times, internally contradictory; for example, generic and specific terms and even negatively and positively valenced words were highly interrelated within the same clusters (e.g., *aware, dazed, in a panic, patient, resilient, unarmed, victim*). Such configurations may indicate reduced semantic coherence, with conceptual groupings reflecting undifferentiation rather than shared meaning (Hoemann et al., 2020; Ip et al., 2024; (though see the *Limitations* for an alternative interpretation of these groupings involving idiosyncratic usage by individual participants or subgroups). In contrast, the high-granularity group showed communities that were more semantically coherent and meaningfully organized, consistent with constructivist accounts proposing that conceptual knowledge is reflected in the organization of affective experience (Hoemann, 2024). Although the network was estimated from intensity ratings rather than semantic judgments, the resulting communities aligned closely with semantic distinctions among emotion concepts in this group. This convergence suggests that conceptually related emotional experiences exhibited similar patterns of covariation in average experienced intensity, indicating that the organization of intensity ratings closely tracked the conceptual structure of emotion representations. Clusters tended to reflect shared connotations, such as in terms of predominantly bodily-inflected descriptors (e.g., *burning, dead, destroyed, drained*) or distinctions in valence (e.g., *happy, safe, satisfied, serene*, vs. *destabilized, fragile, lost, unstable, vulnerable*). This pattern suggests a modular and consistently organized conceptual architecture: emotion concepts appear differentiated into relatively distinct substructures, but these substructures remain embedded within a coherent whole.

Extending this analysis from community-level organization to the nodes that occupy bridging positions between communities, the observed patterns were again consistent with our expectations. Nodes that function as connectors across clusters may index conceptual linkages that enable individuals to traverse bodily–mentalistic, cognitive, and relational meanings without collapsing them into undifferentiated categories. In network terms, such bridging nodes can be understood as structurally central elements that integrate otherwise separable substructures of affective space (Boccaletti et al., 2006). Notably, in the low-granularity group, nodes such as *confused* and *doubtful* appeared to function as central hubs, linking heterogeneous descriptors across valence, specificity, and bodily–mental dimensions. Rather

than connecting semantically coherent clusters, these nodes seemed to aggregate diverse and at times incongruent terms, thereby reducing overall semantic precision. Conceptually, this finding may be interpreted as reflecting a meta-representational ambiguity (Hoemann, 2024): the centrality of a term denoting lack of clarity may itself index difficulty in discriminating among affective states. In this sense, the structural role of such hubs is consistent with the broader pattern of undifferentiated affect observed in the low-granularity network. It is also reminiscent of early work by Gohm characterizing emotional overwhelm as the co-occurrence of intense emotion with low clarity (Gohm, 2003). By contrast, in individuals with higher granularity, communities appeared to be hierarchically integrated by connectors characterized by greater semantic specificity and coherence. Bridging nodes tended to link clusters sharing similar connotations rather than spanning conceptually disparate domains. For example, positively valenced and relatively specific terms (e.g., *tranquil*) functioned as bridges between communities composed of other positive descriptors, suggesting the presence of distinct but related positive conceptual families. Similarly, negatively valenced terms (e.g., *demotivated*) primarily connected clusters of negative affect, and bodily-inflected descriptors (e.g., *sleepy*) linked communities centered on somatic experience. Taken together, this pattern suggests that, in high-granularity individuals, emotion concepts are organized into more differentiated and coherently related families. Bridging nodes do not blur conceptual boundaries but instead articulate them, enabling nuanced transitions across meaningfully related domains. Such architecture may allow for flexible and context-sensitive categorization of affective experience without resulting in conceptual fragmentation or semantic overgeneralization (Hoemann, Nielson, et al., 2021).

Overall, from a constructionist standpoint, the structural differences between the two groups can be interpreted as reflecting variation in the semantic organization and application of emotion concepts. In lower-granularity individuals, dense clustering, crowded and inconsistent communities, and cross-cutting connections may signal broad, weakly delimited categories that are frequently co-activated in response to unpleasant states. In higher-granularity individuals, consistent communities and clearer community boundaries combined with selective interconnections may support more precise categorization of affective states while preserving integration across conceptual domains.

A final consideration concerns the level at which the networks constructed in the present study – which are based on between-person associations – can be interpreted. We interpreted our results above assuming that the conceptual structure of emotion labels is sufficiently consistent across individuals to render group-level patterns meaningful at the individual level. However, it is possible that our results rather reflect the structure of shared understanding of emotion concepts across individuals. For our self-generated labels, a cluster observed in our network may reflect a small community of individuals who share a set of idiosyncratic emotion words that they commonly use. For example, a community in the network might indicate that when people use the word *happy*, they also use the word *content* (within-person association), or alternatively, that the same people that use the word *happy* frequently also use the word *content* frequently (between-person association). These two interpretations carry different theoretical implications. If the latter holds, then greater diversity in the network, as observed in high-granular individuals, would not merely reflect more granular experience, but rather greater experiential

diversity across individuals (reflected in greater heterogeneity in affective language across individuals). In other words, high-granular people may have more differentiated emotion experience from one another, compared with low-granular people. This would suggest that while high-granularity individuals may use more idiosyncratic, person-specific emotion labels, these labels may not be mutually intelligible or communicable between individuals.

5.3. Potential Implications for Adaptive Functioning and Well-being

The present findings offer a window into the structural mechanisms through which emotional granularity may support adaptive psychological functioning. Prior work has consistently linked higher granularity to better coping behaviors (for a meta-analysis, see Seah & Coifman, 2022) and mental health outcomes (for a meta-analysis, see Hong et al., 2025), with the assumption that finer conceptual distinctions among emotional states enable more context-sensitive responses to environmental demands (Kashdan et al., 2015; Thompson, Springstein, et al., 2021). Our study speaks to this assumption by characterizing, for the first time, how the affective space is structurally organized in groups who differ in granularity. Specifically, the denser, more heterogeneous networks of self-generated words observed in low-granularity individuals suggest that emotion concepts may be retrieved with less semantic precision – a pattern consistent with the kind of undifferentiated affect that prior work has linked to poorer adaptive outcomes. Although well-being was not directly assessed in the present study, these structural observations provide a plausible mechanistic account of the established associations between granularity and adaptive functioning.

One pathway through which this mechanism may operate concerns the role of emotion language. Reduced clarity about one's emotional states is thought to lead individuals to recruit a broader and less specific set of emotion labels as a marker of a wide range of undifferentiated stressors. Consistent with this view, prior work has shown that lower granularity is associated with a larger emotion vocabulary, and that both negative granularity and greater use of negative emotion words are, in turn, associated with poorer mental health outcomes (DeLap et al., 2024; Entwistle et al., 2023; Vine et al., 2020). The present findings contribute to this literature by suggesting that it is not merely the availability of emotion words per se, but also their structural organization and context-sensitive application, that may be critical for adaptive functioning. Indeed, the observation of larger emotion vocabularies and more densely connected affective networks in low-granularity participants may not reflect greater emotional expertise, but rather a compensatory attempt to impose meaning on poorly differentiated affective experiences. This pattern is consistent with prior evidence linking greater diversity in the use of negative emotion words and lower emotional granularity to poorer mental health. However, since the present study did not directly assess well-being outcomes, these interpretations remain tentative and should be treated with caution, pending replication in studies that explicitly examine the relationship between affective network structure and mental health.

This interpretive framework takes on added significance when considered in relation to the characteristics of the present sample – women experiencing CPP. In this context, prior research has shown that higher levels of chronic pain are associated with increased verbalization of emotional experience (Herbette & Rimé, 2004), especially among women (Jaworska & Ryan, 2018), and that greater emotional granularity is linked to lower perceived pain intensity (Schmitt et al., 2026). Within this framework, our findings raise the possibility that the extensive and densely connected emotional lexicon observed in low-granularity individuals may reflect heightened experiential salience of pain-related distress coupled with reduced differentiation of affective states. Conversely, a more differentiated and coherently structured affective space may support more adaptive appraisal of and coping with pain-related experiences (Borelli et al., 2018). Building on this line of reasoning, the identification of uncertainty-related (e.g., *confused*, *doubtful*) and need-related terms (e.g., *desperate*, *helpless*) as central hubs in low-granularity networks is particularly noteworthy. The prominence of such nodes suggests that individuals with low granularity may experience pain-related affective states as ambiguous and difficult to interpret and cope. At the same time, the centrality of these terms may represent a valuable entry point for intervention (Goldstein et al., 2020), as supported by research showing that affect labeling can reduce affective biases during the experience of pain (Constantinou et al., 2014, 2015).

5.4. Potential Implications for Emotional Granularity Measurement

By combining self-generated affective labels with network analysis, our study integrates two promising approaches for achieving a less biased and more comprehensive measurement of emotional granularity. While our study aimed merely to describe the affective space of individuals with high or low levels of granularity according to classical ICC-based measures, we suggest that our methods, or further developments of them, may also be useful in generating complementary or alternative quantitative measures of emotional granularity which resolve several problems with ICC-based metrics. Allowing participants to freely generate their own emotion terms eliminates spurious low granularity introduced by participants' idiosyncratic emotion concepts: for example, the label *misunderstood*, generated in the high EG group, might be rated as high in both *anger* and *sadness* on fixed set of emotion labels, resulting in artificially lower EG than if participants could generate the appropriate label themselves. Graph theoretical measures of community size and structure may also be able to disentangle frequent episodes of mixed emotion from genuine undifferentiated affect, providing an advantage over ICC-based methods. These remain preliminary intuitions, and the precise conditions under which network structure maps onto meaningful differences in emotion differentiation will require further theoretical refinement and empirical validation. Particularly, using network analyses of freely-generated labels to create quantitative measures of granularity would require individual level networks, which was not possible in our data given the limited number of time points.

5.5. Limitations and Future Directions

Several limitations warrant consideration. First, because networks were estimated at the dispositional level, they do not capture temporal dynamics or within-person variability in concept application. As such,

we cannot determine whether the co-occurrence of multiple specific labels reflects undifferentiated overlap (i.e., applying several labels to the same undifferentiated affective state) or, conversely, fine-grained differentiation of subtly distinct experiences. Future research employing within-person dynamic network approaches may help clarify this distinction.

Second, although participants were provided with the fixed set of affective labels only after generating their own labels, repeated exposure to these labels across assessments may nonetheless have influenced the emotion terms they generated. Seah and Coifman (2025) found that providing participants with experimenter-generated labels before they generated their own led participants to generate more specific emotion words. Although the order of administration in our study differed (participants provided their own labels before seeing the experimenter-generated labels), the presence of the fixed label set may nonetheless have shaped which terms participants chose to generate freely in later assessments, either by priming certain concepts or by narrowing the range of labels they considered relevant. While the extent to which repeated exposure influenced freely generated labels cannot be determined with certainty, future studies would benefit from designs in which free-label generation and fixed-set ratings are fully decoupled.

Third, the clinical specificity of the sample (i.e., individuals with CPP) may limit generalizability. Although this population offers a theoretically meaningful context for examining the embodied nature of affective experience, the affective episodes sampled were anchored to pain events, which are inherently unpleasant. This context likely constrained the valence distribution of reported experiences and may have shaped both lexical content and network structure. Future research should examine whether similar structural patterns emerge in non-clinical samples and in studies that capture a broader range of affective situations, including neutral and positive events. Direct comparisons between clinical and non-clinical populations would further clarify whether the observed network characteristics are general features of emotional granularity.

Fourth, our analytic approach treats non-reported emotions as zero-intensity ratings, meaning that edge weights between any two labels partially reflect the degree to which these labels were reported by the same participants. This is a known property of networks estimated from sparse, self-generated data (Moller et al., 2018; Wong et al., 2022) and is most pronounced for terms used by only a small subset of participants. Thus, densely connected communities in the network may reflect subgroup-specific (or even individual-specific) lexical usage rather than population-level covariation in affective experience (cf., the cluster of terms including *dazed*, *stupid*, *resilient*, etc. in the low-granularity subsample). Future work employing alternative modeling approaches or larger samples would help disentangle individual differences in lexical usage from intensity-based associations.

Lastly, additional methodological considerations also merit attention. The number of sampling occasions, although substantial for an event-contingent design, was limited to a one-month window and dependent on naturally occurring pain episodes. Consequently, the total number of time points per participant varied and may have constrained the stability of individual lexical repertoires. Moreover, the

overall sample size was modest, which may limit statistical power. Replication in larger samples with greater temporal density would strengthen confidence in the stability and generalizability of the present findings.

6. Conclusion

The present study provides a novel descriptive characterization of affective space in individuals with high and low emotional granularity. By combining freely generated affective language with network graphical modeling, we demonstrate how granularity is reflected in both the affective words individuals use and structural organization of these words within the affective space. Higher granularity was associated with a more diverse and embodied lexicon and with a qualitatively distinct network architecture, suggesting that granularity is reflected in the qualitative organization of the conceptual network through which affective meaning is constructed. Importantly, because our networks incorporated freely generated terms, they provide a broader and ecologically valid representation of affective space than approaches relying exclusively on experimenter-generated mental state terms, addressing concerns about potential category truncation in traditional granularity research. Overall, these findings contribute to a growing literature situating emotional granularity within a broader constructionist framework, and highlight the importance of examining the semantic and structural organization of emotion words and concepts underlying the affective experience.

Declarations

Participant Consent All participants provided informed consent to participate in the study.

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Footnotes

1. An alternative to the consistency-based method involves calculating ICCs with absolute agreement (e.g., Hoemann, Barrett, et al., 2021; Mehak et al., 2024; Seah et al., 2022). While the consistency-based method considers only the correlations among emotion items, the agreement-based method takes both the correlations and the level of the experienced emotions into account (Erbas et al., 2014). It has been argued that, in the context of emotional granularity, only the correlations among the emotions are relevant, and research suggests that ICC estimates for consistency and agreement are highly correlated, with values typically ranging from .95 to .99 (Erbas et al., 2014).
2. Because interpretable ICCs are between 0 and 1, ICCs with a negative value were considered unreliable (Giraudeau, 1996). ICCs with a negative value are common in emotional granularity research. These negative values are typically excluded from further analysis (e.g., Erbas et al., 2018; Hoemann, Barrett, et al., 2021; Sels et al., 2024), as there is no consensus on their interpretation. Few studies (e.g., Thompson et al., 2021) have re-coded negative ICC values as zero (i.e., considering participants with negative ICC values as having high emotional granularity) instead of excluding them. However, due to the lack of agreement on the interpretation of negative ICCs, we chose to exclude them from our analyses to err on the side of caution.

Figures

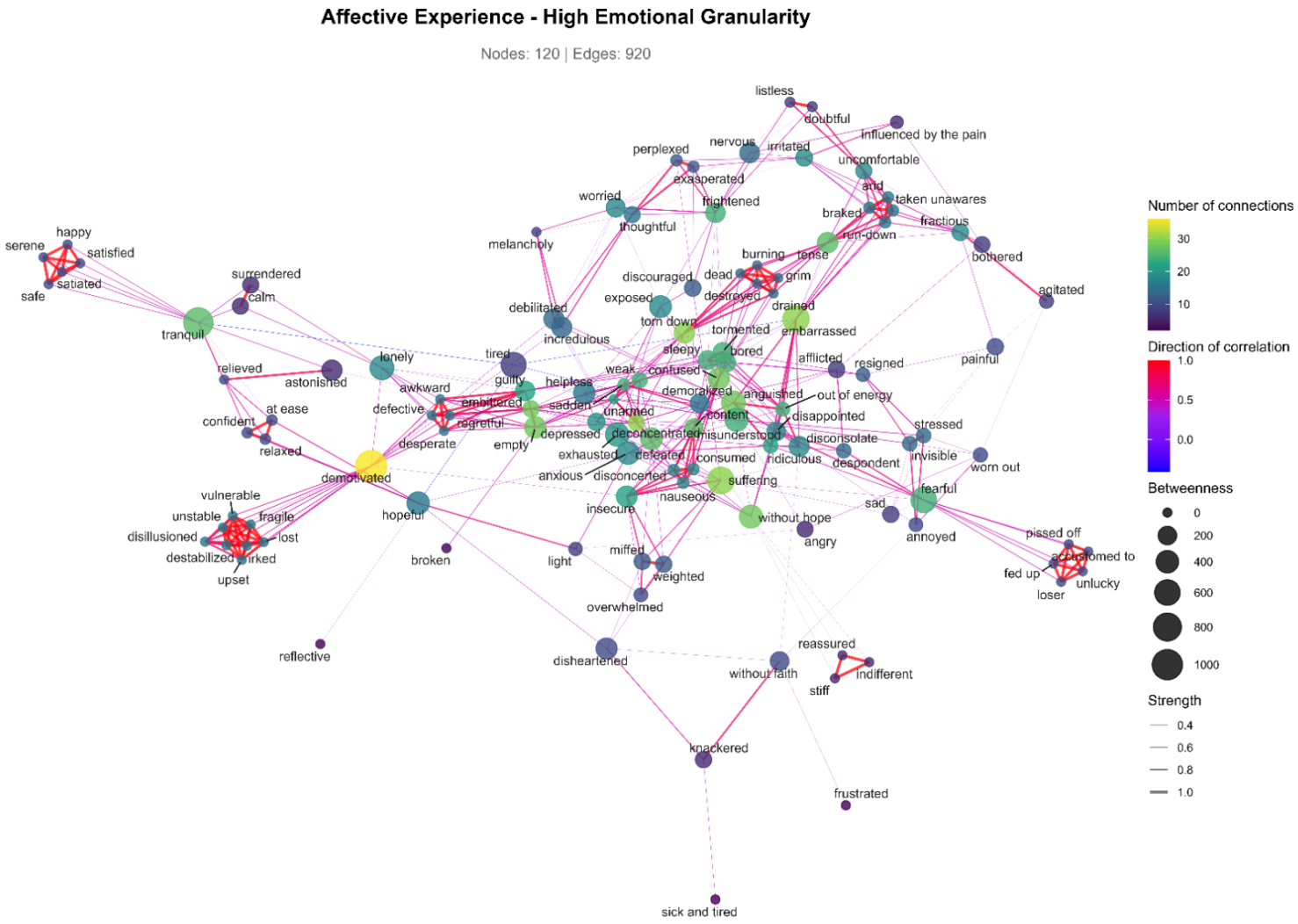


Figure 1

Network visualization of the affective experience for participants with high emotional granularity.

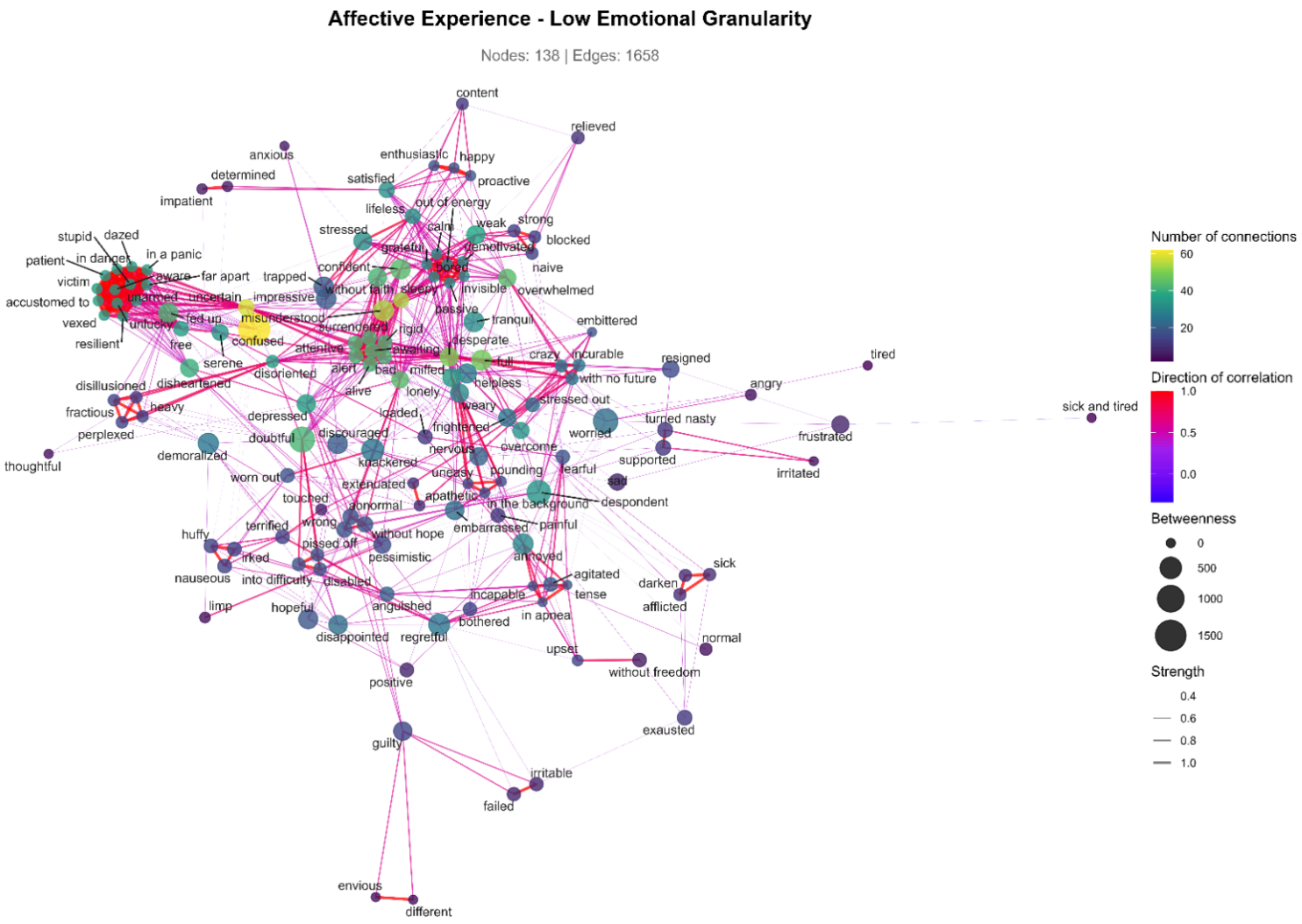


Figure 2

Network visualization of the affective experience for participants with low emotional granularity.

Supplementary Files

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