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Coordinator: Margherita Lanz, Ph.D.

Emotional Granularity: From Methodological Challenges to Real-Word Implications for Embodied Affective Dynamics

Ph.D. Candidate: Ilaria Telazzi

ID Number: 5215850
G.S.D. M-PSI/01

Supervision:

Stefania Balzarotti, Ph.D.
Università Cattolica del Sacro Cuore

Revision:

Katie Hoemann, Ph.D.
University of Kansas

Elise Kalokerinos, Ph.D.
University of Melbourne

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“Variety is the spice of life. This idiom captures one of the great truths
about human existence: There is tremendous richness and diversity
in the mental states that people experience within themselves
and perceive in others. Nowhere is this variability more apparent
than in the experience and perception of emotion.”

(Barrett, 2009, p.1284)

Dedication

To Marti and Ross: You have been my colors on dark days and my compass in moments of haze (the rhyme was unintentional!). Without you, these past three years would have been more tiring and far more barren.

To my friends (especially Ale, Camna, Chicca, Ele, Enri, Fede, Fra, Giaci, Lau, Manu, Marti, Pote, Sara, Sara, Silvia, Teo): You have embraced my struggles, soothed them, and transformed them into generative potential. You are precious.

To my group of dancers: The spaces we created and shared together have been a source of nourishment, relief, and inspiration. I have contemplated the wisdom of your bodies and savored the power of your drives.

To my parents: Even without understanding, you cared. "Simply", thank you.

To Davide: You are the person I care about the most in this world. In these 21 years, you've changed my life for the better. Never forget that.

To Adelia: Our arguments inspired reflection in me and became a driving force for change.

To Gio: As unexpected and surprising as these lines may be, I think there are no words to express my *riconoscenza* [a feeling of conscious gratitude toward those who have done you good, along with the intention of repaying the good you have received].

Finally, as strange as it may seem, I want to express in these last few lines how, throughout the three years that have accompanied this journey, I have felt – at various times – grateful, fortunate, satisfied, proud: For the encounters with people I have never seen again but hold dear in my heart; for the travels, to lands near and far, which have broadened my perspective on the world; for having enjoyed the silence of the mountains; for the new friendships; for having dared, for having had *coraggio* [courage], which is nothing more than *avere il cuore a proprio agio* [having your heart at ease]; for having learned so much from the people around me; for the impulses of life despite the hardship; for having let music and dance permeate me; for the moments of sharing with the people I love; and also, for the moments of *commozione* [being moved in the soul by heartfelt feelings of affection, tenderness, compassion, empathy, admiration]; for having said uncomfortable "no"s and equally challenging "yes"s; for the reconciliations; for the empty spaces in which to savor the road behind me; above all, for having learned new paths to welcome and be welcomed.

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Abstract

Consistent with the Theory of Constructed Emotion, emotional granularity (EG) refers to an individual's ability to construct precise and context-sensitive emotional experiences. During the last two decades, EG has gained increasing empirical attention because of its theorized adaptive relevance for psychological and physical wellbeing. However, foundational questions remain regarding its measurement, underlying mechanisms in overall allostatic regulation, and related implications for broad affective functioning. This dissertation attempts to advance current knowledge addressing three critical gaps in the literature, integrating a methodological and an applied line of inquiry.

First, the intrinsic nature of the construct requires behavioral assessment approaches, which pose numerous challenges for obtaining EG measures that are both valid and reliable. Chapter 1 presents a systematic review that synthesizes existing operationalizations of EG and critically evaluates discrepancies between measurement practices and its underlying theoretical definition. Second, EG is has been speculated to function as an emotion regulation (ER) strategy, positing overlapping processes of emotion generation and regulation. However, the nature of the relationship between EG and ER remains poorly understood. Chapter 2 focuses on clarifying the bidirectional association between within-person positive and negative EG and five ER strategies (suppression, rumination, social sharing, distraction, reappraisal), both in-the-moment and prospectively; to elucidate the mechanisms underlying the EG–ER relationship, we further account for the moderating role of latent sleep patterns, conceived as an index of allostatic regulation in emotional functioning. Third, little is known about how EG is embedded within broader affective functioning and its role in delineating boundaries between emotion and other affective states. Chapter 3 investigates the within-person concurrent and prospective impact of negative EG (both across, between, and within emotion families) on chronic pain intensity. Since interoception is a shared mechanism in both the experience of emotion and pain, we further explored the moderating role of dispositional interoceptive sensibility in the association between EG and pain.

Collectively, the results underscore that, on the one hand, there is substantial heterogeneity in EG assessment practices, often reflecting a lack of coherence and a misalignment between the conceptualization and operationalization of EG. On the other hand, the adaptive function of EG appears to vary across the facets under investigation, to be dependent on modulators of allostatic regulation, and to exhibit intraindividual variability contingent upon temporal framing. Overall, this dissertation proposes critical methodological reflections on how EG is currently conceptualized and assessed and provides a context-sensitive and conditional account of its underlying mechanisms and implications for emotional and affective functioning.

Keywords: emotional granularity, emotion differentiation, measurement, affective dynamics, allostatic regulation, interoception, experience sampling

Summary

Introduction

1. Emotional Granularity: The Theory of Constructed Emotion as a Background

Emotional granularity refers to an individual's ability to create nuanced and context-specific instances of emotions (Barrett et al., 2001). A person with high emotional granularity is able to construct fine-grained and situated instances of emotion, differentiating both between and within various emotional categories. Conversely, individuals low in granularity tend to describe their emotional experience using emotion labels interchangeably (Barrett et al., 2001) or broad, less context-dependent terms (Barrett, 2006). This conceptualization of emotional granularity aligns with constructivist approaches to emotional experience (Barrett, 2004) and, more specifically, with the Theory of Constructed Emotion (TCE; Barrett, 2017a; Barrett et al., 2025; a glossary of the core features of this theory is provided in Table 1).

Within the constructivist paradigm, the brain is conceived as a Bayesian predictive system operating according to the principles of predictive coding (Barrett & Simmons, 2015; Chanes & Barrett, 2016; Clark, 2013a, 2013b; Denève & Jardri, 2016; Friston, 2010; Hohwy, 2013; Seth, 2013; Seth et al., 2012). From this perspective, the brain's primary function is not merely reactive but fundamentally anticipatory: It continuously generates predictions about the future organism's physiological demands, preparing to satisfy them before they occur. Through this process, the brain orchestrates coordinated adjustments across multiple bodily systems (e.g., autonomic, endocrine, and immune systems), thereby maintaining adaptive functioning. This ongoing regulatory mechanism is termed allostasis (Sterling, 2012; Sterling & Laughlin, 2015). Crucially, the same processes that sustain allostatic regulation simultaneously give rise to the sensory and affective qualities of subjective experience (Barrett, 2017a; Hutchinson & Barrett, 2019; Shaffer et al., 2022). According to this view, each moment of conscious experience emerges from the integration of three interdependent sources of information: Exteroceptive input, which conveys information about the external environment and situational context; interoceptive signals, which represent the internal physiological state of the body and inform the subjective sense of how one feels within that context; and prior experience, which encompasses accumulated knowledge about similar bodily states and environmental regularities. These dynamic sources of information jointly contribute to the formation of embodied subjective experiences, some of which are subsequently categorized and labeled as emotions (Barrett, 2017a; Barrett et al., 2025).

According to the TCE, emotional instances are not viewed as biologically hardwired or universally discrete entities; instead, they are conceived as contextually constructed psychological events emerging from the interplay of several components. Importantly, this interplay is informed by a range of scientific disciplines beyond psychology (including neuroanatomy, neurobiology, physiology, biochemistry, linguistics, ethology, and anthropology; Barrett et al., 2025). Formally, an emotional instance is assumed to emerge through the integration of four core elements: (1) A *core affect* (Barrett & Bliss-Moreau, 2009; Russell, 2003; Russell & Barrett, 1999), the fundamental representation of bodily states experienced along continuous dimensions of valence (pleasant–unpleasant) and arousal (activated–deactivated); (2) a conceptual system for emotion, comprising semantic and cultural knowledge about emotion categories stored in long-term memory (Barrett, 2006); (3) controlled attention, which (although not necessarily conscious or deliberate) modulates the activation and suppression of conceptual emotional instances relevant to a given situation (Barrett et al., 2004); and (4) a categorical event, which originates as a distributed pattern of neural signals and culminates in a situated emotional episode (e.g., a specific instance of "anger") whose phenomenological and physiological characteristics vary across time, context, and individuals (Barrett et al., 2025).

Each of these four constitutive components can exhibit variability both between individuals and within the same individual over time. Variation can exist in affective responsiveness, that is, in how strongly and flexibly interoceptive and exteroceptive systems integrate with each other as internal and external conditions change. There can also be differences in the scope, organization, and accessibility of conceptual knowledge about emotion, which determines the range of emotional categories available for constructing experience. Furthermore, variation in attentional control shapes how effectively these conceptual representations are applied to physiological and sensory signals in real time.

Overall, variability in emotional experience arises from differences in the processes that support the construction of emotion (Barrett, 2009). Together, these differences can contribute to inter- and intra-individual variability in emotional granularity. Higher granularity entails the ability to construct differentiated emotional instances that reflect subtle shifts in bodily and contextual cues, whereas lower granularity encompasses broader, less context-dependent categorizations of affective experience. In this sense, emotional granularity can ultimately depend on the interaction between affective reactivity, the accessibility and precision of emotion concepts, and the efficacy in selecting and applying those concepts to momentary interoceptive and exteroceptive signals within the predictive architecture of brain functioning.

Table 1. Glossary of core terms and features of the Theory of Constructed Emotions.

Term	Definition
Affect	Subjective experience of interoceptive signals. It is typically organized along fundamental dimensions such as valence (pleasant–unpleasant) and arousal (activation–deactivation), which constitute core features of conscious experience rather than properties exclusive to discrete emotions. The brain continuously constructs an affective niche in the present moment.
Allostasis	The process by which the body regulates and adjusts physiological systems (such as hormonal, autonomic, and immune systems) in anticipation of or response to changing demands, ensuring stability and adaptive function beyond simple homeostatic restoration.
Categorization	The process by which patterns and consistencies are identified and organized within a given situation in order to serve a specific function. Through this process, sensory inputs and motor signals are structured and interpreted so that they acquire meaning for the perceiver, enabling context-dependent understanding and guiding action appropriate to that function.
Controlled Attention	The limited attentional resources that can be allocated to support the formation of categories and the regulation of the categorization process. It facilitates the selection of which conceptual features are activated and which are inhibited during a specific instance of conceptual processing.
Embodied Simulation	The internal representation of the body situated within its environment. This representation operates through predictive mechanisms that continuously forecast incoming sensory information. Such anticipatory signals guide motor behavior and actively shape perception, as well as broader psychological processes, including affective and emotional experiences.
Emotion Concepts	Individual's accumulated knowledge and past experiences related to specific emotions. They consist of the underlying cognitive and semantic structures associated with emotion labels. These concepts are dynamically constructed in a context-dependent manner, giving rise to situational, ad hoc emotional representations.
Emotion Words	Lexical labels for emotional states. They function to organize and systematize emotion concepts, integrating diverse, context-dependent experiences of feeling and behavior into abstract emotion categories that develop over time.
Emotions	Mental events arising from a dynamic and continuously evolving constructive process, emergent products of psychological components whose combination exceed the sum of each element in isolation. They constitute whole-brain events that integrate and modulate internal physiological processes while simultaneously organizing and directing motor behavior and generating subjective lived experiences in a physical and social world.
Exteroception	The perception and integration of sensations from the external environment.
Interoception	The process by which the nervous system detects, processes, and integrates signals arising from autonomic, endocrine, visceral, and immune systems, thereby representing the body's internal physiological condition.

Prediction	Hypotheses about the reality that can be tested against incoming sensory information processed by the brain.
Prediction Error	The discrepancy between the brain's expected sensory input and the actual incoming information. It represents unexpected signals from the environment that serve as feedback for the brain's embodied simulations.
Situated Conceptualization	A prediction including how sensory information is interpreted as representing specific objects or events in the environment. This process determines which features of the input are relevant and should be prioritized, anticipates appropriate behavioral responses, and forecasts the expected homeostatic and metabolic outcomes.

1.1. Emotional Granularity in the Predictive Brain

The precision with which the brain models and anticipates bodily states in the service of allostasis is reflected in an ongoing cycle of constructing differentiated affective (and then, in some cases, emotional) experiences. To regulate the body effectively within a changing environment, the brain continuously maintains and updates an internal model of the body in the world. This internal model, known as an *embodied simulation* (Barsalou, 2008; Barsalou et al., 2003), underlies allostatic regulation by continuously coordinating bodily adjustments and behavioral responses to maintain metabolic efficiency and adaptive functioning (Barrett & Simmons, 2015; Sterling & Laughlin, 2015). These simulations operate through predictive signals, continuously anticipating changes in the sensory environment and in the body. When predictions fail to match incoming sensory and interoceptive inputs, prediction errors arise and serve as feedback to refine the embodied simulation (Kleckner et al., 2017; Sterling & Laughlin, 2015). Controlled attention further contributes to this process by modulating the weight assigned to internal and external signals, thereby influencing the quality and precision of predictive inference (Barrett, 2009; Friston, 2010).

Through continuous cycles of prediction and error correction, the brain refines its affective map of the body, translating physiological fluctuations into subjective, situated experiences imbued with specific meanings. Individuals who are able to integrate interoceptive and exteroceptive information more effectively and minimize prediction error efficiently are likely to generate more detailed and nuanced embodied representations of ongoing experience (Barrett, 2017b). Accordingly, the precision, coherence, and richness of these embodied simulations reflect the overall quality of the affective experience.

Importantly, these situated affective experiences are characterized by a discrete subjective meaning because embodied simulations rely on concepts (Barrett et al., 2025). Within this framework, concepts are embodied, multimodal representations, constructed from prior experience, that encode expectations about what is likely to occur in the environment and in the body, which actions are most (mal)adaptive in a given situation, and what their consequences will be for allostasis (Barrett, 2017a). When applied to the continuous stream of affective information, concepts structure and refine subjective experience by informing feelings, cognitions, motivational tendencies, and behaviors. An emotional experience is constructed when the brain recruits emotion concepts to interpret and give meaning to the current affective state in light of the ongoing situation (Hoemann et al., 2025). In this framework, an instance of a concept actively shapes the mental event that is ultimately experienced as emotion. Consequently, an individual’s breadth and specificity of these conceptual structures contribute directly to the ongoing emotional experience. Emotion concepts that are richer and more fine-grained enable the construction of emotional experiences that are highly contextually bound, distinctive, and adaptive.

Individuals high in emotional granularity are able to parse subtle variations in affective experience precisely because their conceptual repertoire is more diverse and differentiated, thereby providing a framework for subtly categorizing affective states (Hoemann, 2024). Importantly, granularity is often reflected in the lexical precision with which individuals describe and label emotions. Nevertheless, while language serves as a powerful tool for expressing conceptual knowledge about emotion, its role is not superordinate for the construction of nuanced emotional experiences (Barrett et al., 2025; Lindquist, Satpute, et al., 2015).

Emotion words can be seen as footprints of specific emotion concepts (Hoemann et al., 2019; Lindquist, MacCormack, et al., 2015); however, the relationship between lexical labels and conceptual representations is neither fixed nor perfectly isomorphic (Barrett, 2004; Shiota & Keltner, 2005). For instance, consider the emotion word "sadness": The sadness experienced at the conclusion of a vacation differs qualitatively from the sadness encountered in response to a bereavement. In this example, the same emotion word is applied to distinct emotion concepts. An emotion word functions as an abstract tool that enables the brain to identify functional similarities across experiences, even though these experiences do not share statistical regularities in their sensorimotor features (Barrett & Lida, 2024; Barrett & Theriault, 2025). In this sense, emotion words allow the brain to group diverse instances of emotion into a single conceptual category, despite considerable variability among the underlying experiences. Emotion words thus operate as a conceptual binder, maintaining cohesion across different emotion concepts within a defined emotion category (Hoemann et al., 2019; Lindquist, MacCormack, et al., 2015).

There is substantial, and non-random, variability in how concepts are distributed within each emotion category, both across individuals and within the same individual. On the one hand, across people, such variation reflects differences in conceptual repertoires and emotion vocabularies, which are shaped by their unique background of affective learning and experiences. On the other hand, within a single individual, variability may arise depending on the contextual demands (Barrett et al., 2025). Far from being a byproduct of noise, such variability supports the functional utility of emotional experiences, allowing individuals to tailor situated affective adjustments to the shifting demands of their environments (Barrett, 2017b; Hoemann, Nielson, et al., 2021; Springstein et al., 2023). And definitely, to the extent that emotion concepts are categorized and applied across diverse contexts, this very variability constitutes a matter of emotional granularity (Barrett et al., 2025).

1.2. Emotional Granularity as a Competence: Implications for Its Measurement

Emotional granularity can be understood not merely as a descriptive feature of emotional life but as a competence (Kashdan et al., 2015), since it reflects the ability to flexibly generate, differentiate, and deploy emotion concepts and emotion words in alignment with the demands of a given context. This competence enables individuals to construct emotional experiences with high contextual sensitivity.

As a skill, emotional granularity can be developed and enhanced over time (Hoemann, Barrett, et al., 2021; Matt et al., 2024; Van Der Gucht et al., 2019; Vedernikova et al., 2021; Widdershoven et al., 2019). Crucially, both one's understanding of emotions and the variety of emotion words a person actively uses 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). Consequently, emotional knowledge and a rich emotion vocabulary can support the development of granularity. For example, knowledge about the features of emotions may enable individuals to more readily perceive similarities and differences among emotional states, fostering a more context-sensitive ability to discern subtle nuances (Vedernikova et al., 2021). Similarly, expanding one's repertoire of emotion words may provide the conceptual tools necessary to identify and differentiate subtle variations in emotional experiences (Matt et al., 2024). However, it is important to note that 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. For example, an individual might understand the distinction between terms such as "dejected" and "melancholic," yet use them interchangeably or resort to the broader label "unpleasant" for vaguely negative affective states. Conversely, both "dejected" and "melancholic" can be employed simultaneously in a granular manner to highlight distinct aspects of an emotional experience. As previously discussed, emotion concepts are not reducible to the words that label them (Hoemann et al., 2025), and individuals vary in their ability to apply these words with precision and nuance.

From a theoretical standpoint, on the one hand, emotional granularity refers to the structure, quality (Barrett et al., 2001; Tugade et al., 2004) and breadth of conceptual knowledge (Barrett, 2017b), requiring nuanced and non-overlapping concepts. On the other hand, it accounts for the verbal representation of emotional experiences, encompassing the identification, labeling, and description of emotions and implying a normatively appropriate use of language (Barrett, 2004; Lee et al., 2017), without necessarily requiring explicit subjective awareness (Barrett, 2017a,b). These defining features distinguish emotional granularity from related emotional constructs and open the way for its acquisition through deliberate, context-sensitive practice (Hoemann, K., Nielson, et al., 2021). In this sense, individuals can improve their granularity (Barrett, 2017b) by becoming "collectors of experience" (Hoemann, K., Nielson, et al., 2021, p. 1173), actively seeking novel situations that expand their perspectives and foster the development of more refined emotional concepts.

These theoretical premises in the conceptualization of emotional granularity naturally carry important implications for its measurement. Since granularity has been conceptualized as a skill, it has been argued that it must be assessed via behavioral methods rather than self-report, retrospective measures – as the latter may conflate granularity with emotional knowledge or with the breadth of one's emotion vocabulary (Kashdan et al., 2015). Such behavioral methods include capturing individuals' emotional experiences on a moment-to-moment basis. One of the most widely adopted approaches is Experience Sampling Methods (ESM), in which participants report their emotions multiple times across a predefined period, relying on a fixed set of emotion terms selected by the researcher (Thompson, Springstein, et al., 2021). Although ESM yield ecologically valid data, they are not without practical challenges, including participant burden and the influence of individual life circumstances on reported emotions (Erbas et al., 2013, 2015). To overcome these limitations, alternative laboratory-based methods, such as emotion differentiation (ED) tasks, have been developed (Erbas et al., 2014). However, a fundamental limitation of any granularity assessment based on repeated emotion ratings (in both daily life and laboratory settings) lies in its reliance on a fixed list of emotion terms (Kashdan et al., 2015). As alternatives, emerging methods have begun to adopt open-response formats rather than closed-ended emotion lists (Ottenstein & Lischetzke, 2020; Williams & Uliaszek, 2022), although these procedures are still in their early stages of development.

While the conceptualization of granularity implies that highly granular individuals flexibly generate nuanced mental representations and descriptions of their emotional experiences across situations, operationalizing this construct in a manner that truly captures its complexity is methodologically challenging (Ip et al., 2024; Thompson, Springstein, et al., 2021). These challenges pertain to the nature of the emotion lexicon under analysis, the procedures used to capture emotional experiences, and the statistical techniques employed to compute granularity indices (Thompson, Springstein, et al., 2021). Beyond the necessity of behavioral measures of granularity (to avoid merely indexing emotional knowledge or the breadth of one's emotion vocabulary), it is important to recognize that granularity, as an ability, is always applied to an emotional experience that is inherently subjective and individual-specific. Underlying any granularity measure is a person's experiential world: Their inner sensations, prior learning, conceptual repertoire, known emotion words, and the variability of contexts in which they can deploy them. Taken together, these factors underscore the downstream complexity of obtaining a fully generalizable measure of granularity and the inherent challenges in developing assessments of this skill that are both highly valid and reliable.

1.3. The Putatively Adaptive Function of Emotional Granularity

Emotional granularity has been proposed as a functional ability that likely supports adaptive psychological functioning (Hong et al., 2025; Kashdan et al., 2015; O'Toole et al., 2020; Seah & Coifman, 2022a; Smidt & Suvak, 2015; Tan et al., 2022; Thompson, Springstein, et al., 2021). The capacity to identify, differentiate, and label one's emotional states in a subtle and nuanced manner might contribute to greater accuracy in recognizing the sources and functions of affective states, thereby allowing for a more targeted and proportionate adaptive responding (Thompson, Springstein, et al., 2021). In other words, high emotional granularity might facilitate a precise appraisal of the emotional event being experienced and its correlates: The antecedents and associations that led to the categorization of that affective state as a particular emotional instance; the immediate implications of that emotional instance for oneself and others; the relevant goals that emerge from the situation; how one positions oneself in relation to these goals in terms of motivation, action tendencies, and the skills required to achieve them; and, ultimately, the selection of appropriate actions and behaviors. For example, distinguishing between feeling “irritated”, “frustrated”, or “disappointed”, in relation to the source of information that contributed to the construction of that emotional event, may enable the identification of distinct goals and associated action tendencies, each serving a different adaptive function.

Despite these theoretical premises, the empirical evidence examining the adaptive function of emotional granularity has shown mixed findings. For instance, it has been suggested that higher granularity may be associated with reductions in maladaptive coping behaviors, such as alcohol consumption (Emery et al., 2014; Kashdan et al., 2010), cigarette craving (Sheets et al., 2015; Walters et al., 2023), and impulsivity (S. E. Racine et al., 2024; Tomko et al., 2015). However, this protective role of granularity does not appear to apply uniformly across all types of maladaptive behaviors and, even within the same category of behaviors, evidence is inconsistent. For example, some studies have reported that higher granularity is linked to reduced aggressive behavior (Pond Jr. et al., 2012), whereas others have found a positive association (Edwards & Wupperman, 2017; Y. Yang, 2023). Mixed results have also been observed for substance use (Anand et al., 2017; Walukevich-Dienst et al., 2023) and dysfunctional eating behaviors (Jones & Herr, 2018; Mehak et al., 2024; Mikhail et al., 2020; Seah, Sidney, et al., 2022; Williams-Kerver & Crowther, 2020). Other studies further suggested that emotional granularity provides information that can support the context-sensitive and flexible implementation of certain, but not all, emotion regulation strategies, sometimes yielding contrasting results (Barrett et al., 2001; Kalokerinos et al., 2019; O’Toole et al., 2021; Sels et al., 2024). Associations between higher granularity and improved psychological well-being and mental health have also been reported (Erbas et al., 2018; Williams & Uliaszek, 2022); yet other studies have found these associations to be non-significant (Grühn et al., 2013; Ikeda, 2023; Zhang et al., 2021) or have suggested that the adaptive role of granularity is conditional upon specific trait factors (V. Y. S. Oh & Tong, 2020). Still, others have found that the protective effect of granularity disappears when controlling for emotional intensity (Dawel et al., 2023; Willroth et al., 2020). Despite these mixed findings in non-clinical samples, research comparing clinical and non-clinical populations consistently indicates that individuals with schizophrenia (Kimhy et al., 2014), major depressive disorder (Demiralp et al., 2012; Thompson, Liu, et al., 2021), social anxiety disorder (Kashdan & Farmer, 2014; Seah et al., 2020), post-traumatic stress disorder (Pugach et al., 2023), and borderline personality (Zaki et al., 2013) exhibit lower emotional granularity than healthy controls do.

Notably, meta-analytic evidence suggests that there may be substantial differences in the adaptive role of the ability to differentiate between negative versus positive emotions (that is, negative granularity versus positive granularity), with the latter being less consistently associated with adaptive outcomes. Even for negative granularity, however, the results across meta-analyses are mixed. For example, negative, but not positive, granularity appears to be associated with depressive symptoms, with this association moderated by emotional intensity (for review and meta-analysis, see Hong et al., 2025). Negative granularity also seems to exert a small effect on behavioral adaptation, whereas positive granularity shows no such effect (for review and meta-analysis, see O'Toole et al., 2020). Nevertheless, other evidence indicates that, irrespective of the intensity of negative emotions, negative granularity is associated with reduced engagement in maladaptive behaviors (for review and meta-analysis, see Seah & Coifman, 2022).

Collectively, these findings underscore that research on emotional granularity is still in its early stages. While there is a solid theoretical rationale supporting the notion that granularity may serve an adaptive and protective function, the specific conditions under which these effects manifest, the underlying mechanisms driving such benefits, and the facets, circumstances, or processes through which granularity may instead produce adverse outcomes remain poorly understood (Kashdan et al., 2015). Importantly, mixed empirical evidence may reflect variability in effect size (often manifesting as small or non-significant associations) rather than consistent indications that granularity produces maladaptive outcomes. Accordingly, advancing the field will require greater attention to underlying conditions and mechanisms, and methodological approaches capable of capturing when, how, and for whom emotional granularity meaningfully contributes to adaptive functioning.

2. The Present Dissertation

As outlined in the preceding paragraphs, in the last two decades interest in the construct of emotional granularity has increased due to its potential adaptive role. Despite this increasing attention, critical gaps remain in the literature, both with respect to its measurement and the subtle mechanisms underlying its implications for well-being. The present dissertation aims to address some of these gaps by integrating methodological and applied lines of inquiry, reflecting a twofold objective. First, it seeks to critically examine the measurement of emotional granularity. As discussed, the intrinsic nature of the construct requires behavioral assessment approaches, which pose numerous challenges for obtaining granularity measures that are both valid and reliable. Second, the dissertation aims to investigate how granularity is embedded within affective dynamics while accounting for correlates of allostatic regulation. As noted, the mechanisms and processes underlying the potential role of granularity in adaptive functioning remain poorly understood. Given that emotional granularity is conceptualized within a complex theoretical framework that emphasizes mind-body integration and holism (rather than dualism), it is important to examine its dynamics while accounting for this broader perspective.

These two objectives are addressed through three studies, presented in a sequential progression across three distinct chapters of this dissertation. The first chapter focuses on the measurement-related objective, whereas the second and third chapters build upon the methodological insights gained from the first study to address the second objective. Each chapter is structured in the form of a scientific manuscript intended for submission to peer-reviewed journals relevant to the field of psychological science, particularly research on affect and emotion. Moreover, an appendix containing supplementary materials follows each chapter, while the references for all three chapters are compiled in a single section at the end of the dissertation for the sake of clarity and completeness.

The first chapter presents a systematic review aimed at synthesizing existing operationalizations of emotional granularity and critically evaluating potential discrepancies between measurement practices and the underlying theoretical definition of the construct. Focusing on empirical studies conducted in non-clinical adult populations, this review pursues three main objectives, rooted in the well-documented methodological heterogeneity in granularity assessment (Thompson, Springstein, et al., 2021). First, it seeks to map how existing literature has conceptualized granularity and its facets, for example, whether granularity has been studied as a trait-like characteristic or as a context-dependent skill that fluctuates within individuals, whether studies have focused predominantly on positive or negative emotional experiences, or whether research has targeted particular families of emotions. Second, it provides a comprehensive synthesis of the methodological approaches employed to assess, measure, and compute granularity. Methodological divergences across studies are highlighted, and potential inconsistencies between the conceptualization and operationalization of granularity are identified. Finally, the review considers the constructs and variables that researchers have commonly examined as potential correlates of granularity, discussing the results in light of methodological heterogeneity. Overall, the chapter aims to offer a detailed and critical overview of the state of the art in granularity assessment, identifying strengths and weaknesses of existing methods and providing insights and directions for future research.

The second chapter focuses on clarifying the general functioning and potential adaptive role of granularity within the dynamics of individuals' moment-to-moment emotional experience. Specifically, it examines the interplay between positive and negative momentary granularity and five emotion regulation strategies (i.e., suppression, rumination, distraction, social sharing, and reappraisal) while also accounting for emotional intensity. These components of emotional experience are analyzed via a network-based approach that highlights their mutual relationships and temporal influences, both at the momentary level and across time. This network framework enables a detailed investigation of how granularity is jointly associated with both adaptive and maladaptive regulatory strategies and how it operates within the broader pattern of prospective mutual associations among other facets of emotional functioning. Importantly, given that emotional events represent an experiential correlate of allostatic regulation (Barrett, 2017a; Barrett et al., 2025) and that sleep is a key modulator of both allostatic functioning (Irwin, 2015; McEwen & Karatsoreos, 2022) and emotional states (ten Brink et al., 2022), the interplay between granularity, emotion regulation, and emotional intensity is further across distinct latent sleep profiles. Specifically, I evaluate whether individuals characterized by different latent sleep patterns exhibit distinct within-person emotional functioning both in-the-moment and prospectively over time. By integrating a person-centered perspective on the conditional role of sleep-related allostatic regulation, this chapter seeks to delineate how emotional granularity is intertwined with (mal)adaptive emotion regulation and how it operates within overall emotional dynamics over time.

Finally, the third chapter investigates how granularity lies at the intersection between emotion and other affective states in the context of chronic neuropathic and nociplastic pelvic pain (i.e., chronic pain in the absence of tissue damage). Both emotions and pain fall under the broader domain of affective experience. It has been proposed that, in the presence of chronic pain without tissue damage, granularity may serve as a mechanism shaping the experience and perpetuation of chronic neuropathic and nociplastic pain (Barrett, 2017b). This hypothesis is examined by analyzing the concurrent and prospective impacts of negative granularity (both across different emotional categories and within specific categories) on momentary pain experience. Furthermore, given that both emotion and pain arise from interoceptive predictions (Barrett et al., 2025; Craig, 2003; Ongaro & Kaptchuk, 2018), interoceptive sensibility is considered a potential moderator of this association. By accounting for the role of interoception, which lie at the core of allostatic regulation (Kleckner et al., 2017) and the construction of affective experience (Barrett, 2017a), I focus on how granularity contributes to the characterization of broader affective experiences, encompassing both emotion and pain. Overall, this chapter seeks to clarify the conditions and mechanisms through which emotional granularity contributes to the delineation of affective boundaries between emotion and pain and to the chronification of pain in the absence of tissue damage.

Chapter 1

Assessing and Measuring Emotional Granularity: A Systematic Review of the Existing Methodological Approaches

Ilaria Telazzi[1], Michela Zambelli[1], & Stefania Balzarotti[1,2]

[1]Università Cattolica del Sacro Cuore di Milano, Italy

[2]Communication Psychology Lab, Università Cattolica del Sacro Cuore di Milano, Italy

Abstract

Emotional granularity (EG), also referred to as emotion differentiation, consists in the ability to create instances of emotions in a precise manner. Although EG has received increasing empirical attention in recent years, its operationalization and measurement remain highly heterogeneous. By focusing on empirical studies conducted in nonclinical adult populations, this systematic review aims to synthesize existing operationalizations and assessment approaches of EG to critically evaluate potential discrepancies between measurement practices and underlying theoretical definition.

A comprehensive literature search was conducted across Scopus, PsycInfo, PubMed, and Web of Science up to January 2025, yielding 96 eligible articles (115 studies).

The reviewed studies revealed substantial variability in EG operationalization, measurement, and computation. This diversity among methodological practices raises concerns about construct validity, cross-study comparability, and the interpretability of findings linking EG to psychological functioning. We discuss key challenges and propose directions for improving the consistency, transparency, and theoretical coherence of EG assessment.

Keywords: emotional granularity, emotion differentiation, measurement, assessment, method, review

1. Introduction

Emotional granularity (EG), or emotion differentiation, reflects the ability to create nuanced, situated instances of emotions (Barrett et al., 2001). Individuals with high levels of EG can distinguish subtle variations in their emotional experiences in a precise and context-specific manner. This includes differentiating between emotions of similar valence and arousal, as well as making fine-grained distinctions both across emotion categories (e.g., fear, sadness, anger) and within a single category (e.g., anger, frustration, nervousness). In contrast, low-EG individuals struggle to make such distinctions. They are more likely to rely on a broad pleasant–unpleasant dimension and often use same-valence emotion terms interchangeably to reflect the general valence of their feelings.

One of the most prominent theoretical frameworks underlying EG is the Theory of Constructed Emotion (TCE), which posits that emotions are not innate, discrete entities but are dynamically constructed through predictive brain processes (Barrett, 2017a; Barrett et al., 2025). According to the TCE, language and conceptual knowledge are central to shaping emotional experience by providing structure and meaning to affective states (Barrett, 2014; Hoemann, 2024; Hoemann et al., 2025). Thus, individual differences in EG may reflect the extent to which people access and apply emotional concepts and vocabulary during emotional episodes. By definition, EG has been conceived as an ability: In other words, it does not merely consist in the possession of emotion labels or concepts, but it also implies the capacity to apply such labels and concepts to lived experience. As such, EG relies on both the acquisition of emotion-related language and the ongoing refinement of one's ability to categorize affective states with increasing precision (Hoemann, 2024). Individuals with a richer emotional vocabulary and a more nuanced understanding of emotion categories are therefore better equipped to differentiate and label their emotional experiences with situated specificity (Barrett, 2017b; Lindquist & Barrett, 2008).

Notably, EG is thought to have relevant implications for the individual's psychological functioning. EG theorists have advanced the hypothesis that the ability to put one's feelings into words with precision and detail is a critical competence to adaptively regulate and manage one's emotions and ultimately leads to positive mental health outcomes and adaptive behavior (Kashdan et al., 2015). Guided by this hypothesis, in the last two decades, research on EG and its potential role for healthy psychological functioning has rapidly grown (Erbas, Gendron, et al., 2022; Nook, 2021; O'Toole et al., 2020; Seah et al., 2020; Tan et al., 2022). This growing attention, however, has confronted researchers with notable conceptual and methodological challenges regarding EG operationalization and measurement. Since it is conceptualized as a skill or ability, EG cannot be assessed via standard self-report questionnaires; rather, it requires behavioral or performance-based methods (Kashdan et al., 2015). Over the years, a variety of assessment strategies have been developed, with different studies using different methods to operationalize and measure EG. A widely used approach involves repeated ratings of momentary emotions using fixed emotion terms, with EG inferred from the within-person variability (e.g., intra-class correlation) in these ratings. Other emerging methods involve allowing participants to freely describe their emotions, and EG is then quantified based on the specificity of self-generated emotional lexicon (Thompson, Springstein, et al., 2021). Thus, despite the relatively well-established theoretical definition of EG (Barrett et al., 2001), its operationalization and assessment look far less consistent. This heterogeneity raises questions about the extent to which existing methods adequately capture the core features of this construct and casts doubt on the degree of coherence in how EG has been operationalized in the existing literature.

Along this line of reasoning, Thompson, Springstein, et al. (2021) have recently provided a first critical examination of methodological practices in the EG literature, addressing both healthy and clinical populations. Although their review provides valuable insights and methodological rigor, it remains narrative in nature. Building on this work, we argue that the increasing attention from emotion research to EG and its potential benefits for psychological functioning highlight the need for a systematic synthesis of existing studies with a focus on assessment practices. The body of research on EG has continued to expand considerably in the last years, and new methods to assess EG are now emerging. To our knowledge, a comprehensive review that systematically examines how EG has been conceptualized and measured is still lacking.

Focusing on empirical studies conducted in nonclinical adult populations and using a systematic approach, the present review has three main goals. First, we aim to map how existing literature has conceptualized EG and its facets. Second, we aim to provide a comprehensive synthesis of the methodological approaches that existing research has employed to assess, measure and compute EG. Through this analysis, we aim to highlight methodological divergences across studies and to identify potential inconsistencies between its conceptualization and operationalization. Finally, we consider the constructs and variables that researchers have commonly examined as potential EG correlates or outcomes. Overall, our main goal is to provide a detailed and critical overview of the state of the art in EG assessment and measurement by identifying the strengths and weaknesses of existing methods and to propose insights and directions for future studies.

2. Method

A comprehensive literature search was conducted from inception to January 2025 via the following databases: Elsevier – Scopus, PsycInfo, PubMed, and Web of Science. Boolean search strings were used to identify relevant studies, combining the following terms: [Title-Abs-Key("emotion* granularity" OR "emotion* differentiation")]AND[Full-Txt("intraclass correlation*" OR "intra-class correlation*" OR "ICC*") OR Title-Abs-Key("measur*" OR "method*")]. Additional studies were identified by manually screening the reference lists of identified articles and earlier reviews relevant to the topic.

Studies were deemed eligible if they conceptualized EG as the ability to precisely create instances of emotions, as defined by Barrett et al. (2001). Studies that did not adhere to this conceptualization and/or failed to assess EG behaviorally were excluded[1]. We considered peer-reviewed, published journal articles reporting empirical studies only. Studies published in languages other than English were excluded from the review. Additional selection criteria were based on sample characteristics: We excluded studies involving individuals under the age of 18 or clinical populations[2]. Studies including individuals with physical illnesses were retained if they did not have a diagnosed psychological disorder.

The identification and screening process are displayed in the PRISMA diagram (Figure 1). Two reviewers independently performed the screening of all the records (by examining the title and abstract first and then the full text). A third reviewer was asked to resolve disagreements if they emerged. The two reviewers also performed the extraction of the relevant information. Additional details concerning the screening process, data extraction procedures, and synthesis approach are provided in the Supplemental Material. This systematic review was preregistered on the Open Science Framework (OSF) at https://osf.io/tk3wf/overview prior to the initiation of article screening and data extraction.

3. Results

As shown in Figure 1, a total of 548 articles were initially identified; of these, 96 (115 studies) met the inclusion criteria (Cohen's $k = .744$, $p < .001$).

The results have been thematically organized into five content areas, each including a number of subcategories. The first area concerns the analysis of EG conceptualizations, including whether EG has been conceived as a dispositional or state level variable and the specific facets of EG under investigation (i.e., positive vs. negative vs. global EG; integral, between-category, and within category EG). The second area concerns EG operationalization, focusing on the use of emotion vocabulary to assess EG (predefined lists of emotional labels vs. natural language). The third and fourth areas concern

[1] Consequently, studies that explicitly conceptualized EG within a theoretical framework other than the TCE were excluded. Similarly, studies assessing EG exclusively through self-report measures were also excluded, as retrospective self-reports primarily capture individuals' beliefs about their emotional abilities rather than providing a behavioral assessment of the skill itself (see Kashdan et al., 2015 for further discussion). In contrast, studies that did not explicitly state their theoretical background but provided a definition of EG consistent with the TCE (e.g., Barrett et al., 2001) and employed behavioral measures for the assessment of EG were retained.

[2] By restricting the review to adult non-clinical samples, the present work aims to provide a clearer evaluation of the core methodological characteristics, assumptions, and psychometric properties of EG measures. This foundational step is necessary to establish methodological consistency and comparability before extending conclusions to non-adult and/or clinical populations, where further adaptation of EG assessment methods may be required.

existing measurement approaches (ecological versus non-ecological) and statistical procedures to compute EG indices. Finally, the last area concerns EG correlates and outcomes.

An overview of the contents of each area and the count of studies reporting relevant information in the paper is presented in Tables 1–4. Additional details regarding how EG has been measured in each study included in the review are provided in Table S3 in the Supplemental Material. Finally, more details regarding the EG correlates examined by each study (variables, type of analysis, significance and direction of the effect) are reported in Table S4 in the Supplemental Material.

3.1. Conceptualization of Emotional Granularity

3.1.1. Theoretical Background

Although all studies included in the review conceptualized EG as defined by Barrett et al. (2001) and measured it behaviorally in accordance with the inclusion and exclusion criteria, the majority of studies did not explicitly state their theoretical background. The bibliographic references cited in the reviewed papers frequently align with the TCE (Barrett, 2017b; Barrett et al., 2025), within which EG was originally conceptualized (Barrett et al., 2001). Nonetheless, only a small proportion of the reviewed included studies explicitly declared that their work was firmly grounded in a constructionist account of emotion (Table 1).

3.1.2. Temporal Framing

Our analysis revealed that most studies have thus far examined EG as a dispositional construct (Table 1). In other words, EG has been most often conceptualized as a relatively stable tendency reflecting how individuals generally differentiate between emotions over extended periods of time. Nonetheless, a small, yet growing, body of research has begun to investigate EG at more fine-grained temporal levels, such as on a daily basis (Bicaker et al., 2022; Erbas et al., 2018; Hoemann, Barrett, et al., 2021; Lischetzke et al., 2021; O'Toole et al., 2021) or in-the-moment (Erbas, Kalokerinos, et al., 2022; Racine et al., 2024; Schmitt et al., 2024; Seah & Coifman, 2024; Sels et al., 2024; Springstein et al., 2023). At the daily level, EG is conceived as a dynamic phenomenon and examined in terms of within-person fluctuations from day to day, capturing short-term variability rather than enduring patterns. Likewise, an in-the-moment level of EG captures immediate experiences as they unfold in real time. Notably, research on state-level (i.e., daily or momentary) EG is still in its early stages: While the first study on dispositional EG dates back to 2001 (Barrett et al., 2001), the first studies on daily (Erbas et al., 2018) and momentary EG (Erbas, Kalokerinos, et al., 2022) have been published more recently.

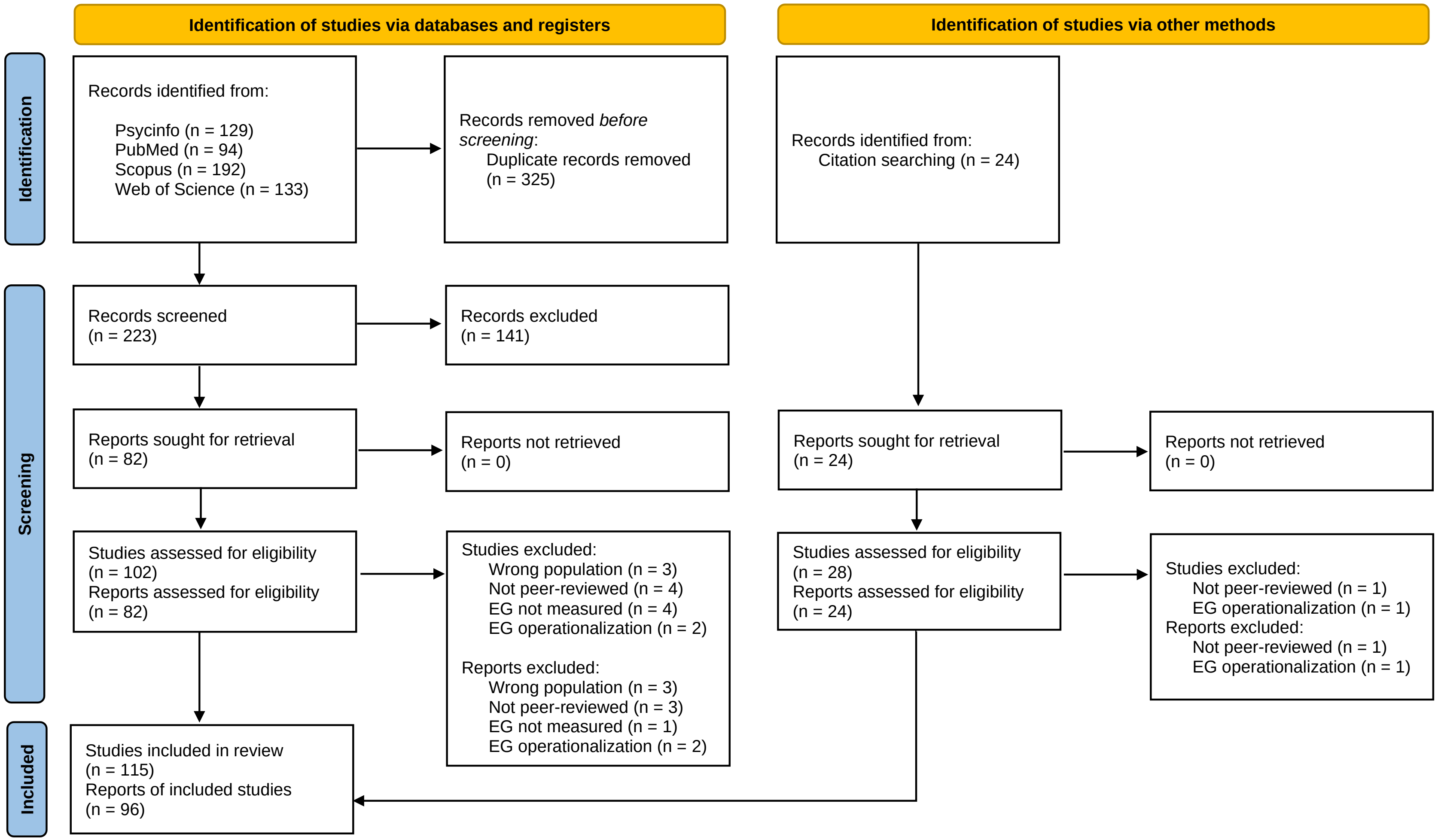

Figure 1. PRISMA diagram summarizing the progress made over the screening process.

3.1.3. Positive, Negative and Global Emotional Granularity

EG can be assessed either for positive (i.e., *positive EG*) or negative emotional experiences (i.e., *negative EG*); alternatively, it can be measured as the capacity to differentiate across both positive and negative experiences (i.e., *global EG*). Our review of existing research revealed that most studies have examined positive and negative EG as separate constructs (Table 1). A relatively consistent number of studies has focused on negative EG only, while very few studies (Tugade et al., 2004; Wang, Shangguan, et al., 2020; Zhang et al., 2021) have focused exclusively on positive EG. Similarly, only a small subset of studies has assessed global EG (Edwards & Wupperman, 2017; Grühn et al., 2013; Hoemann, Khan, et al., 2021; Huggins et al., 2019; Ikeda, 2023; Kimhy et al., 2014a; Lee et al., 2017; Liu et al., 2020; Lukic et al., 2023; O'Toole et al., 2014; Ready et al., 2019).

3.1.4. Integral, Between-category and Within-category Emotional Granularity

As displayed in Table 1, we found that nearly all studies have so far measured *integral* EG, that is, EG has been evaluated across different emotion labels (i.e., without distinguishing emotion categories in EG computation). Only a small number of studies have examined *between-category* EG (i.e., the ability to distinguish among different emotion categories; Erbas et al., 2019) or *within-category* EG (i.e., the ability to make nuanced distinctions between emotions that belong to the same emotional family; Erbas et al., 2019; Plonsker et al., 2017; Ready et al., 2019; Willroth et al., 2020).

3.2. Emotional Vocabulary

Because emotional lexicon provides the basis for categorizing and articulating affective states, the assessment of EG has been so far dependent on the use of emotional vocabulary[3]. In more detail, we can distinguish between two main approaches: A top-down approach, in which participants are asked to rate the intensity of their momentary emotional experiences via a predefined set of emotional labels provided by researchers, and a bottom-up approach, which relies on open-ended formats that allow participants to describe their emotional experiences in their own words.

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[3] Given that emotional lexicon varies considerably across languages and cultures, the way individuals conceptualize and express emotions is deeply influenced by their linguistic and cultural context (Mesquita et al., 2017). The current body of literature is heavily skewed toward English-speaking contexts; the majority of studies (n = 73) have been conducted in countries such as the United States, Australia, the United Kingdom, Canada, New Zealand, and Singapore. A smaller number of studies have been carried out in other languages, including Dutch (n = 18; Netherlands and Belgium), Chinese (n = 10), German (n = 8; Germany and Austria), Danish (n = 4), Japanese (n = 4), Hebrew (n = 2; Israel), Russian (n = 1; Russia), and Hindi (n = 1; India).

Table 1. Overview of the levels of analysis concerning the conceptualization of emotional granularity and the number of studies adopting each operationalization strategy.

Area of Analysis	Dimension of Analysis	Operationalization	Study Count
EG Conceptualization			*N =115*
	Theoretical Background	TCE	n = 21
		Not explicitly stated	n = 94
	Temporal framing	Dispositional EG	n = 106
		Daily EG	n = 5
		Momentary EG	n = 10
	Emotional Valence	Positive EG	n = 3
		Negative EG	n = 53
		Both Positive and Negative	n = 56
		Global EG	n = 10
	Emotional Category	Integral EG	n = 114
		Within-category EG	n = 3
		Between-category EG	n = 1

Note: EG = Emotional Granularity; TCE = Theory of Constructed Emotions.
The sum of the analytical components (n) may be greater than the total number of studies (*N*) because some studies included multiple dimensions of operationalization (e.g., some studies investigated both dispositional and momentary emotional granularity or both positive, negative, and global emotional granularity).

3.2.1. Use of Predefined Emotion Labels in Assessing Emotional Granularity

The large majority of studies (97.39%, n = 112) have so far assessed EG using predefined sets of emotional labels. Nonetheless, a major weakness of this approach is that several differences exist in the number and type of labels employed, as well as in the rating scales that participants are instructed to use to assess the intensity of their emotional experience (Table 2). A complete list of emotional labels, categorized by valence and ranked by frequency of use across studies, is presented in Table S2 in the Supplemental Material.

A first source of variability lies in the valence of emotional labels presented to participants: Consistent with the goal of examining positive and negative EG, most studies have included both positive and negative emotion labels; a second group of studies has used negative-valence labels only, whereas a few studies (Tugade et al., 2004; Wang, Shangguan, et al., 2020; Zhang et al., 2021) have focused on positive-valence labels only. Notably, few studies also included a "neutral" label, which was then used in the calculation of both positive and negative EG scores (Hoemann, Barrett, et al., 2021; Hoemann et al., 2023; Hoemann, Khan, et al., 2021; Petagna & Wormwood, 2025).

Second, we observed considerable variability in the number of emotional labels, ranging from a minimum of 3 to a maximum of 39 (M = 12.40, SD = 6.51). Researchers have generally privileged the inclusion of negative emotional labels (M = 8.25, SD = 5.19, range 3–35) over the inclusion of positive emotional labels (M = 6.62, SD = 3.20, range 1–19).

A third difference concerns the nature (i.e., mentalistic vs. bodily; Ip et al., 2024) and level of specificity of emotion words (e.g., Brown et al., 2021; Kashdan et al., 2010; Lazarus et al., 2022; Matt et al., 2024; Qiu et al., 2023; Sheets et al., 2015; Starr et al., 2017; Vandercammen et al., 2014; Walters et al., 2023). Regarding the nature of emotional labels, most studies have used mentalistic emotion labels (e.g., *contented*, *enraged*), whereas a smaller yet significant subset of studies has also administered "bodily" terms (e.g., *tired*, *relaxed*, *energetic*). When using a limited number of labels, researchers have relied mostly on terms reflecting the so-called "basic emotions" (*e.g., happy, angry*). Other mentalistic labels used in this literature reflect social (e.g., *ashamed*, *embarrassed*, *guilty*, *scornful*) or cognitively laden emotions (e.g., *curious*, *interested*, *distracted*, *capable*). Concerning the level of specificity, some researchers have included only highly specific and presumably more "granular" emotion terms (e.g., *repentant*, *blameworthy*, and *resentful*), whereas others have also administered more generic descriptors (e.g., *uneasy*, *dislike*, *down*, and *droopy*).

Additional heterogeneity comes from the number of emotion categories considered and the number of labels included within each category by each study. Some studies have included multiple labels belonging to different emotion families (e.g., Hill & Updegraff, 2012; Israelashvili et al., 2019; Mehak et al., 2024), whereas other studies have employed a single label per category, thus resulting in limited representativeness of the broader emotional spectrum (e.g., Lv et al., 2024; Walukevich-Dienst et al., 2023; Yang, 2023). Negative emotion categories are more frequently represented, encompassing clusters related to sadness (e.g., *depressed*, *tearful*), fear (e.g., *anxious*, *worried*), anger (e.g., *irritable*, *enraged*), guilt (e.g., *guilty*, *blameworthy*), shame (e.g., *embarrassed*, *humiliated*), and disgust (e.g., *repulsed*, *scornful*). Positive emotion categories most often include happiness (e.g., *joyful*, *content*), excitement (e.g., *enthusiastic*, *exhilarated*), and calmness (e.g., *peaceful*, *serene*). Notably, the number of labels included in positive and negative emotion categories is often not equal.

Finally, most studies have used Likert-type scales, with the number of scale points varying from a minimum of 4 to a maximum of 11. A smaller subset of studies has employed slider scales, generally ranging from 0–100 or from 1–100 (for an exception see Matyi & Spielberg, 2023).

3.2.2. Natural Language Approaches to Emotional Granularity

As shown is Table 2, a still limited number of studies (5.22%, n = 6) have assessed EG using natural language approaches: Participants have been asked to describe their emotional experience through open-ended narratives (Williams & Uliaszek, 2022) or through freely generated emotion labels (Ottenstein & Lischetzke, 2020; Potthoff et al., 2023; Seah & Coifman, 2024; Wabnegger et al., 2024).

Compared with the use of predefined sets of labels, the natural language approach requires some sort of coding procedures to identify emotion-related words and distinguish them from a more general affective language. Notably, we found that only roughly half of the studies described such procedures, which included the use of text analysis software such as RIOT Scan (Boyd, 2014) and Linguistic Inquiry and Word Count ([LIWC]; Pennebaker et al., 2015), or the use of a preexisting corpus of emotion words (e.g., Johnson-Laird and Oatley, 1989). In this latter case, custom dictionaries were developed by expanding existing emotion corpora and including the emotion terms generated by the participants.

Coding procedures have also been employed to determine the valence and specificity of emotion words. Positive and negative emotion terms have been commonly distinguished via either valence ratings (Potthoff et al., 2023; Wabnegger et al., 2024) or top-down categorization based on inter-rater agreement (Seah & Coifman, 2024). However, half of the studies did not report the criteria used to distinguish positive, negative, and neutral words.

Likewise, although all the studies have made distinctions between specific versus general terms (or between specific, general, and basic emotion terms; Williams & Uliaszek, 2022), in many cases, the criteria used to make such distinctions have not been explicitly reported. Some exceptions include Williams and Uliaszek (2022), who relied on the corpus by Johnson-Laird and Oatley (1989), and Ottenstein and Lischetzke (2020), who used the Levels of Emotional Awareness Scale (LEAS; Lane et al., 1990).

Finally, within this approach, only two studies (out of six) have asked the participants to rate the intensity of each self-generated emotion label (Seah & Coifman, 2024; Wabnegger et al., 2024).

Table 2. Overview of the levels of analysis concerning the emotional vocabulary in the assessment of emotional granularity and the number of studies adopting each operationalization strategy.

Area of Analysis	Dimension of Analysis	Operationalization			Study Count
Emotion Vocabulary					
Fixed Labels					*N = 112*
	Valence of Labels	Positive			n = 68
		Negative			n = 109
		Neutral			n = 4
	No. of Labels	< 4 Labels	Positive		n = 6
			Negative		n = 4
		4–6 Labels	Positive		n = 40
			Negative		n = 54
		7–10 Labels	Positive		n = 22
			Negative		n = 40
		> 10 Labels	Positive		n = 4
			Negative		n = 15
	Intensity Rating	Slider Scale	Interval:	0–20	n = 1
				1–100	n = 4
				0–100	n = 13
		Likert Scale	Points:	4–5	n = 41
				6–7	n = 41
				> 7	n = 9
Emotion Vocabulary					
Natural Language					*N = 6*
	Format	Open-ended Narratives			n = 1
		Freely Generated Labels			n = 5
	Emotion Lexicon Identification	Relying on Existing Lexicons			n = 4
		Not Stated			n = 2
	Valence of Emotion Lexicon	Positive			n = 2
		Negative			n = 6
	Criteria for Valence Classification	Self-report Valence Rating			n = 2
		Inter-judge Agreement			n = 1
		Not Stated			n = 3
	Intensity Rating of Emotion Lexicon	Present			n = 2
		Absent			n = 4
	Criteria for Emotion Lexicon Classification	Drew on Existing Resources			n = 3
		Not Stated			n = 3

Note: The sum of the analytical components (n) may be greater than the total number of studies (*N*) because some studies included multiple dimensions of operationalization (e.g., some studies administered both positive and negative emotional labels). The sum of the total number of studies employing each computational method (*N*) exceeds the total number of studies included in the review (i.e., 115 studies) because some studies assessed emotional granularity scores via both fixed emotion labels and natural language. "Emotion Lexicon Classification" refers to the method used to classify the identified emotion lexicon as specific, basic, or generic.

3.3. Measurement Approach

As illustrated in Table 3, most studies have thus far employed ecological approaches to assess EG, such as Experience Sampling Methods (ESM) that require participants to report their emotional states in response to everyday events (usually in real time or shortly thereafter). A second group of studies has relied on nonecological approaches based on the use of an Emotion Differentiation (ED) task. In this case, participants are presented with emotion-evocative stimuli and are asked to report their emotional experience. A third group of studies has combined multiple measurement approaches, using both the ESM and the ED tasks (Erbas et al., 2015; Lee et al., 2017; Ventura-Bort et al., 2021). Finally, two studies have employed approaches that do not fit into either the ESM or ED task categories (Ready et al., 2019; Williams & Uliaszek, 2022).

3.3.1. Ecological Measurement Approaches: Experience Sampling Methods

ESM studies have employed three main types of methods: The Ecological Momentary Assessment (EMA), a daily or weekly diary method, or the Day Reconstruction Method (DRM). One study (Kashdan & Farmer, 2014) employed an event-contingent design, asking participants to complete a diary entry each time they engaged in a social interaction. Notably, while EMA captures emotions in real time and thus reflects immediate subjective experience, diary methods and the DRM most often rely on retrospective recall, requiring participants to reconstruct past events. With respect to the EMA studies (37.39%, n = 43), our review revealed that there is substantial variability in both the sampling period duration (ranging from a single day to a maximum of 35 consecutive days; $M = 10.05$, $SD = 6.96$) and the number of daily prompts (ranging from a minimum of 2 to a maximum of 23 per day; $M = 8.49$, $SD = 3.99$). Although one could expect to observe an inverse relationship between the number of sampling days and the number of daily prompts, we found considerable variability across both dimensions.

A similar degree of variability was observed in the diary (25.22%, n = 29) and DRM studies (6.09%, n = 7). For instance, diaristic research protocols have asked participants to answer diaries weekly over a period of 10–12 months (Seah & Coifman, 2022b), three times a week over 25 days (Pond et al., 2012), or every day for 1–3 weeks (e.g., Lazarus et al., 2022; Oh & Tong, 2020; Seah et al., 2020; Sels et al., 2024). In some studies, data collection lasted for longer time periods, such as 45 (Mikhail et al., 2020) or 50 days (Jacobson et al., 2023).

Likewise, DRM study protocols (6.09%, n = 7) varied substantially in terms of the number of days and episodes (see Table 3). It is worth noting that some studies (Hoemann, Barrett, et al., 2021; Hoemann et al., 2023; Hoemann, Khan, et al., 2021) have combined the use of a modified version of the DRM over 14 consecutive days with an EMA protocol (14 days, 20 prompts/day). At the end of the day, participants reviewed a brief description of each EMA entry and selected three events per day to be described in more detail.

3.3.2. Nonecological Measurement Approaches: The Emotion Differentiation Task

Most of the studies using the ED task were conducted in laboratory settings, whereas a smaller number of studies were conducted online. Once again, we observed a high degree of variability in the methods employed, such as in the type and number of emotional stimuli, or in the instructions provided to the participants (Table 3).

Most studies have used affective pictures (e.g., Berman et al., 2022; Huggins et al., 2019; Lee et al., 2017), whereas less commonly used stimuli are autobiographical recalls (Edwards et al., 2020; Edwards & Wupperman, 2017; Fogarty et al., 2015; Grossmann et al., 2016; Mikkelsen et al., 2021), scenarios (Boden et al., 2013; Cameron et al., 2013; Erbas et al., 2014; Jones & Herr, 2018; Vedernikova et al., 2021), affective movie clips (Aaron et al., 2018; Erbas et al., 2015; Potthoff et al., 2023; Zhang et al., 2021), pictures combined with news headlines (Jeong et al., 2023), visual art images (Fayn et al., 2018), decision-making trials (Li & Ashkanasy, 2019), and tasks involving naming and rating target persons (Erbas et al., 2014). More broadly, we can distinguish between tasks involving immediate responses to emotion evocative stimuli (e.g., affective pictures or movie clips) and tasks that prompt reflection on past autobiographical events. In approximately half of the studies, participants were presented with both positive and negative emotional stimuli, whereas the remaining studies used either positive or negative stimuli (or it was not possible to determine emotional valence in advance). The number of stimuli ranged from 6–50 when both positive and negative stimuli were included and from 10–34 in studies focusing on either positive or negative valence.

The instructions provided to participants also varied considerably, even within groups of studies employing the same type of stimuli. For example, concerning autobiographical recall, studies have used different recall cues, asking participants to recall the past events in which they experienced an instance of a specific emotion family or using a predefined list of situations and, for each situation or event, asking the participants to recall their most recent experience. In contrast, other studies have asked participants to recall negative, neutral or positive life events without any further specification.

Table 3. Overview of the levels of analysis concerning the measurement approaches in the assessment of emotional granularity and the number of studies adopting each methodological choice.

Area of Analysis	Dimension of Analysis	Methodological Choice			Study Count
Measurement Approach					
Ecological: ESM					*N = 80*
	EMA	< 7 Days	Prompts:	5–10	n = 4
				> 15	n = 3
		7 Days	Prompts:	< 5	n = 2
				5–6	n = 4
				8–10	n = 11
		9–10 Days	Prompts:	< 6	n = 2
				6–10	n = 6
		14–16 Days	Prompts:	< 6	n = 3
				6–10	n = 4
		> 20 Days	Prompts:	< 10	n = 2
				> 10	n = 2
	Diary	Daily Diary	Days:	7–10	n = 9
				11–15	n = 7
				20–30	n = 7
				> 30	n = 3
		Weekly Diary	Weeks:	≅ 4	n = 2
				≅ 44	n = 1
	DRM	1 Day	Episodes:	15	n = 2
		2–3 Days	Episodes:	5	n = 1
			Episodes:	15	n = 1
		14 Days	Episodes:	1	n = 3
	Event-contingent	14 Days			n = 1
Measurement Approach					
Non-ecological: ED Task					*N = 38*
	Setting	Laboratory			n = 29
		Online			n = 9
	Type of Stimuli	Affective Pictures			n = 19
		Autobiographical Recalls			n = 6
		Scenarios			n = 5
		Affective Movie Clips			n = 4
		Pictures + News Headlines			n = 2
		Other			n = 2
	Valence of Stimuli	Positive			n = 2
		Negative			n = 14
		Positive + Negative			n = 18
		Not Applicable			n = 4

No. of Stimuli	6–10	n = 11
	11–15	n = 6
	16–20	n = 13
	> 20	n = 6
	Not Stated	n = 2

Note: EG = Emotional Granularity; DRM = Day Reconstruction Method; EMA = Ecological Momentary Assessment; ED Task = Emotion Differentiation Task; ESM = Experience Sampling Methods; No. = Number.

The sum of the total number of studies employing each measurement approach (*N*) exceeds the total number of studies included in the review (i.e., 115 studies) because some studies assessed emotional granularity both via ecological and non-ecological methods. "Episodes" refers to the number of emotional episodes reconstructed each day. "Prompts" refers to the number of measurement occasions per day. For ED tasks, the number of stimuli refers to the total set (i.e., the sum of positive, negative, and/or neutral stimuli).

3.4. Emotional Granularity Indices: Computational Methods and Techniques

We can distinguish between two main computational approaches that have been implemented to derive EG indices. The first approach relies on the variability of the intensity ratings provided to a fixed set of emotion labels that have been repeatedly administered over time (either through ESM protocols or the ED task). The second approach derives the EG index from an evaluation of the specificity of the emotion lexicon generated by participants with their own words.

When examining EG computation methods based on the variability of intensity ratings, we were confronted with a complex puzzle of different measures. In more detail, the procedures employed to compute EG indices were different depending on whether the study intended to capture dispositional, daily, or momentary EG and on the facet of EG under investigation (Table 4).

3.4.1. Indices Based on the Variability of Intensity Ratings

Dispositional Emotional Granularity. As shown in Table 4, the most widely used approach to measure dispositional EG (81.74%, n = 94) involves the computation of intraclass correlation (ICC) coefficients, typically followed by Fisher's *r*-to-*z* transformation for normalization. ICCs represent the proportion of variance in emotion ratings attributable to within-emotion fluctuations across time versus between-emotion differences at a given time point. Lower ICCs indicate greater EG; thus, values are usually reverse-coded (either by multiplying by -1 or subtracting from 1). ICCs can be estimated on the basis of either absolute agreement, which combines correlations among emotion ratings and their magnitude (e.g., Eckland et al., 2021; Emery et al., 2014; Mankus et al., 2016), or consistency, which reflects correlations only (e.g., Dawel et al., 2023; Seah, Almahmoud, et al., 2022; Van Der Gucht et al., 2019). However, approximately one-third of the studies did not report any information regarding the type of method employed (e.g., Decker et al., 2008; Tong & Keng, 2017; Wang et al., 2024; Yang, 2022). Although it has been argued that only correlations are theoretically meaningful for EG, empirical evidence suggests that consistency and agreement estimates are highly correlated ($r = .95–.99$, $p < .001$; Erbas et al., 2014).

Another (far less common) method to derive dispositional EG is calculating average inter-item correlation (AIC) coefficients, which quantify the average degree of correlation among all possible emotion pairs across time. As for ICCs, correlations are Fisher-transformed and reverse-coded.

Finally, a small number of studies have employed even less conventional methods such as principal component analysis (PCA) (Grühn et al., 2013; Mikkelsen et al., 2020), the mean-standard-deviation (MSD) method (i.e., averaging the standard deviations of same-valence emotion ratings across measurements; Huggins et al. 2023), the average daily variance of emotion ratings (VAR; Mikhail et al. 2020), and the Multiple Emotion Co-Activation (MECA) index (i.e., this index considers the number of coactivated emotions beyond the target elicited emotion in response to a corresponding eliciting stimulus; Ready et al., 2019).

Although the computational approaches described above have typically been applied to the computation of positive and negative EG indices, similar procedures have also been used to derive measures of global, between- and within-category EG. Concerning global EG, most studies have computed separate ICC-based indices (Edwards & Wupperman, 2017; Hoemann, Khan, et al., 2021; Huggins et al., 2019; Ikeda, 2023; Liu et al., 2020) or AIC-based indices (O'Toole et al., 2014) for positive and negative emotions and then averaged the two indices to derive a measure of dispositional global EG. Others have calculated global ICC-based (Grühn et al., 2013; Lukic et al., 2023), AIC-based (Kimhy et al., 2014) or PCA-based (Grühn et al., 2013) indices across positive and negative emotion labels.

Likewise, to derive a between-category EG index (Erbas et al., 2019), emotion ratings have been first averaged within each emotion category, and then an overall ICC has been calculated across these category-level means. Finally, the most widely used method to compute a within-category EG index consists of calculating an ICC-based index across emotions within that category (Erbas et al., 2019; Willroth et al., 2020; for an exception, see Plonsker et al., 2017) It is worth noting that Erbas et al. (2019) have also proposed a method to compute an aggregated within-category EG index that is obtained by averaging the within-category ICC-based indices across all categories. This aggregated index is meant to reflect the extent to which an individual is able to differentiate, on average, between emotions within the same category.

Momentary and Daily Emotional Granularity. The most widely adopted approach to compute momentary EG indices (Table 4) consists of an adaptation of the dispositional ICC-based method to the level of single measurement occasions (Erbas, Kalokerinos, et al., 2022; Seah & Coifman, 2024; Sels et al., 2024; Springstein et al., 2023). The procedure involves computing, for each observation, the mean of person-mean centered emotion ratings, multiplying it by the number of emotion items, squaring the result, and dividing it by the sum of the variances of the centered emotion ratings. The resulting index is reverse-coded, with higher values indicating greater momentary EG (Erbas et al., 2022).

Although few studies have so far examined momentary EG, alternative approaches have been proposed to account for the variability in EG patterns over time, such as the Latent Markov Factor Analysis (LMFA) (Schmitt et al., 2024). This method extracts discrete latent states reflecting distinct patterns of covariation among emotion ratings and estimates within-person transitions between such states over time. Another approach is the variance components procedure (PROC VARCOMP), in which an adjusted ICC-like index is computed as the ratio of structured and unstructured variance (Racine et al., 2024).

The PROC VARCOMP approach has also been used to compute daily EG (Bicaker et al., 2022), averaging momentary indices across multiple assessments within the same day. In contrast, Lischetzke et al. (2021) have calculated daily EG by adapting the Erbas et al. (2022) formula to the daily level. Other studies (Erbas et al., 2018; Hoemann, Barrett, et al., 2021; O'Toole et al., 2021) have computed daily ICC-based EG relying on observations confined to a single day.

Table 4. Overview of the levels of analysis concerning the emotional granularity index computation and the number of studies adopting each computational approach.

Area of Analysis	Computational Approach	Components of Analysis			Study Count
EG Index Computation					
Relying on Ratings of Fixed Labels					*N = 114*
	ICC-based	Dispositional *(Positive, Negative, Global, Within-category, Between-category)*	ICCs Method	ICC(A, k)	n = 35
				ICC(C, k)	n = 31
				Not Stated	n = 27
			Negative ICCs	Excluded	n = 12
				C. as Missing	n = 16
				C. as Zero	n = 10
				Not Applicable	n = 7
				Not Stated	n = 48
			Zero-variance	Excluded	n = 2
				C. as Missing	n = 1
				Not Applicable	n = 1
				Not Stated	n = 89
		Daily *(Positive, Negative)*	ICCs Method	ICC(A, k)	n = 1
				ICC(C, k)	n = 3
			Negative ICCs	Excluded	n = 3
				C. as Missing	n = 1
			Zero-variance	Not Stated	n = 4
		Momentary *(Positive, Negative)*	ICCs Method	ICC(C, k)	n = 8
			Negative ICCs	C. as Missing	n = 2
				Not Stated	n = 6
			Zero-variance	Not Stated	n = 8
	AIC-based	Dispositional *(Positive, Negative, Global)*	Zero-variance	Excluded	n = 1
				Not Stated	n = 8
	PCA-based	Dispositional *(Negative, Global)*	Zero-variance	Not Stated	n = 2
	PROC VARCOMP	Daily *(Negative)*	Zero-variance	Excluded / C. as High/Low	n = 1
		Momentary *(Negative)*	Zero-variance	Excluded / C. as High/Low	n = 1

Area of Analysis	Computational Approach	Components of Analysis			Study Count
	Other Methods	Dispositional *(Positive, Negative, Global, Within-category)*	Zero-variance	Not Applicable Not Stated	n = 1 n = 3
		Momentary *(Positive, Negative)*	Zero-variance	Not Stated	n = 1
EG Index Computation					
Relying on Natural Language					*N = 6*
	SI	Dispositional *(Positive, Negative)*		Specific–General Lexicon	n = 4
		Momentary *(Positive, Negative)*		Specific–General Lexicon	n = 1
	Modified SI	Dispositional *(Negative)*		Specific–General Lexicon	n = 1
	NS	Dispositional *(Negative)*		Specific–Basic–General Lexicon	n = 1

Note: AIC = Average Inter-item Correlation; C. as – = Coded as –; EG = Emotional Granularity; ICC = Intraclass Correlation; MECA Index = Multiple Emotion Co-Activation Index; NS = Nuance Score; PCA = Principal Component Analysis; PROC VARCOMP = Variance Components Procedure; SI = Specificity Index.

The sum of the total number of studies employing each computational method (*N*) exceeds the total number of studies included in the review (i.e., 115 studies) because some studies computed emotional granularity scores via multiple methods (e.g., some studies have computed both ICC-based and AIC-based emotional granularity indices). "ICC(A, k)" indicates Absolute Agreement-Method for intraclass correlation; "ICC(C, k)" indicates Consistency-Method for intraclass correlation. "Zero-variance" indicates handling of measurement occasions where all emotion labels were rated identically. "Other Methods" includes LMFA-based index (momentary emotional granularity), MECA index, MSD-based index, sum of the correspondence ratings of items, and average of daily variances (dispositional emotional granularity). For global emotional granularity, across index computation procedures, some studies derived separate valence-specific indices and subsequently combined them (e.g., by summing or averaging), whereas others computed indices using all emotion ratings irrespective of valence. For daily emotional granularity, across computational approaches, some studies adapted dispositional methods to the daily level, whereas others implemented daily adaptations of momentary index computation procedures.

3.4.2. Methodological Issues in the Computation of Indices Based on the Variability of Intensity Ratings

Besides the significant variability in the computation methods of EG indices we described above, an additional shortcoming concerns the different ways in which researchers have handled some methodological issues related to the computation itself. The first issue concerns negative ICCs. Although these coefficients are theoretically constrained between 0 and 1, negative values can emerge due to measurement error (Shrout & Fleiss, 1979). Negative ICCs can be excluded from further analysis (e.g., Liao et al., 2025; Oh & Tong, 2020; Seah, Sidney, et al., 2022), or recorded as zero (e.g., Seah et al., 2020; Thompson, Liu, et al., 2021). Although negative ICCs are common in EG research (for exceptions, see Kalokerinos et al., 2019; Pugach et al., 2023), we could not find any information about how they were handled in about half of the studies included in the review (e.g., Erbas et al., 2016; Kashdan et al., 2014; Yue et al., 2024).

Another common issue, which encompasses all the computational methods, concerns the instances in which emotion ratings exhibit no variability. Such within-person zero-variability cases may stem from both high levels of EG (e.g., a high-EG individual may not find their emotional state adequately represented by any of the provided emotional labels) or low levels of EG (e.g., low-EG individuals may rate in the same way all emotions). Although zero-variability cases are not rare in practice, information about their prevalence and the methods used to handle them is largely absent from most studies. Among the few studies reporting it, some researchers using ICC-based indices opted to exclude these cases from the analysis (Berman et al., 2022; Kashdan & Farmer, 2014; Matt et al., 2024) due to their non-interpretability. Other researchers using PROC VARCOMP-based indices have either coded these ICCs as zero/one or excluded them from the analyses, depending on the specific characterization of the zero-variability cases (e.g., excluding cases where both positive and negative items are all rated as "very slightly or not at all", while imputing scores as 1 when all items of only one valence were rated as "very slightly or not at all") (Bicaker et al., 2022; Racine et al., 2024).

Of note, the issue concerning zero-variability cases is particularly relevant when computing state-level EG indices via either the PROC VARCOMP procedure or the formula proposed by Erbas et al. (2022). Both methods depend on variance terms in the denominator, making the index non-computable when the variance is zero. For PROC VARCOMP, this occurs when items exhibit no variability both within and across observations, whereas for the Erbas et al. (2022) formula, the problem arises when each item shows no variability across observations. While the two studies employing the PROC VARCOMP procedure have included an explanation about how they handled such zero-variability instances (Bicaker et al., 2022; Racine et al., 2024), only one study (Matt et al., 2024) adopting the Erbas et al. formula provided information about how they handled such cases.

Finally, a last methodological concern inherent to the Erbas et al. (2022) formula involves those instances in which the numerator equals zero. Critically, a zero numerator may arise either when at a certain time point every emotion rating equals the person's mean for that emotion (i.e., each person-mean-centered value is exactly 0), or when the person-mean centered ratings for each emotion at a certain time point, once averaged, canceled out to (approximately) zero, even though there is variability in the ratings. These two scenarios reflect distinct underlying interpretations of EG; however, none of the studies included in the review explicitly reported how such cases were treated.

3.4.3. Indices Based on the Specificity of the Emotional Lexicon

Within the natural language approach, Ottenstein and Lischetzke (2020) have introduced a Specificity Index (SI) of EG that is calculated by coding freely generated emotion words as either specific (e.g., *anxious, irritated, sad*) or general (e.g., *bad, negative, unpleasant*). The SI is then computed as the proportion of specific adjectives out of the total number of emotion adjectives used. The SI has been calculated at the state level (Seah & Coifman, 2024) and at the dispositional level by aggregating all momentary or daily entries across time (Ottenstein & Lischetzke, 2020; Potthoff et al., 2023; Williams & Uliaszek, 2022).

A revised version of the SI has been recently proposed by Williams and Uliaszek (2022) with the introduction of the nuance score (NS). To derive this index, emotion words are first coded as either general (coded as 1), basic (coded as 2), or specific (coded as 3); then, the ratings of all adjectives are summed and divided by the total number of terms used. Like the SI, the NS has been originally developed to quantify EG at the dispositional level but is also suitable for state-level assessments.

Finally, a third, more recent version of the SI (Wabnegger et al., 2024) consists of a performance-based EG score that is calculated based on interrater agreement, with scores averaged across reports to produce an overall index[4] (Table 4).

3.4.4. Convergent Validity among Different Computational Methods and Techniques

Given the considerable variety of computational methods, some studies included in this review have compared multiple computational approaches to examine convergence across indices. The results, however, are mixed. For instance, no significant correlations have been found between the ICC-based index on the one side and the PCA-based index (Grühn et al., 2013) or the VAR-based index on the other (Mikhail et al., 2020). Likewise, the VAR- and AIC-based indices were also found to be unrelated (Mikhail et al., 2020). Conversely, the ICC-based and AIC-based indices appeared to be highly correlated (Mikhail et al., 2020).

Other studies have also examined the associations between EG indices derived from different assessment approaches (i.e., fixed sets of emotion labels vs. spontaneous use of emotional vocabulary). The

[4] Beyond the articles included in this review, additional studies are exploring novel procedures for computing EG from natural language. However, these studies were excluded from this review because they are available only as not-peer reviewed preprints or conference proceedings and therefore did not meet the inclusion criteria. For example, Vishnubhotla et al. (2024) proposed assessing EG from social media posts by constructing emotion arcs across time and computing EG as the correlation among these arcs. Faraji-Rad et al. (2024) assessed EG using advanced natural language processing techniques, focusing on whether distinct emotion terms were applied in differentiated contexts or used interchangeably.

correlations between the ICC-based index and the SI or the NS were nonsignificant or inconsistent for both positive and negative emotions (Ottenstein & Lischetzke, 2020; Seah & Coifman, 2024; Williams & Uliaszek, 2022). By contrast, the SI and NS were found to be moderately correlated (Williams & Uliaszek, 2022).

Finally, few studies have compared within-category, between-category, and integral ICC-based indices. The integral and between-category indices were highly correlated, whereas their correlation with the aggregated, within-category index was lower (Erbas et al., 2019). When examining separate within-category indices referring to different emotion categories, weak intercorrelations were found, suggesting that the ability to differentiate within an emotion category (e.g., anger) should not be generalized to other categories (e.g., fear). Similar findings have been reported by Willroth et al. (2020).

3.5. Emotional Granularity Correlates

When examining the potential correlates of EG, we found that these variables can be grouped into two main areas. First, several studies (38.26%, n = 44) have examined the relationship between EG and constructs such as emotion regulation, alexithymia, emotional intensity, emotional clarity, and dialecticism. Emotion regulation emerges as the most common correlate – unsurprisingly, as EG has been speculated to function as a form of regulation (Kashdan et al., 2015). Despite this thematic overlap, these studies revealed substantial methodological heterogeneity. Approximately one-third of the studies assessed EG via the ED task, while merely all the studies employed a fixed set of emotion labels (for an exception, see Seah & Coifman, 2024). EG conceptualizations also varied: Most studies investigated dispositional EG, with only few studies investigating momentary (Schmitt et al., 2024; Seah & Coifman, 2024; Sels et al., 2024; Springstein et al., 2023) and daily EG (Hoemann, Barrett, et al., 2021; O'Toole et al., 2021). Notably, negative EG was examined nearly twice as often as positive EG. Furthermore, about half of these studies were conducted with English-speaking participants and student samples.

The second area concerns psychological well-being and mental health (27.83%, n = 32). Within this area, EG has been associated with both adaptive (e.g., life satisfaction, subjective well-being) and maladaptive (e.g., stress, depressive and anxiety symptoms) outcomes. Some studies have directly compared EG in clinical and nonclinical populations, including individuals suffering from schizophrenia (Kimhy et al., 2014), posttraumatic stress (Pugach et al., 2023) and depression (Springstein et al., 2023). Measurement approaches emerged as relatively balanced across ecological methods (i.e., EMA, diary) and ED tasks. Despite some studies assessed EG using natural language reports (Ottenstein & Lischetzke, 2020), most studies employed fixed emotion labels. Few studies assessed momentary EG (Erbas et al., 2022), while all other studies examined EG at the dispositional level. Again, approximately half were conducted with English-speaking participants and student samples.

Other studies have investigated the association between EG and maladaptive behaviors, such as verbal or physical aggression; substance (alcohol, tobacco, or cannabis) use and craving; and impulsivity. All these studies assessed dispositional EG using the ICC-based method to compute the index (for an exception examining momentary EG using the PROC VARCOMP, see Racine et al., 2024). All but one (Edwards & Wupperman, 2017) employed ecological designs. These studies were all conducted with English-speaking participants and approximately three-quarters were based on student samples.

Finally, a smaller set of studies have examined EG in relation to cognitive processes (6.09%, n = 7; e.g., moral judgment), social behavior (4.35%, n = 5; e.g., helping behavior), mindfulness (3.48%, n = 4), personality traits (2.61%, n = 3; e.g., neuroticism), romantic relationships (1.74%, n = 2; e.g., relationship quality), and adaptive behavior (n = 1; i.e., medication adherence). Across all these topics, methodological heterogeneity remains a defining feature. Studies differed in EG conceptualization, measurement approach and study designs, the statistical method to index computation, and the type of sample included.

4. Discussion

The main goal of the present systematic review is to provide a detailed synthesis of the state of the art in EG assessment and measurement. Overall, our analysis reveals a complex picture. Taken together, the 115 included studies show consistent methodological heterogeneity, so that the same or similar definitions of EG are mirrored by different approaches used to operationalize this construct. We discuss this substantial divergence in assessment strategies and computational procedures, highlighting the implications for the comparability, interpretation, and cumulative integration of findings across studies. Table 5 synthesizes recommendations for future research on emotional granularity, both in terms of measurement options and reporting requirements.

Table 5. Recommendations for future research on emotional granularity, both in terms of measurement options and reporting requirements.

Area of Analysis	Dimension of Analysis	Operationalization and Methodological Choices	Reporting Requirements
Conceptualization			
	Theoretical Background	▪ TCE ▪ Other	Authors should clearly specify the theoretical framework underlying the study (e.g., TCE, alternative models). The research question should be explicitly grounded in this framework, and the operationalization and measurement of EG should be conceptually consistent with it.
	Temporal framing	▪ Dispositional EG ▪ Daily EG ▪ Momentary EG	Studies should justify whether EG is conceptualized and measured as a dispositional trait or a state-level (i.e., daily, momentary) construct. The choice of temporal framing should be theoretically motivated and aligned with the research question.
	Emotional Valence	▪ Positive EG ▪ Negative EG ▪ Global EG	Authors should report whether EG is examined for positive emotions, negative emotions, or globally across valences. The rationale for focusing on a specific valence (or combining valences) should be explicitly stated.
	Emotional Category	▪ Integral EG ▪ Between-category EG ▪ Within-category EG	Researchers should clarify whether EG is assessed as integral (across all emotions), between-category (across different emotion families), or within-category (within the same emotion family). Authors should discuss whether and how distinguishing between emotion categories adds theoretical or empirical value relative to the study aims or justify why such distinctions are not considered.
Emotion Vocabulary ***Fixed Emotion Labels***			
	Valence of Labels	▪ Positive ▪ Negative ▪ Neutral	The valence of the selected emotion labels (positive, negative, neutral) should correspond to the valence specified in the conceptualization of EG. Particular attention should be paid to labels that may carry both positive and negative connotations depending on context.
	Type of Labels	▪ Degree of Specificity ▪ Bodily, Mental, Cognitive Connotations	Authors should describe the criteria used to select emotion labels. The label set should be appropriate for the research objectives, sufficiently broad to capture subtle emotional distinctions, and representative across different levels of emotional experience. Studies should report whether participants were given the option to select an “other” category and/or to self-generate emotion labels if none of the provided options adequately captured their experience.

Area of Analysis	Dimension of Analysis	Operationalization and Methodological Choices	Reporting Requirements
	No. of Labels	–	The rationale for the number of emotion labels included should be reported. Authors should clarify whether a variable number of emotion terms was used to represent emotion categories within or across emotion families. When both positive and negative valences are examined, comparability in the number of labels across valences should be addressed.
	Intensity Rating	▪ Slider Scale ▪ Likert Scale	The method used to assess emotional intensity (e.g., Slider Scale, Likert Scale), along with the number of scale points or intervals, should be specified.
Emotion Vocabulary ***Natural Language***			
	Format	▪ Open-ended Narratives ▪ Freely Generated Labels	Authors should report whether emotional language was collected via open-ended narratives or freely generated emotion labels. Instructions provided to participants should be described and evaluated for consistency with the declared EG conceptualization (e.g., the temporal frame of reference).
	Emotion Lexicon Identification	▪ Relying on Existing Lexicons ▪ Relying on Criteria Defined by the Authors	Researchers should specify whether emotion words were identified using existing lexicons or criteria defined by the authors. When author-defined criteria are used, these criteria should be explicitly articulated and described in full; in such cases, inter-judge agreement procedures should be preferred.
	Criteria for Valence Classification	▪ Relying on Existing Lexicons ▪ Relying on Criteria Defined by the Authors ▪ Self-report Valence Rating by the Participants	The criteria for classifying emotion words as positively or negatively valenced should be clearly stated, including existing lexicons, participant self-reporting, or author-defined criteria. In this latter case, inter-judge agreement procedures should be employed.
	Intensity of Emotion Lexicon	▪ Evaluated ▪ Not Evaluated	Studies should indicate whether and how emotional intensity was evaluated in natural language data. This may include participant-rated intensity of generated emotion words (e.g., using Slider or Likert Scales) or linguistic markers such as modifiers (e.g., adverbs, adjectives).
	Criteria for Emotion Lexicon Classification	▪ Relying on Existing Lexicons	Authors should describe the coding procedures used to classify emotion-related terms as specific, basic, or general for EG scoring. Inter-judge agreement should be reported when classification criteria are defined by the authors.

Area of Analysis	Dimension of Analysis	Operationalization and Methodological Choices	Reporting Requirements
		▪ Relying on Criteria Defined by the Authors	
	Use of Paraphrased or Metaphorical Language	▪ Evaluated ▪ Not Evaluated	Researchers should state whether paraphrased or metaphorical emotional language was considered in EG assessment. If so, criteria for its identification, interpretation, and classification should be specified.
Measurement Approach ***Ecological: ESM***			
	EMA	▪ Days ▪ Prompts per Day ▪ Frequency ▪ Temporal Frame of Reference	Authors should report the duration of the EMA period, whether days were consecutive, the number of prompts per day, and prompt timing (random, semi-random, or fixed). The daily time window for assessments should be specified, along with the temporal frame of reference for emotional reports (e.g., in-the-moment, since last prompt). Justification should be provided for whether the number of daily prompts adequately captures emotional experience relative to the research question. Inclusion criteria for participant compliance (e.g., minimum number of completed prompts) should be clearly described and justified.
	Diary	▪ Days ▪ Frequency ▪ Moment of the Day ▪ Temporal Frame of Reference	Studies should report the total duration, assessment frequency (e.g., daily, weekly), and time of day of diary completion. The temporal anchoring of emotional reports (e.g., entire day/week, specific emotional episode) should be specified. Criteria for participant inclusion based on completed entries should be illustrated and motivated.
	DRM	▪ Days ▪ Frequency ▪ Episodes ▪ Moment of the Day ▪ Temporal Frame of Reference	Authors should indicate the duration of DRM administration, assessment frequency, number of episodes reconstructed per day, and timing of completion. The temporal frame of reference for emotional reports (e.g., same day, previous day) should be specified.
	Event-contingent	▪ Sampled Events	Researchers should describe the types of emotional events sampled and justify their relevance to the study aims. Criteria used to limit between-person variability in the number and characterization of sampled events should be reported.

Area of Analysis	Dimension of Analysis	Operationalization and Methodological Choices	Reporting Requirements
Measurement Approach ***Non-ecological: ED Task***			
	Setting	▪ Laboratory ▪ Online	The administration context (laboratory vs. online) should be specified. For laboratory studies, procedures to reduce social desirability bias should be described. For online studies, steps taken to standardize and control the testing environment should be reported.
	Stimuli	▪ Type ▪ Valence ▪ Number ▪ Temporal Frame of Reference	Authors should describe the type of stimuli used, as well as the criteria guiding stimulus selection and the instructions provided at the time of administration. The use of standardized and validated stimuli should be reported, along with standardization procedures if non-validated stimuli are used. Authors should clarify whether stimulus valence can be determined a priori. The number of stimuli and trials administered should be declared and justified. It should be specified whether tasks involve immediate responses to in-the-moment emotion-eliciting stimuli or reflective evaluations of past autobiographical events.
EG Index Computation ***Relying on Fixed Labels***			
	Method	▪ Variance-based Methods ▪ Other	The method used to compute the EG index should be specified (e.g., ICC-based, AIC-based, PCA-based, PROC VARCOMP). For ICC-based approaches, authors should report whether absolute agreement or consistency was estimated and how negative ICC values were handled (e.g., coded as zero, treated as missing).
	Handling of Zero-variance Cases	▪ Excluded ▪ Recoded	Authors should describe how zero-variance cases were managed. For dispositional EG, procedures for handling measurement occasions with no variance should be reported. For state-level EG computed, the treatment of zero-variance cases in numerators or denominators should be clearly specified.
	Grouping of Emotion Labels	▪ Global EG ▪ Between- and Within-category EG	For global EG, authors should clarify whether positive and negative EG indices were computed separately and then averaged, or whether all labels were used simultaneously. Differences in results across methods should be reported if relevant. For within- and between-category EG, the grouping procedure and exact computational steps should be explicitly described.

Area of Analysis	Dimension of Analysis	Operationalization and Methodological Choices	Reporting Requirements
EG Index Computation			
Relying on Natural Language			
	Method	▪ Emotion Lexicon Classification ▪ Computational Procedure	Authors should specify which emotion lexicon categories (e.g., specific, basic, general) were defined and which computational procedures were used to derive EG indices (e.g., SI, NS).
	Grouping of Emotion Labels	▪ Global EG ▪ Between- and Within-category EG	Authors should report whether global EG was computed by averaging valence-specific indices or by pooling all emotion terms, and whether results differ across methods. Procedures for computing within- and between-category EG should be described in detail.

Note. AIC = Average Inter-item Correlation; DRM = Day Reconstruction Method; EMA = Ecological Momentary Assessment; ED Task = Emotion Differentiation Task; ESM = Experience Sampling Methods; EG = Emotional Granularity; ICC = Intraclass Correlation; No. = Number; NS = Nuance Score; PCA = Principal Component Analysis; PROC VARCOMP = Variance Components Procedure; SI = Specificity Index; TCE = Theory of Constructed Emotions.

4.1. Considerations on Emotional Granularity Conceptualization

First, our review revealed that most studies did not clearly report their theoretical background, and the limited number of studies explicitly grounding their work in the TCE points to a degree of theoretical under-specification in the literature on EG. This lack of clear theoretical positioning may contribute to variability in the operationalization and interpretation of EG across studies, despite apparent conceptual convergence. Future research would benefit from more clearly articulating the theoretical framework guiding study design and the interpretation of findings.

Second, EG has thus far been mostly examined as a relatively stable, dispositional tendency, with little existing research on daily or momentary EG. This recent empirical evidence, however, suggests that EG fluctuates over time and is sensitive to contextual influences, thus challenging the common view that EG may reflect an enduring personality trait, in favor of a conceptualization of EG as a dynamic, situated individual tendency (Erbas et al., 2018; Schmitt et al., 2024; Springstein et al., 2023).

The assessment of EG with more fine-grained temporal framing raises some important questions. First, an important issue to be addressed by future research concerns the potential mechanisms underlying short-term fluctuations in EG. Some studies have already attempted to examine this issue by extracting contextual variables at the time of the emotional report to better account for situational influences (e.g., Hoemann, Barrett, et al., 2021; Hoemann et al., 2023; Hoemann, Khan, et al., 2021). According to the TCE, EG is conceived as the individual's ability to create instances of emotion that are diverse and context specific. Consistent with this view, initial evidence suggests that this ability may not be equal across different types of contexts, life periods, situations or events (Erbas et al., 2018; Schmitt et al., 2024; Springstein et al., 2023).

A related issue concerns the relationship between dispositional and state-level EG. For instance, individuals high in dispositional EG may nonetheless show momentarily reduced EG levels when confronted with overwhelming events that temporarily impair their ability to differentiate emotional states in a precise and nuanced way. Conversely, individuals low in dispositional EG may exhibit momentarily high granularity in particular situations, contexts or life circumstances (Erbas et al., 2018; Schmitt et al., 2024; Springstein et al., 2023). Future studies should thus examine whether dispositional and state-level EG reflect distinct yet complementary processes and whether they influence each other over time. Specifically, dispositional EG may shape momentary fluctuations, and, in turn, state-level EG may contribute to the development of more enduring emotion differentiation abilities.

Another result emerging from our review is the marked attention given to negative compared to positive and global EG. This may be due to the fact that negative emotional states are easier to capture, as they are often very skewed in daily life (they are more relevant for personal strivings and goal pursuits; Barrett et al., 2001; Erbas et al., 2014). In contrast, positive experiences tend to exhibit greater fluidity, weaker categorical boundaries, and more blended labeling (Vlasenko et al., 2021).

Given that the operationalization of positive EG may thus raise greater methodological challenges, future research is needed to advance both conceptual reflection and empirical work on the most appropriate methods to measure it.

In a similar way, current knowledge mostly concerns integral EG, whereas few studies have examined individuals' ability to distinguish among different emotion categories or to make nuanced distinctions between emotions that belong to the same emotion family. Preliminary evidence suggests that differentiating between distinct emotional categories is typically easier than distinguishing emotions within a given category. Furthermore, the ability to differentiate between similar emotions may vary depending on the specific emotion family, rather than reflecting a general skill across all emotion domains (Erbas et al., 2019). Identifying and accounting for these sources of variability in the individuals' capacity to precisely distinguish among emotional states represents a promising avenue for future research to refine and extend our understanding of EG.

Of note, between- and within-category EG may be informative variables to consider when investigating context-dependent dynamic fluctuations in EG. Existing evidence suggests that individuals show greater or lower ability to differentiate emotions depending on the specific emotion category (Erbas et al., 2019), and this may be linked to the particular situation/event they are experiencing. In other terms, dynamic fluctuations in EG may emerge from the interplay of dispositional differentiation abilities and contextual influences, leading to higher vs. lower state-level ability to differentiate among emotion categories and among emotions within a given category. So far, however, between- and within- EG have been examined as dispositional variables only.

4.2. Emotion Vocabulary: Assessing Emotional Granularity Using Fixed Emotion Labels

To date, EG has been generally assessed using fixed sets of emotional labels. An advantage of this approach is that it offers standardization across participants within the same study; nonetheless, some shortcomings deserve careful consideration. First and foremost, when providing them with predefined labels, researchers implicitly assume that participants are familiar with those labels and that such terms can comprehensively represent their current emotional experience (Ip et al., 2024; Y. Li et al., 2020). However, this assumption may not hold true across individuals and thus the use of a fixed-label approach may lead to biased knowledge of people's actual EG skills (Ottenstein & Lischetzke, 2020).

Second, we have shown that a high variability exists in the type (e.g., specificity, nature, valence) and number of emotion terms that current studies have used to assess EG. This lack of shared criteria for label selection, however, may lead to inconsistent measurement of EG and low cross-study comparability. For instance, some studies have relied on highly granular emotion terms only (e.g., *frustrated*), while others have also included labels that refer to broader, generic states (e.g., *unpleasant*).

Our analysis has also shown that emotion labels are often not equally distributed in emotion categories and that negative emotion terms are typically overrepresented. Moreover, studies have included a variable number of emotion words as representative of an emotion category. The lexical context in which emotion labels are presented plays a crucial role, as the presence or absence of semantically similar terms in a list can influence both the granularity of differentiation and the interpretation of the meaning of a given emotion label. Thus, participants' ability to capture subtle emotional distinctions may be greatly reduced when they are presented with lists of labels in which emotional categories are represented by few (or a single) terms. It is therefore recommended that future research includes a sufficiently broad and representative set of labels both within and across multiple emotional families (compatible with the need to avoid overburdening participants).

To improve cross-study comparability, research on EG would benefit from the elaboration of shared norms or guidelines to make uniform researchers' choices. Of course, we acknowledge that the choice of the type and number of labels is tight to several aspects, such as the study aims, time constraints, and cultural context (i.e., the emotional lexicon is culture-specific, and the frameworks used to construct emotional experiences are culturally mediated; Mesquita et al., 2017). Nonetheless, even if studies may differ in several aspects, we believe that the maintenance of a comparable level of lexical variability within and across emotion categories is a fundamental aspect for consistency in EG measurement. Along this line of reasoning, meta-analyses that systematically examine the impact of these different choices on study results could provide valuable hints and suggestions to develop methodological recommendations.

4.3. Emotion Vocabulary: Assessing Emotional Granularity Using Natural Language

Although assessment methods based on natural language (e.g., free labeling and open-ended descriptions) have been far less frequently employed in EG research, they offer a promising alternative to fixed-label approaches, since they have the potential to capture more authentic and contextually grounded verbal expressions. Similar to the fixed-label approach, however, we identified some shortcomings that must be carefully addressed, as they may hinder construct validity and cross-study comparability.

First, a key issue concerns the coding procedures that researchers have used to identify "emotion" terms and to classify such terms as "specific", "basic", or "general" for EG scoring. People use emotion words to categorize and label emotion concepts; nonetheless, although emotion words reflect emotion concepts, the concepts themselves cannot be fully reduced to the corresponding lexical terms (Hoemann, 2024; Hoemann et al., 2019, 2025; Hoemann & Barrett, 2019; Lindquist, MacCormack, et al., 2015). Therefore, the top-down coding of an emotion word as "specific" to "general" inherently involves some form of arbitrary interpretation of the underlying conceptual features. Although one can rely on inter-rater agreement among judges as a measure of consistency and reliability, the coding process may be influenced by judges' own conceptual backgrounds. This is particularly relevant when judges are emotion researchers, since their theoretical expertise and emotional fluency may introduce significant biases. To overcome this limitation, some studies have employed standardized emotion lexicons as a guide in the classification process; nonetheless, even this method is not without problematic issues. First, standardized emotion lexicons reflect the choices and theoretical assumptions of their creators and are therefore not entirely free from subjective influence. Second, such lexicons typically do not capture the context in which emotion words are used and therefore cannot fully account for context-dependent meaning or conceptual nuance. Lastly, standardized lexicons are not equally available for all languages and cultures. Language alone does not ensure shared emotional meaning, as emotional concepts are deeply shaped by individuals' personal background (Barrett, 2009; Barrett et al., 2007) and cultural context (Mesquita et al., 2017). Thus, differences in lexical availability and conceptual repertories both within and across languages and cultures may limit the validity of EG measures and their comparability between studies and populations. Overall, while the use of standardized lexicons can reduce some sources of bias, a careful consideration of language, culture, and of the theoretical basis of the lexicon remains essential for ensuring valid and reliable assessments.

A second issue related to coding procedures concerns the need to classify emotional terms as either positive or negative (to assess positive and negative EG), and for some words, the distinction may not be straightforward (e.g., *surprised, impressed, impatient*). Some studies have used participant-generated valence ratings (Wabnegger et al., 2024), which reduces the impact of researchers' subjective inferences. Overall, however, we were unable to identify a single, consistent approach to address this issue.

Third, a still open issue concerns how to deal with participants' use of paraphrased or metaphorical language (e.g., "*I missed the ground beneath my feet*", "*finally feeling at home*"). Paraphrased expressions may reflect either partially articulated emotions that do not easily map onto conventional labels, or highly complex emotional experiences for which no single term adequately captures their nuance. As broader expressions of abstract emotional concepts, paraphrases and metaphors inherently introduce ambiguity with respect to the interpretation of EG levels. This likely explains why no study to date has incorporated their coding into the EG scores. Nevertheless, they often represent blended and complex emotional experiences that, despite being difficult to categorize, are still informative (Fetterman et al., 2022).

Finally, while fixed-label approaches have generally used Likert scales, intensity ratings have rarely been employed in research assessing EG through natural language (Seah & Coifman, 2024; Wabnegger et al., 2024). Although modifiers (i.e., adverbs and adjectives) may be used as indicators of the intensity of a participant's emotional experience, they can also reflect an individual's EG levels. For example, if the term "furious" suggests a high intensity emotional experience (e.g., compared with "angry"), the expression "*extremely* furious" could be interpreted as either additional intensity information or a more fine-grained emotional experience. Therefore, more work is needed to discuss the role of modifiers and how to potentially treat them (Sintsova et al., 2017; Yu & Lai, 2014).

Of note, we remark that a major shortcoming of existing studies is that, in many cases, detailed information about the coding procedures we described above is omitted. To ensure replicability, we thus recommend that future research provides a more transparent and careful description of these methodological choices due to their impact on EG measurement.

4.4. Emotional or Affective Vocabulary?

As discussed above, both the fixed-label approach and the natural language approach require researchers to make a distinction between terms that are considered "emotional" and terms that are not. While some affective terms are readily categorized as non-emotional (e.g., *thirsty*, *hungry*) and others as clearly emotional (e.g., *content*, *sad*), many terms lie on a more ambiguous boundary. In line with the TCE, emotional experience should be understood holistically, wherein mental and bodily processes are conceived as a whole rather than through the lens of a classical Cartesian mind–body dualism (Barrett et al., 2025). This perspective poses clear challenges for defining a set of putative "emotional" words for the assessment of EG.

In the fixed-label approach, some studies have limited emotion labels to descriptors of purely "mentalistic" (even though emotional terms cannot be assumed to be entirely devoid of bodily components) emotional states such as "*happy*" or "*joyful*", whereas other studies have also considered affective terms including a straightforward bodily component (e.g., *energetic*, *relaxed*). Importantly, a subset of studies additionally incorporated mentalistic emotion labels with a cognitive connotation (e.g., *concentrated*, *distracted*). Likewise, in the natural language approach, standardized emotion lexicons may either include or exclude affective terms with bodily or cognitively connotations (e.g., *exhausted, curious*). Besides representing a difference in the method used to assess EG, such inconsistencies in the way emotional language is conceptually defined raise a broader question, regarding the distinction between "emotional" and "affective" language.

Both emotion lexicons and vernacular expressions are inherently shaped by the language and culture in which they are embedded, resulting in the presence of emotion terms in some languages and cultural contexts that reflect more bodily-oriented emotional concepts (Ip et al., 2024; Mesquita et al., 2017). At the same time, it is important to recognize that, beyond cross-linguistic and cross-cultural variability, there is also substantial inter-individual variability in how emotional experiences are embodied. Specifically, individuals may differ in the extent to which they experience emotions as bodily sensations, and this tendency may vary depending on the particular emotion or the situational context in which it occurs (Barrett, 2009).

Consequently, although it is currently unclear how terms that lie at the intersection of bodily sensations and emotions should be treated, it appears important that EG assessments encompass a range of emotion words that capture the continuum between mentalistic and bodily connotations of emotional experience (Ip et al., 2024). Regardless of the assessment approach employed, achieving greater conceptual consistency in this regard is essential for studies investigating EG to guarantee conceptual clarity and methodological rigor.

4.5. Addressing Heterogeneity in Measurement Approaches

Our review revealed substantial variability in measurement approaches across studies. These approaches can be broadly divided into ecological (EMA, diary studies, DRM) and non-ecological methods (ED tasks). ED tasks were originally introduced to address a key limitation of ESM: The natural variability in the number and type of emotional episodes a participant may encounter over time (Erbas et al., 2014). By using standardized stimuli, researchers have attempted to enhance control and comparability across individuals. However, the extent to which individual differences in the impact of emotional stimuli (e.g., personal relevance or valence) influence the measurement of EG remains unclear.

A common issue that emerged from our review concerns the high variability and low consistency of methods and protocols across studies. Within EMA studies, our analyses revealed high variability in the duration of data collection and in the sampling rate of emotional episodes. Although such variability may reflect different research aims, it also raises important questions concerning the existence of a “reasonable” maximum number of emotional episodes per day and the minimum number of measurement occasions that is needed to capture meaningful emotional experiences. Similarly, among DRM-based studies, participants have been asked to reconstruct the previous day (Bonar et al., 2023; Ikeda, 2023; Ventura-Bort et al., 2021), or the same-day, supported by prompts sent throughout the day to aid memory (Hoemann, Barrett, et al., 2021; Hoemann et al., 2023; Hoemann, Khan, et al., 2021). Finally, we also found inconsistencies in ED task studies, with large differences in the number of trials, the instructions, and the setting of data collection.

Overall, empirical research is needed to evaluate how specific design choices impact the assessment of EG. Along this line of reasoning, a meta-analytic synthesis would be valuable for identifying best practices to guarantee measurement reliability and cross-study comparability. With respect to ESM studies, future meta-analyses could consider the moderating role of the number of measurement occasions, the type of instructions given to participants, and the interval length between assessments. Likewise, for ED tasks, it would be important to assess intervening variables such as the number of trials and the type of stimuli. Without such efforts, the current heterogeneity in study designs and procedures represents a potential threat to the comparability and cumulative value of research findings.

A second critical common issue concerns differences in the temporal frame of reference (Thompson, Springstein, et al., 2021). While some methodological approaches (e.g., EMA, ED tasks involving an immediate response to some sort of emotional stimuli) are meant to measure current emotional experience, other approaches (e.g., diary methods, the DRM, ED tasks based on autobiographic recall) require participants to remember and reconstruct past events. This variability also extends to studies assessing EG through open-ended descriptions, where participants may be asked to report on either present or past emotional events (Williams & Uliaszek, 2022). Although retrospective evaluations may provide more nuanced emotional descriptions due to the cognitive processing of experiences (Kashdan et al., 2015; Thompson, Springstein, et al., 2021), such methods cast doubt on what the researcher is actually measuring, whether meta-reflective processes related to emotional understanding or EG.

Finally, a last major point of debate is whether ecological and nonecological methods yield convergent results (Thompson, Springstein, et al., 2021). Erbas et al. (2014) reported that EG indices derived from both EMA and ED tasks produced similar results, suggesting that the two methods may capture overlapping constructs. In contrast, Ventura-Bort et al. (2021) reported divergent results when EG scores from an ED task and the DRM were compared. Likewise, (Erbas et al. (2019) observed that EG indices obtained via ESM and ED tasks were only weakly correlated, further challenging the assumption that these approaches tap into the same underlying construct. Taken together, these discrepancies suggest the need for further research to determine whether ecological and nonecological methods assess the same construct, capture distinct dimensions of EG or tap related but separate constructs. Clarifying this issue is essential for advancing theoretical conceptualizations of EG and for ensuring methodological coherence across studies.

4.6. Indices Computation: Are We Measuring What We Intend to Measure?

So far, research has used a plethora of computational indices to quantify EG. Ideally, an EG score (i.e., observed variable) should reflect whether an individual is high or low in EG ability (i.e., levels in the latent construct). The use of different indices, however, raises questions concerning the way in which each index captures differences in the levels of the latent construct. Notably, on the theoretical side, different assumptions have been made regarding the conceptualization of EG as a continuum from low to high levels (Barrett et al., 2001; Barrett, 206; Thompson, Springstein, et al., 2021; Hoemann, 2024). According to its original conceptualization (Barrett et al., 2001), low levels of EG reflect a tendency to represent emotional experiences along a broad pleasant–unpleasant continuum without distinguishing between discrete emotional states. Therefore, low-EG individuals could either use different emotion terms interchangeably (leading to strong positive correlations among similarly valenced emotions across episodes) or describe their emotional experience using generic valence-based terms (Barrett et al., 2001, 2006).

Our review shows that most studies have thus far quantified EG levels via variance-based scores (especially ICCs). Since these indices are derived from covariance-based or variance decomposition methods, they depend on the presence of both within- and between-emotion variance to accurately reflect EG levels. For example, a participant who repeatedly reports the same emotional state across observations would score low on this type of index, with the score being interpreted as a reflective index of a low EG ability. However, this conclusion may be inaccurate under certain conditions. For example, the participant could indeed have experienced only one emotion across time because of recurring daily circumstances (e.g., anger experienced after multiple daily fights with a partner on the same issue).

Likewise, the reporting of multiple co-occurring emotions within a single episode may reflect emotional complexity rather than low EG levels. Individuals may use multiple emotion terms to describe their emotional state not because of a lack of granularity but because a single term cannot adequately and comprehensively capture a nuanced experience[5]. On the one hand, different facets of the same event often lead to the experience of co-occurring emotions (e.g., after betrayal one might feel sad due to the end of the relationship, angry for misplaced trust, and indignant at the moral violation). On the other hand, it can happen that no single word exists to fully capture one's emotional state (e.g., complex or culturally nuanced emotions that lack a direct linguistic equivalent in the individual's native language[6]). Individuals may also report no emotion terms precisely because their experience is highly differentiated and cannot be meaningfully conveyed by available labels.

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[5] EG closely relies on the clarity and differentiation of one's conceptual representation of an emotional experience at a given moment (Hoemann, 2024). It could be argued that experiencing complex or mixed emotions in the moment might reduce one's ability to have a clear representation of their emotional state at that time. While this is certainly possible, such that low EG may occasionally co-occur with high emotional complexity, the use of multiple emotion labels in the context of a complex experience should not automatically be interpreted as reflecting low EG, provided that the underlying conceptual representation remains well defined. This is not to suggest that EG measures are always inaccurate when individuals report low granularity under high complexity (this can only be determined empirically by measuring both granularity and complexity). Nevertheless, we argue that it is important to develop EG measures capable of capturing instances of high EG even in the presence of high emotional complexity (Thompson, Springstein, et al., 2021), and this may also allow for a more nuanced understanding of the relationship between these two constructs.

[6] According to a constructionist account of emotion (Barrett, 2017a; Barrett et al., 2025), emotional experience arises when the brain uses emotion concepts to make sense of ongoing affective states in relation to the situational context. The more fine-grained and contextually specific these concepts are, the more granular the resulting emotional experience. One might argue, then, that in the absence of a specific situated emotion concept, the emotional experience itself cannot occur. However, given that affect serves as an index of allostatic status, and that emotion concepts are applied for the purpose of allostatic regulation (based on interoceptive signals, contextual cues, and past experiences), it is plausible that emotional experiences can emerge even in the absence of a single, discrete concept. In such cases, the brain may draw upon culturally learned patterns that integrate

Additionally, cases in which individuals do not select any emotional label among those provided may have multiple interpretations. This response pattern could reflect a genuine difficulty in identifying or distinguishing one's emotional state, but it may also occur when none of the available labels adequately capture the person's experience.

All these scenarios emphasize that the accuracy of existing variance-based methods is strongly sensitive to within-person variability, thereby raising concerns about their validity and between-person comparability. Thus, greater methodological caution is needed when interpreting variance-based EG indices to avoid the risk of confounding the richness and contextual flexibility of emotional expression with a lack of granularity and to be able to capture the nuanced ways in which individuals represent and communicate their emotional experiences.

A second group of computational methods is based on natural language. These methods have been used less frequently and derive from the assumption that low-EG individuals tend to describe their affect in broad, global terms. Thus, individuals reporting either the same emotion across episodes or cooccurring emotions in a single episode do not score low in EG in this measurement approach. Nonetheless, natural language-based methods may be scarcely sensitive to instances of low EG levels in which individuals use multiple specific terms interchangeably.

Overall, these differences in computation methods highlight a fundamental issue regarding how EG is conceptualized and the theoretical assumptions guiding its measurement (Thompson, Springstein, et al., 2021). To rely on accurate measures of the latent construct, rather than producing statistical artifacts, future research should focus on reinforcing the conceptual–methodological integration in EG assessment. As a promising initial step, empirical investigations have started to examine the degree of convergence among different EG indices, both in terms of their statistical consistency and their associations with relevant psychological constructs (Bicaker et al., 2022; Grühn et al., 2013; Mikhail et al., 2020; Mikkelsen et al., 2020; Ottenstein & Lischetzke, 2020; C. Racine et al., 2013; Seah & Coifman, 2024; Williams & Uliaszek, 2022). Although this line of research remains at an early stage, current evidence suggests that the various indices used to assess EG often fail to correlate with one another. Of note, ICC-derived indices seem to be largely unrelated to those based on spontaneous narrative reports (i.e., SI and NS), suggesting that these methods likely capture complementary, but different, facets of the construct. Future meta-analytic syntheses could test this hypothesis.

Last, but not least, we observed large differences even among studies employing the same computation method. To name a few, among ICC-based indices, some studies have computed consistency, while others agreement; some studies have excluded negative ICC values, while others interpret negative scores as indicators of high EG. Additionally, global EG has sometimes been calculated across both positive and negative emotional labels, whereas in other cases, separate indices

multiple emotion concepts simultaneously, resulting in an emotional experience that is best understood as a blend of emotions rather than one definable by a single term (Mesquita, 2022).

were computed and then averaged. Key steps in the data preprocessing and computation process (e.g., how zero-variance cases are handled) are often not reported in the articles, making it difficult to assess the robustness of indices and hindering the replicability of findings. These gaps highlight the need for more transparent reporting of computation procedures, aligning with open science principles to enhance reproducibility and cumulative knowledge in the field.

Overall, future research should aim to refine current EG indices and develop new computational strategies that can more accurately reflect the theoretical conceptualization of EG. This would strengthen the alignment between conceptualization and operationalization, enhance construct validity and measurement reliability, and ultimately support the robustness and comparability of research findings.

4.7. Emotional Granularity Adaptivity in Light of Methodological Heterogeneity

The present review revealed that studies examining the same or closely related correlates of EG do not necessarily employ comparable methodological approaches. Substantial variability was observed in study design, EG measurement strategies, and computational procedures used to derive EG indices. This methodological heterogeneity is particularly noteworthy given that findings across studies regarding the correlates, outcomes, and purported benefits of EG are often inconsistent, complicating efforts to draw firm conclusions about its functional significance.

Some studies have documented that only negative, but not positive EG plays a protective role toward key indicators of emotional functioning, psychological wellbeing, and adaptive behaviors (e.g., emotion regulation, alexithymia, positive and negative affect, depressive symptoms, eating disorder symptoms, caloric intake, and substance use; Aaron et al., 2018; Barrett et al., 2001; Jones & Herr, 2018; Seah, Sidney, et al., 2022; Starr et al., 2017; Walters et al., 2023; Williams-Kerver & Crowther, 2020; Willroth et al., 2020), whereas other studies have suggested that both positive and negative EG contribute adaptively (e.g., Emery et al., 2014; Erbas, Kalokerinos, et al., 2022; Hill & Updegraff, 2012; Lazarus et al., 2022; Liu et al., 2020; Mikhail et al., 2020; Vandercammen et al., 2014; Yang, 2022). The results regarding the beneficial role of positive EG are thus mixed and highlight the need for a deeper understanding of its implications for an individual's adaptive functioning (Tan et al., 2022).

Some authors have proposed that these inconsistencies may depend on intervening variables such as situational factors and individual characteristics (e.g., emotion reactivity; Thompson, Springstein, et al., 2021). Of note, studies that have assessed global EG besides positive and negative EG have also yielded inconsistent results (e.g., Liu et al., 2020; O'Toole et al., 2014). In some cases, global EG appears to impact mental health and emotional functioning while positive or negative EG does not, whereas other studies have observed the reverse pattern of results. Such inconsistencies may stem from individual differences (for instance, in the relative capacity to differentiate negative versus positive emotions) or from methodological factors related to the operationalization of the construct and the computation of the EG index.

Since most research has so far concerned dispositional EG, it would be important to understand whether EG fluctuations captured by daily and momentary assessments are beneficial or maladaptive. Additionally, it remains an open question whether the adaptive role of EG depends primarily on contextual demands, on the type of outcome under consideration, or on the interaction of these two elements (Erbas et al., 2018; Springstein et al., 2023). Because individuals may show different levels of EG across distinct emotion categories (Erbas et al., 2019), the ability to differentiate among emotions within one category (e.g., anger) may be associated with an aspect of psychological functioning (e.g., stress, expressive suppression), whereas the ability to differentiate among emotions within another emotion category (e.g., sadness) may be related to a different outcome (e.g., depressive symptoms, rumination).

Finally, some studies have suggested that EG, as a competence, has the potential to improve over time (e.g., Matt et al., 2024; Van Der Gucht et al., 2019; Vedernikova et al., 2021). In this context, it is worth emphasizing that certain assessment methods (particularly ESM) have been shown to serve not only as measurement approaches but also as practices with intervention functions (Hoemann, Barrett, et al., 2021). This potential twofold nature of EG assessment presents a methodological conundrum: On the one hand, because EG is a skill, it requires being measured behaviorally (Kashdan et al., 2015); on the other hand, methodological choices that direct participants' attention to their emotional experiences may foster the elaboration and diversification of emotion concepts, thereby potentially biasing the measurement of EG itself. This issue further highlights the complex array of factors that may undermine the validity and reliability of EG measures, contributing to mixed and inconsistent findings. In light of these considerations, we suggest that future meta-analytic work examining the associations between EG and psychological correlates, as well as its potential adaptive function, would carefully account for (where possible) key methodological factors underlying EG assessment.

5. Conclusion

We have shown that the assessment of EG is shaped by a complex network of methodological decisions. These include the theoretical background within which EG is conceptualized, the specific facet of EG being targeted (e.g., positive, negative, or global; integral, between-category, or within-category), its temporal framing (momentary, daily, or dispositional), the linguistic format used (fixed emotion labels versus freely generated natural language), the measurement approach (e.g., laboratory-based versus ecological assessment), the study design (e.g., cross-sectional, longitudinal, or experimental), and the computational approach adopted to derive EG indices (e.g., variance-based methods versus natural language processing techniques).

In all these areas, our review highlighted high variability and low consistency across studies. Such methodological heterogeneity raises important concerns about the alignment between the conceptual definition of EG and its operationalization, particularly in terms of reliability and construct validity. Moreover, this lack of methodological consistency across studies hinders cross-study comparison and the interpretation of the (mixed) results regarding the associations between EG and psychological functioning, limiting our chance to draw conclusions about its potential adaptive role.
To address these limitations, the adoption of more transparent and detailed reporting of methodological practices would improve and facilitate the reproducibility of future empirical research. Additionally, meta-analytic syntheses are needed to systematically evaluate how different methodological choices impact construct validity, identify best practices, and inform the development of more robust and theoretically grounded approaches for valid construct measurement.

Assessing and Measuring Emotional Granularity: A Systematic Review of the Existing Methodological Approaches

Chapter 1 Supplemental Material

List of Content:

1. Method

1.1. Screening Process

The screening process involved the following steps.

1. All identified study records were uploaded to the Rayyan platform (Ouzzani et al., 2016) and automatic deduplication procedures were applied. Two researchers independently performed a double-blind screening of titles and abstracts to determine the inclusion or exclusion of each record. Any disagreement was solved by involving a third reviewer, who facilitated the consensus process.
2. Full-text screening: The records that passed the initial screening were subjected to a double-blind reading of their full texts. The assessment for inclusion or exclusion was based on predefined criteria, and the reasons for the decisions were documented. Disagreements were once again solved through discussion among the three researchers. Interrater agreement was calculated via Cohen's Kappa coefficient, with a k value of 0.70 or higher considered acceptable.
3. The reference list of all eligible articles was examined to identify additional studies that explicitly mentioned the constructs "emotional granularity" or "emotion differentiation". The same screening process (title and abstract screening, full-text review, and conflict resolution) was applied to these newly identified studies.

1.2. Data Extraction

For each eligible study, data extraction was carried out by two independent reviewers through a two-step process including an extraction and a verification stage. In the extraction stage, the first reviewer recorded the following information: metadata (citation details, corresponding author's contact information), methodological details, sample characteristics, study objectives, and main findings regarding EG correlates. Details regarding the information included in each category are displayed in Table S1.

During the verification stage, the second reviewer independently cross-checked all the extracted data to ensure accuracy and consistency. In cases of discrepancies between the two reviewers, a second round of independent extractions was conducted.

1.3. Synthesis

Due to the heterogeneity of the study designs and methodologies in the field, we employed a narrative synthesis approach to integrate findings across studies. Employing a deductive thematic analysis approach (Braun & Clarke, 2006), the final synthesis combined all the components into a structured and coherent narrative. The findings are reported thematically and supported by summary tables to enhance clarity and comparability across studies.

2. Tables

2.1. Table S1: Summary of the Information Recorded during the Extraction Stage

Table S1. Summary of the information recorded during the extraction stage.

Type of Information	Content Area	(Sub)category of Content
Method	▪ Study design	
	▪ EG conceptualization	o Dispositional vs. state o Positive vs. negative vs. global o Integral vs. within- vs. between-category
	▪ Vocabulary	o Quantitative approach - Valence of labels - Number of labels - Type of labels - Intensity Rating scale o Qualitative approach - Type of text - Instructions provided to participants - Valence of identified lexicon - Criteria for valence classification - Criteria for lexicon classification - Intensity rating
	▪ Assessment	o Experience Sampling Method (ESM) - Type of sampling (e.g., Ecological Momentary Assessment, EMA; diary; Day Reconstruction Method, DRM). - Number of assessment days - Number of prompts/events per day - Overall sampling frequency o Emotion Differentiation tasks - Type and number or emotional stimuli - Instructions - Number of trials - Setting - Number and type of affective labels - Rating scale
	▪ Computation method	o Data preprocessing o Statistical procedures o Computational choices
Sample characteristics	▪ Sample size ▪ Population ▪ Age, gender ▪ Spoken language ▪ Psychopathology	
EG correlates	▪ Study's objectives ▪ Constructs/outcomes related to EG	o Statistical analysis o Significance of the effect o Direction of the effect

2.2. Table S2: Emotional labels categorized by valence and frequency of use across studies.

Table S2. Emotional labels categorized by valence and frequency of use across studies.

	Negative Labels	*N*	Positive Labels	*N*	Neutral Labels	*N*
1.	Sad	95	Happy	49	Neutral	4
2.	Angry	92	Excited	36	–	–
3.	Guilty	55	Proud	25	–	–
4.	Disgusted	43	Amused	23	–	–
5.	Anxious	42	Enthusiastic	23	–	–
6.	Nervous	41	Relaxed	22	–	–
7.	Ashamed	39	Interested	17	–	–
8.	Fear	35	Calm	15	–	–
9.	Depressed	24	Content	15	–	–
10.	Afraid	21	Satisfied	14	–	–
11.	Embarrassed	21	Joyful	13	–	–
12.	Distressed	20	Alert	12	–	–
13.	Bored	19	Grateful	12	–	–
14.	Irritable	18	Inspired	11	–	–
15.	Frustrated	17	Relieved	10	–	–
16.	Hostile	17	Active	9	–	–
17.	Lonely	17	Love	9	–	–
18.	Scared	17	Pride	9	–	–
19.	Irritated	16	Cheerful	8	–	–
20.	Jittery	16	Determined	8	–	–
21.	Shame	15	Strong	8	–	–
22.	Upset	15	Attentive	7	–	–
23.	Worried	15	Serene	7	–	–
24.	Stressed	11	Surprised	6	–	–
25.	Downhearted	10	Awe	5	–	–
26.	Jealous	10	Affection	4	–	–
27.	Unhappy	8	Elated	4	–	–
28.	Disappointed	7	Energetic	4	–	–
29.	Regret	6	Enjoyment	4	–	–
30.	Sluggish	6	Hopeful	4	–	–
31.	Tired	6	Peaceful	4	–	–
32.	Rage	5	Pleased	4	–	–
33.	Tense	5	Calm / Tranquil	3	–	–

	Negative Labels	*N*	Positive Labels	*N*	Neutral Labels	*N*
34.	Annoyed	4	Cheerful / Happy	3	–	–
35.	Blameworthy	4	Confident	3	–	–
36.	Blue	4	Curious	3	–	–
37.	Dissatisfied	4	Enthusiasm	3	–	–
38.	Hopeless	4	Excited / Enthusiastic	3	–	–
39.	Scornful	4	Optimistic	3	–	–
40.	Alone	3	Appreciative	2	–	–
41.	Angry at self	3	Contented	2	–	–
42.	Anxious / Afraid	3	Contented / Satisfied	2	–	–
43.	Disgusted with self	3	Lively	2	–	–
44.	Dissatisfied with self	3	Restful	2	–	–
45.	Envious	3	Sympathy	2	–	–
46.	Frightened	3	Admiring	1	–	–
47.	Gratitude	3	Adore	1	–	–
48.	Guilty / Ashamed	3	Aesthetics	1	–	–
49.	Inferior (Dutch synonym)	3	Amazed	1	–	–
50.	Loathing	3	At ease	1	–	–
51.	Miserable	3	Awe inspiring	1	–	–
52.	Restless	3	Beautiful	1	–	–
53.	Shaky	3	Bittersweet	1	–	–
54.	Uneasy	3	Capable	1	–	–
55.	Worn out	3	Closeness	1	–	–
56.	Anxious / Nervous	2	Comfortable	1	–	–
57.	Confused	2	Compassion	1	–	–
58.	Contempt	2	Delighted	1	–	–
59.	Dislike	2	Energized	1	–	–
60.	Distracted	2	Euphoric	1	–	–
61.	Down	2	Exceptional	1	–	–
62.	Dull	2	Family affection	1	–	–
63.	Fatigued	2	Fascinated	1	–	–
64.	Gloomy	2	Focused	1	–	–
65.	Hateful	2	Fond	1	–	–
66.	Inferior	2	Friendship	1	–	–
67.	Pity	2	Glad	1	–	–
68.	And distressed	1	Humor	1	–	–
69.	Awkward	1	Joyous	1	–	–
70.	Concerned	1	Liberation	1	–	–
71.	Defensive	1	Overjoyed	1	–	–

	Negative Labels	*N*	Positive Labels	*N*	Neutral Labels	*N*
72.	Dejected	1	Pleasant	1	–	–
73.	Discouraged	1	Pleasure	1	–	–
74.	Disgraced	1	Profound	1	–	–
75.	Disgusting	1	Respect	1	–	–
76.	Disturbing	1	Resting	1	–	–
77.	Dreariness	1	Reverence	1	–	–
78.	Droopy	1	Self-assured	1	–	–
79.	Embarrassment / Shame	1	Strength	1	–	–
80.	Enraged	1	Successful	1	–	–
81.	Everything was an effort	1	Superior	1	–	–
82.	Fidgety	1	Talkative	1	–	–
83.	Furious	1	Trust	1	–	–
84.	Grief	1	Wishful	1	–	–
85.	Haunting	1	Worthy	1	–	–
86.	Helpless	1	–	–	–	–
87.	Horrified	1	–	–	–	–
88.	Humiliated	1	–	–	–	–
89.	Impatience	1	–	–	–	–
90.	Irritability / Frustration	1	–	–	–	–
91.	Lethargic	1	–	–	–	–
92.	Numb	1	–	–	–	–
93.	Pain	1	–	–	–	–
94.	Panic	1	–	–	–	–
95.	Remorseful	1	–	–	–	–
96.	Repentant	1	–	–	–	–
97.	Repulsed	1	–	–	–	–
98.	Resentful	1	–	–	–	–
99.	Reserved	1	–	–	–	–
100.	Shocked	1	–	–	–	–
101.	So sad no one could cheer you up	1	–	–	–	–
102.	Sorry	1	–	–	–	–
103.	Terrified	1	–	–	–	–
104.	Unpleasant	1	–	–	–	–
105.	Worthless	1	–	–	–	–

Note. N refers to the number of studies that used the given emotional label. Emotional labels, divided by valence, are presented in descending order of frequency, from the most to the least frequently used.

2.3. Table S3: Overview of the Assessment Approaches to Emotional Granularity in the Reviewed Studies

Table S3. Overview of the assessment approaches to emotional granularity in the reviewed studies.

Autor(s) (Year)	EG Facets	Measurement Approach	Emotion Vocabulary	Language	EG Index Computation
1. Aaron et al. (2018)	Dispositional - positive - negative	ED task: - 14 standardized film-clips (Gross & Levenson, 1995) - valence: 4 positive, 8 negative, 2 related to surprise - laboratory-based setting	Fixed emotion labels (n = 31) on a 5-point Likert scale (1 = not at all; 5 = extremely) Positive (n = 13): *amusement, contentment, happiness, interest, relief, surprise, enthusiasm, excitement, inspiration, interest, pride, strength, calm* Negative (n = 18): *anger, confusion, contempt, sadness, disgust, embarrassment, fear, pain, tension, distress, guilt, hostility, irritated, jittery, nervousness, shame, upset, pity*	English (USA)	ICC-based - ICCs for absolute agreement - negative ICCs: // - no-variance cases: //
2. Barrett et al. (2001) °	Dispositional - positive - negative	Daily diary: - 1 entry/day - 14 consecutive days	Fixed emotion labels (n = 9) on a 5-point Likert scale (0 = not at all; 4 = very much) Positive (n = 4): *happiness, joy, enthusiasm, amusement* Negative (n = 5): *nervous, angry, sad, ashamed, guilty*	English (USA)	AIC-based - no-variance cases: //
3. Berman et al. (2022)	Dispositional - negative	ED task: - 10 standardized images (IAPS; Lang et al., 1995) - valence: negative - laboratory-based setting	Fixed emotion labels (n = 10) on a 6-point Likert scale (1 = not at all felt; 6 = extremely felt) Negative (n = 10*): fear, worried, lonely, sad, guilty, ashamed, jealous, embarrassed, angry, disgusted*	English (USA)	ICC-based - ICCs for consistency - negative ICCs coded as missing values - exclusion of no-variance cases

4. Bicaker et al. (2022)	Daily - negative	EMA: - 7 prompts/day - 10 consecutive days	Fixed emotion labels (n = 23) on a 5-point Likert scale (1 = very slightly or not at all; 5 = extremely) Negative (n = 23): *afraid, scared, frightened, nervous, jittery, shaky, angry, hostile, irritable, scornful, disgusted, loathing, guilty, ashamed, blameworthy, angry at self, disgusted with self, dissatisfied with self, sad, blue, downhearted, alone, lonely*	English (Canada)	PROC VARCOMP - ICCs for consistency - negative ICCs: // - no-variance cases coded as complete differentiation or excluded
5. Boden et al. (2013), Study 1	Dispositional - positive - negative	ED task: - 20 scenarios (Dizén & Berenbaum, 2011) - valence: 10 positive, 10 negative - laboratory-based setting	Fixed emotion labels (n = 12) on a 7-point Likert scale (0 = not at all; 6 = extremely) Positive (n = 6): *happy, proud, joyful, love, excited, satisfied* Negative (n = 6): *ashamed, angry, worried, sad, jealous, guilty*	English (USA)	ICC-based - ICCs for absolute agreement - negative ICCs coded as zero - no-variance cases: //
6. Boden et al. (2013), Study 2	Dispositional - positive - negative	EMA: - 4 prompts/day - 15 consecutive days	Fixed emotion labels (n = 12) on a 7-point Likert scale (0 = not at all; 6 = extremely) Positive (n = 6): *happy, proud, joyful, love, excited, satisfied* Negative (n = 6): *ashamed, angry, worried, sad, jealous, guilty*	English (USA)	ICC-based - ICCs for absolute agreement - negative ICCs coded as zero - no-variance cases: //
7. Bonar et al. (2023) °	Dispositional - positive - negative	DRM: - recall of 3–5 episodes from the previous day - 3 consecutive days	Fixed emotion labels (n = 20) on a 7-point Likert (1 = not at all; 7 = very much) Positive (n = 10): *amusement, awe, contentment, excitement, gratitude, happiness, love, pleased, proud, bittersweet* Negative (n = 10): *anger, anxious, boredom, disgust, embarrassed, fear, guilt, irritable, jealous, sadness*	English (USA)	ICC-based - ICCs for absolute agreement - negative ICCs coded as zero - no-variance cases: not stated
8. Brown et al. (2021)	Dispositional - negative	Daily diary: - 1 entry/day	Fixed emotion labels (n = 8) on a 5-point Likert scale (1 = not at all; 5 = extremely)	English (USA)	ICC-based - ICCs for absolute agreement

		- 30 consecutive days each year for up to 4 years	Negative (n = 8): *sad, dejected, nervous, jittery, angry, hostile, guilty, ashamed*		- no cases with negative ICCs - no-variance cases: //
9.	Cameron et al. (2013), Study 1 °	Dispositional - negative	ED task: - 10 standardized scenarios (LAES; Lane et al., 1990) - valence: negative - laboratory-based setting	Fixed emotion labels (n = 4) on a 5-point Likert scale (1 = not at all; 5 = extremely) Negative (n = 4): *anger, guilt, sadness, shame*	English (USA)	ICC-based - ICCs method: // - negative ICCs: // - no-variance cases: //
10.	Dawel et al. (2023)	Dispositional - positive - negative	ED task: - 12 images depicting social connection, health and work - valence: -- - online	Fixed emotion labels (n = 10) on a 6-point Likert scale (from 1= not at all; 6 = extremely strongly) Positive (n = 5): *excited, happy, hopeful, relaxed, surprised* Negative (n = 5): *angry, anxious, disgusted, fearful, sad*	English (Australia)	ICC-based - ICCs for consistency - negative ICCs: // - no-variance cases: //
11.	Decker et al. (2008)	Dispositional - positive - negative	Daily diary: - 1 entry/day - 9 consecutive days	Fixed emotion labels (n = 9) on a 5-point Likert scale (0 = not at all; 4 = very much) Positive (n = 4): *happy, joy, enthusiastic, amusement* Negative (n = 5): *nervous, angry, sad, ashamed, guilty*	English (USA)	AIC-based - no-variance cases: //
12.	Eckland et al. (2021)	Dispositional - positive - negative	Daily diary: - 1 entry/day - 7 consecutive days	Fixed emotion labels (n = 10 in sample 1; n = 8 in sample 2; n = 10 in sample 3) on a 5-point Likert scale (1 = not at all; 5 = great deal) Positive (n = 5 in sample 1; n = 4 in sample 2; n = 5 in sample 3): *calm/tranquil, contented/satisfied, cheerful/happy, proud, excited/enthusiastic* (sample 1); *calm/tranquil, cheerful/happy, proud, excited/enthusiastic* (sample 2); *calm/tranquil, contented/satisfied,*	English (USA)	ICC-based - ICCs for absolute agreement - negative ICCs: // - no-variance cases: //

			cheerful/happy, proud, excited/enthusiastic (sample 3) Negative (n = 5 in sample 1; n = 4 in sample 2; n = 5 in sample 3): *sad, guilty/ashamed, anxious/afraid, angry, bored* (sample 1); *sad, guilty/ashamed, anxious/afraid, angry* (sample 2); *sad, guilty/ashamed, anxious/afraid, angry, bored* (sample 3)		
13. Edwards & Wupperman (2017)	Dispositional - positive - negative - global	ED task: - 6 autobiographical recalls (N. Schwarz & Clore, 1983) - valence: 6 negative, 6 positive or neutral - laboratory-based setting	Fixed emotion labels (n = 20) on a 5-point Likert scale Positive (n = 10): *interested, excited, strong, enthusiastic, proud, inspired, determined, active, attentive, alert* Negative (n = 10): *distressed, upset, guilty, scared, hostile, irritable, ashamed, nervous, jittery, afraid*	English (USA)	ICC-based * - ICCs for absolute agreement - negative ICCs: // - no-variance cases: //
14. Edwards et al. (2020)	Dispositional - positive - negative	ED task: - 6 autobiographical recalls (N. Schwarz & Clore, 1983) - valence: 6 negative, 6 positive or neutral - laboratory-based setting	Fixed emotion labels (n = 20) on a 5-point Likert scale (1 = very slightly or not at all; 5 = extremely) Positive (n = 10): *interested, excited, strong, enthusiastic, proud, inspired, determined, active, attentive, alert* Negative (n = 10): *distressed, upset, guilty, scared, hostile, irritable, ashamed, nervous, jittery, afraid*	English (USA)	ICC-based - ICCs for absolute agreement - negative ICCs: // - no-variance cases: //
15. Emery et al. (2014)	Dispositional - positive - negative	EMA: - 8 prompts/day - 28 consecutive days	Fixed emotion labels (n = 14) on a 11-point Likert scales (1 = not at all; 11 = extremely) Positive (n = 5): *happy, joyful, excited, energetic, enthusiastic* Negative (n = 9): *sad, blue, downhearted, nervous, jittery, anxious, angry, hostile, irritable*	English (USA)	ICC-based - ICCs for absolute agreement - negative ICCs: // - no-variance cases: //

16. Erbas et al. (2019)	Dispositional - negative - between-category (negative) - within-category (negative)	ED task: - 20 standardized images (IAPS; Lang et al., 1995) - valence: negative - laboratory-based setting	Fixed emotion labels (n = 16 + 4 negative labels unrelated to the present study) on a 7-point Likert scale (1 = not at all; 7 = very much) Negative (n = 16 + 4 unrelated to the present study): *fear, worry, anxiety, nervousness, anger, irritation, disgust, rage, shame, guilt, regret, embarrassment, sadness, loneliness, unhappiness, depression (+ jealous, envious, and two Dutch words for inferior)*	Dutch (Belgium: dataset 1, 2, 3, 5, 6; Netherlands: dataset 4)	ICC-based - ICCs for consistency - negative ICCs coded as missing values - no-variance cases: //
17. Erbas et al. (2018)	Dispositional - negative Daily - negative	EMA: - 10 prompts/day - 7 consecutive days	Fixed emotion labels (n = 6) on a 101-point slider scale (0 = not at all; 100 = very much) Negative (n = 6): *stressed, angry, sad, anxious, depressed, lonely*	Dutch (Belgium)	ICC-based - ICCs for consistency - negative ICCs coded as missing values - no-variance cases: //
18. Erbas et al. (2015), Study 1 °	Dispositional - positive - negative	EMA: - 10 prompts/day - 14 consecutive days	Fixed emotion labels (n = 10) on a 100-point slider scale (1 = not at all; 100 = very much) Positive (n = 4): *relaxed, happy, satisfied, excited* Negative (n = 6): *angry, stressed, depressed, anxious, irritated, sad*	Dutch (Belgium)	ICC-based - ICCs for consistency - negative ICCs: // - no-variance cases: //
19. Erbas et al. (2015), Study 2 °	Dispositional - positive - negative	ED task: - 10 standardized film-clips (Schaefer et al., 2010) - valence: positive, negative, neutral - laboratory-based setting EMA: - 10 prompts/day - 6 consecutive days	Fixed emotion labels (n = 6) on a 100-point slider scale (1 = not at all; 100 = very much) during the EMA; on a 7-point Likert scale (0 = not at all; 6 = very much) during the ED task Positive (n = 2): *happy, relaxed* Negative (n = 4): *sad, depressed, anxious, angry*	Dutch (Belgium)	1. ICC-based (negative index) - ICCs method: // - negative ICCs: // - no-variance cases: // 2. AIC-based (positive index) - no-variance cases: //
20. Erbas et al. (2014), Study 1	Dispositional - negative	EMA: - 10 prompts/day	Fixed emotion labels (n = 4) on a 6-point Likert scale (0 = not at all; 5 = very much)	English (Australia)	ICC-based - ICCs for consistency

		- 7 consecutive days	Negative (n = 4): *angry, anxious, depressed, stressed*		- negative ICCs: // - no-variance cases: //
21. Erbas et al. (2014), Study 2	Dispositional - negative	ED task: - names of 22 target persons - valence: -- - laboratory-based setting	Fixed emotion labels (n = 35) Negative (n = 35): *bored, awkward, sad, reserved, pity, angry, confused, dislike, inferior, sad, frustrated, jealous, concerned, defensive, scared, nervous, unpleasant, disgust, upset, hateful, and others not stated*	Dutch (Belgium)	ICC-based - ICCs method: // - negative ICCs: // - no-variance cases: //
22. Erbas et al. (2014), Study 3	Dispositional - negative	ED task: - 20 standardized scenarios (Dizén & Berenbaum, 2011) - valence: negative - laboratory-based setting	Fixed emotion labels (n = 20) on a 7-point Likert scales (0 = not at all; 6 = very much) Negative (n = 20): *fear, worry, anxiety, nervousness, anger, irritation, disgust, rage, shame, guilt, regret, embarrassment, sadness, loneliness, unhappiness, depression, jealous, envious, 2 Dutch words for inferior*	Dutch (Belgium)	ICC-based - ICCs for consistency - negative ICCs: // - no-variance cases: //
23. Erbas et al. (2022), Study 1	Dispositional - positive - negative Momentary - positive - negative	EMA: - 10 prompts/day - 7 consecutive days	Fixed emotion labels (n = 8) on a 101-point slider scale (0 = not at all; 100 = very much) Positive (n = 3): *relaxed, happy, cheerful* Negative (n = 5): *angry, sad, anxious, depressed, lonely*	Dutch (Belgium)	1. ICC-based - ICCs for consistency - exclusion of cases with negative ICCs - no-variance cases: // 2. Derived from ICC - numerator equals zero: // - denominator equals zero: // - no-variance cases: //
24. Erbas et al. (2022), Study 2	Dispositional - positive - negative Momentary - positive - negative	EMA: - 10 prompts/day - 7 consecutive days	Fixed emotion labels (n = 9) on a 101-point slider scale (0 = not at all; 100 = very much) Positive (n = 4): *satisfied, relieved, happy, proud* Negative (n = 5): *anxious, ashamed, disappointed, angry, sad*	Dutch (Belgium)	ICC-based - ICCs for consistency - exclusion of cases with negative ICCs - no-variance cases: //

					2. Derived from ICC - numerator equals zero: // - denominator equals zero: // - no-variance cases: //
25. Erbas et al. (2016)	Dispositional - positive - negative	EMA: - 10 prompts/day - 7 consecutive days	Fixed emotion labels (n = 8) on a 100-point slider scale (1 = not at all; 100 = very much) Positive (n = 4): *relaxed, happy, satisfied, excited* Negative (n = 4): *angry, depressed, anxious, sad*	Dutch (Belgium)	ICC-based - ICCs for consistency - negative ICCs: // - no-variance cases: //
26. Fayn et al. (2018)	Dispositional - positive - negative	ED task: - 18 visual art images - valence: -- - laboratory-based setting	Fixed emotion labels (n = 10) on a 7-point Likert scale (not at all; yes, definitely) Positive (n = 6): *interesting, profound, exceptional, awe inspiring, pleasant, beautiful* Negative (n = 4): *disturbing, disgusting, upsetting, haunting*	English (Australia, Belgium)	ICC-based - ICCs method: // - negative ICCs coded as missing values - no-variance cases: //
27. Fogarty et al. (2015)	Dispositional - positive - negative	ED task: - autobiographical recall followed by a recovery period - valence: negative, neutral - laboratory-based setting	Fixed emotion labels (n = 20) on a 5-point Likert scale (1 = very slightly or not at all; 5 = very much) Positive (n = 10): *interested, excited, strong, enthusiastic, proud, inspired, determined, active, attentive, alert* Negative (n = 10): *distressed, upset, guilty, scared, hostile, irritable, ashamed, nervous, jittery, afraid*	English (New Zeland)	ICC-based - ICCs with absolute agreement - negative ICCs: // - no-variance cases: //
28. Grossmann et al. (2016), Study 2	Dispositional - positive - negative	ED task: - 10 autobiographical recalls (Kitayama et al., 2009)	Fixed emotion labels (n = 9) on a 6-point Likert scale (1 = not at all; 6 = very strongly) Positive (n = 4): *proud, elated, calm, happy*	Dutch (Germany), English (UK, USA), Hindu (India), Japanese (Japan), Russian (Russia)	ICC-based † - ICCs method: // - negative ICCs: // - no-variance cases: //

		- valence: positive, negative, neutral - laboratory-based setting	Negative (n = 5): *ashamed, frustrated, guilty, angry, unhappy*		
29. Grossmann et al. (2016), Study 3	Dispositional - positive - negative	ED task: - 10 autobiographical recalls (Kitayama et al., 2009) - valence: positive, negative, neutral - laboratory-based setting	Fixed emotion labels (n = 9) on a 6-point Likert scale (1 = not at all; 6 = very strongly) Positive (n = 4): *proud, elated, calm, happy* Negative (n = 5): *ashamed, frustrated, guilty, angry, unhappy*	English (USA), Japanese (Japan)	ICC-based † - ICCs method: // - negative ICCs: // - no-variance cases: //
30. Grühn et al. (2013)	Dispositional - positive - negative - global	EMA: - 5 prompts/day - 7 consecutive days	Fixed emotion labels (n = 20) on a 5-point Likert scale (1 = not at all; 2 = extremely) Positive (n = 10): *interested, excited, strong, enthusiastic, proud, inspired, determined, active, alert, attentive* Negative (n = 10): *distressed, upset, guilty, scared, hostile, irritable, ashamed, nervous, afraid, jittery*	English (USA)	1. ICC-based (positive, negative, global index) ** - ICCs with absolute agreement - negative ICCs: // - no-variance cases: // 2. PCA-based (global index) ** - no-variance cases: //
31. Hill & Updegraff (2012) °	Dispositional - positive - negative	EMA: - 6 prompts/day - 7 consecutive days	Fixed emotion labels (n = 21) on a 7-point Likert scale (1 = not at all; 7 = a great deal) Positive (n = 10): *interested, happy, content, peaceful, calm, overjoyed, fascinated, curious, comfortable, proud* Negative (n = 11): *sad, angry, ashamed, nervous, irritated, enraged, depressed, miserable, fearful, afraid, guilty*	English (USA)	ICC-based - ICCs method: // - negative ICCs: // - no-variance cases: //
32. Hoemann, Barrett, et al. (2021) °	Daily - positive - negative	Modified DRM: - recall of 3 daily episodes, selected from up to 20 prompts completed during the day	Fixed emotion labels (n = 18) on a 7-point Likert scale (0 = not at all; 6 = very much) Positive (n = 9): *amused, calm, excited, grateful, happy, proud, relieved, serene, surprised*	English (USA)	ICC-based - ICCs for absolute agreement - exclusion of cases with negative ICCs - no-variance cases: //

		- 14 consecutive days	Negative (n = 8): *afraid, angry, bored, disgusted, embarrassed, frustrated, sad, worn out* Other (n = 1): *neutral*		
33. Hoemann, Khan, et al. (2021) °	Dispositional - global	Modified DRM: - recall of 3 daily episodes, selected from up to 20 prompts completed during the day - 14 consecutive days	Fixed emotion labels (n = 18) on a 7-point Likert scales (0 = not at all; 6 = very much) Positive (n = 9): *amused, calm, excited, grateful, happy, proud, relieved, serene, surprised* Negative (n = 8): *afraid, angry, bored, disgusted, embarrassed, frustrated, sad, worn out* Other (n = 1): *neutral*	English (USA)	ICC-based * - ICCs for absolute agreement - negative ICCs coded as zero - no-variance cases: //
34. Hoemann et al. (2023), Study 1 °	Dispositional - positive - negative	Modified DRM: - recall of 3 daily episodes, selected from up to 20 prompts completed during the day - 14 consecutive days	Fixed emotion labels (n = 18) on a 7-point Likert scales (0 = not at all; 6 = very much) Positive (n = 9): *amused, calm, excited, grateful, happy, proud, relieved, serene, surprised* Negative (n = 8): *afraid, angry, bored, disgusted, embarrassed, frustrated, sad, worn out* Other (n = 1): *neutral*	English (USA)	ICC-based - ICCs for consistency - no cases with negative ICCs - no-variance cases: //
35. Hoemann et al. (2023), Study 2 °	Dispositional - positive - negative	EMA: - 10 prompts/day - 16 consecutive days	Fixed emotion labels (n = 39) on a 5-point Likert scales (1 = not at all; 5 = very much) Positive (n = 19): *admiring, amazed, amused, appreciative, calm, content, elated, enthusiastic, excited, grateful, happy, joyous, peaceful, prideful, relaxed, restful, successful, superior, surprised* Negative (n = 20): *angry, bored, contemptuous, depressed, disgusted, dislike, down, fearful, furious, guilty, hateful,*	English (USA)	ICC-based - ICCs for consistency - no cases with negative ICCs - no-variance cases: //

			irritated, nervous, remorseful, repulsed, sad, scornful, shocked, sorry, terrified		
36. Hoemann et al. (2023), Study 3 °	Dispositional - positive - negative	EMA: - 10 prompts/day - 14 consecutive days	Fixed emotion labels (n = 7) on a 100-point slider scale Positive (n = 2): *happy, relaxed* Negative (n = 5): *anxious, sad, stressed, angry, tired*	Dutch (Belgium)	ICC-based - ICCs for consistency - negative ICCs coded as zero - no-variance cases: //
37. Huggins et al. (2019) °	Dispositional - positive - negative - global	ED task: - 20 standardized images (NAPS; Marchewka et al., 2014) - valence: 10 positive, 10 negative - laboratory-based setting	Fixed emotion labels (n = 10) on a 7-point Likert scale (0 = not at all; 6 = extremely) Positive (n = 5): *happy, enthusiastic, amused, hopeful, relaxed* Negative (n = 5): *ashamed, nervous, angry, sad, guilty*	English (UK)	ICC-based * - ICCs for consistency - negative ICCs coded as missing values - no-variance cases: //
38. Huggins et al. (2023)	Dispositional - positive - negative	ED task: - 20 standardized images (NAPS; Marchewka et al., 2014) - valence: 10 positive, 10 negative - laboratory-based setting	Fixed emotion labels (n = 10) on a 7-point Likert scale (0 = not at all; 6 = very strongly) Positive (n = 5): *happy, enthusiastic, amused, hopeful, relaxed* Negative (n = 5): *ashamed, nervous, angry, sad, guilty*	English (UK), Japanese (Japan)	MSD-based - no-variance cases: //
39. Ikeda (2023) °	Dispositional - global	DRM: - recall of 15 episodes from the previous day - 1 day	Fixed emotion labels (n = 20) on a 7-point Likert (from 0 to 6) Positive (n = 10): *amusement, awe, contentment, excitement, gratitude, happiness, love, pleased, pride, serenity* Negative (n = 10): *anger, boredom, disgust, dissatisfied, downhearted, embarrassment, fear, gratitude, sadness, tired*	Japanese (Japan)	ICC-based * - ICCs method: // - negative ICCs: // - no-variance cases: //

40. Israelashvili et al. (2019), Study 1	Dispositional - negative	ED task: - 20 standardized images (IAPS; Lang et al., 1995) - valence: negative - laboratory-based setting	Fixed emotion labels (n = 20) on a 7-point Likert scale (0 = not at all; 6 = very much) Negative (n = 20): *anger, anxiety, depression, disgust, embarrassment, envy, fear, guilt, inferior (2 Dutch synonyms), irritation, jealousy, loneliness, nervousness, rage, regret, sadness, shame, unhappiness, worry*	Dutch (Netherlands)	ICC-based - ICCs for consistency - exclusion of cases with negative ICCs - no-variance cases: //
41. Israelashvili et al. (2019), Study 2	Dispositional - negative	ED task: - 20 standardized images (IAPS; Lang et al., 1995) - valence: negative - laboratory-based setting	Fixed emotion labels (n = 20) on a 7-point Likert scale (0 = not at all; 6 = very much) Negative (n = 20): *anger, anxiety, depression, disgust, embarrassment, envy, fear, guilt, inferior (2 Dutch synonyms), irritation, jealousy, loneliness, nervousness, rage, regret, sadness, shame, unhappiness, worry*	English (USA)	ICC-based - ICCs method for consistency - exclusion of cases with negative ICCs - no-variance cases: //
42. Jacobson et al. (2023)	Dispositional - positive - negative	Daily diary: - 1 entry/day - 50 consecutive days	Fixed emotion labels (n = 20) on a 101-point slider scale (0 = not at all; 100 = extremely) Positive (n = 10): *interested, excited, strong, enthusiastic, proud, inspired, determined, active, alert, attentive* Negative (n = 10): *distressed, upset, guilty, scared, hostile, irritable, ashamed, nervous, afraid, jittery*	English (USA)	ICC-based - ICCs for consistency - negative ICCs: // - no-variance cases: //
43. Jeong et al. (2023), Study 1	Dispositional - negative	ED task: - 14 items including pictures and news titles - valence: // - online	Fixed emotion labels (n = 7 + 4 positive labels unrelated to the present study) on a 4-point Likert scale (1 = not at all = 1; 4 = a great deal) Positive (n = 4, unrelated to the present study): *happy, excited, active, alert* Negative (n = 7): *sad, anxious, angry, frustrated, ashamed, disgusted, guilty*	Chinese (China)	AIC-based - no-variance cases: //

44. Jeong et al. (2023), Study 2	Dispositional - negative	ED task: - 14 items including pictures and news titles - valence: // - online	Fixed emotion labels (n = 7 + 4 positive labels unrelated to the present study) on a 4-point Likert scale (1 = not at all = 1; 4 = a great deal) Positive (n = 4, unrelated to the present study): *happy, excited, active, alert* Negative (n = 7): *sad, anxious, angry, frustrated, ashamed, disgusted, guilty*	Chinese (China)	AIC-based - no-variance cases: //
45. Jones & Herr (2018)	Dispositional - positive - negative	ED task: - 20 standardized scenarios (Dizén & Berenbaum, 2011) - valence: 10 positive, 10 negative - laboratory-based setting	Fixed emotion labels (n = 12) on a 6-point Likert scale Positive (n = //): *excited, satisfied, and others not stated* Negative (n = //): *ashamed, worried, sad, and others not stated*	English (USA)	ICC-based - ICCs for absolute agreement - negative ICCs: // - no-variance cases: //
46. Kalokerinos et al. (2019), Study 1	Dispositional - negative	EMA: - 10 prompts/day - 7 consecutive days	Fixed emotion labels (n = 6) on a 101-point slider scale (0 = not at all; 100 = very much) Negative (n = 6): *sad, depressed, lonely, angry, anxious, stressed*	Dutch (Belgium)	ICC-based - ICCs for consistency - exclusion of cases with negative ICCs - no-variance cases: //
47. Kalokerinos et al. (2019), Study 2	Dispositional - negative	EMA: - between 63 and 70 prompts - 9 consecutive days	Fixed emotion labels (n = 6) on a 101-point slider scale (0 = not at all; 100 = very much) Negative (n = 6): *sad, angry, disappointed, ashamed, anxious, stressed*	Dutch (Belgium)	ICC-based - ICCs for consistency - no cases with negative ICCs - no-variance cases: //
48. Kashdan & Farmer (2014)	Dispositional - positive - negative - related to social interactions (positive and negative)	Daily diary: - 1 entry/day - 14 consecutive days EMA: - 5 prompts/day - 14 consecutive days	Fixed emotion labels (n = 8 during social interactions; n = 12 at the end of the day) on a 5-point Likert scale (1 = very slightly or not at all; 5 = extremely) Positive (n = 4 during social interactions; n = 6 at the end of the day): *content, relaxed, enthusiastic, joyful* (during social interactions); *relaxed, enthusiastic, joyful,*	English (USA)	ICC-based - ICCs for absolute agreement - negative ICCs: // - exclusion of no-variance cases

		Event-contingent assessment: - targeting social interactions - 14 consecutive days	*content, proud, interested* (at the end of the day) Negative (n = 4 during social interactions; n = 6 at the end of the day): *anxious/nervous, angry, sad, sluggish* (during social interactions); *anxious, angry, sluggish, sad, irritable, distressed* (at the end of the day)		
49. Kashdan et al. (2014)	Dispositional - negative	Daily diary: - 1 entry/day - 21 consecutive days	Fixed emotion labels (n = 10) on a 5-point scale (1 = very slightly or not at all; 5 = extremely) Negative (n = 10): *anger, boredom, disgust, dissatisfied, downhearted, embarrassment, fear, sadness, tired*	English (USA)	ICC-based - ICCs with absolute agreement - negative ICCs: // - no-variance cases: //
50. Kashdan et al. (2010)	Dispositional - negative	EMA: - 14,002 random prompts in total - 21 consecutive days	Fixed emotion labels (n = 6) on an 11-point Likert scale Negative (n = 6): *sad, anxious, angry, tired, distracted, fatigued*	English (USA)	ICC-based - ICCs with absolute agreement - negative ICCs: // - no-variance cases: //
51. Kimhy et al. (2014)	Dispositional - negative - global	EMA: - 10 prompts/day - 2 consecutive days	Fixed emotion labels (n = 4) on a 100-point slider scale (0 = not at all; 100 = very much) Positive (n = 1): *happiness* Negative (n = 3): *sadness, anger, anxiety*	English (USA)	AIC-based [**] - no-variance cases: //
52. Lazarus et al. (2022)	Dispositional - positive - negative	Daily diary: - 1 entry/day - 3 consecutive weeks	Fixed emotion labels (n = 17) on a 5-point scale (not at all; very much) Positive (n = 8): *worthy, capable, pleased, content, happy, cheerful, energetic, lively* Negative (n = 9): *sad, depressed, hopeless, angry, irritated, resentful, anxious, restless, tensed*	Hebrew (Israel)	ICC-based - ICCs method: // - negative ICCs coded as missing values - no-variance cases: //

53. Lee et al. (2017) °	Dispositional - global	ED task: - 50 standardized images (IAPS; Lang et al., 1995) - valence: positive, negative, neutral - laboratory-based setting DRM: - recall of 15 episodes from the previous day - 1 day	Fixed emotion labels (n = 20) on a 7-point Likert scale (from 0 to 6) Positive (n = 10): *amusement, awe, contentment, excitement, gratitude, happiness, love, pleased, pride, serenity* Negative (n = 10): *anger, boredom, disgust, dissatisfied, downhearted, embarrassment, fear, gratitude, sadness, tired*	English (USA)	ICC-based * - ICCs method: // - negative ICCs: // - no-variance cases: //
54. Li & Ashkanasy (2019)	Dispositional - negative	ED task: - decision trials - valence: -- - laboratory-based setting	Fixed emotion labels (n = 3) Negative (n = 3): *sad, angry, nervous*	English (Australia)	AIC-based - no-variance cases: //
55. Liao et al. (2025) °	Dispositional - negative	EMA: - 6 prompts/day - 7 consecutive days	Fixed emotion labels (n = 8) on a 5-point scale (1 = not at all; 5 = extremely) Negative (n = 8): *angry, nervous, anxious, stressed, depressed, guilty, ashamed, sad*	Chinese (China)	ICC-based - ICCs for consistency - negative ICCs coded as missing values - no-variance cases: //
56. Lischetzke et al. (2021)	Dispositional - negative Daily - negative	Daily diary: - 1 entry/day - 20 consecutive days	Fixed emotion labels (n = 8) on a 101-point slider scale Negative (n = 8): *anger, fear, disappointment, sadness, embarrassment/shame, regret, boredom, loneliness*	German (Germany)	Derived from ICC - numerator equals zero: // - denominator equals zero: // no-variance cases: //
57. Liu et al. (2020)	Dispositional - positive - negative - global	EMA: - 8 prompts/day - 7 consecutive days	Fixed emotion labels (n = 13) on a 5-point scale (0 = not at all; 4 = extremely) Positive (n = 6): *happy, calm, excited, relaxed, enthusiastic, content*	English (USA)	ICC-based * - ICCs for consistency - negative ICCs coded as zero - no-variance cases: //

			Negative (n = 7): *frustrated, hostile, sluggish, sad, disappointed, dull, nervous*		
58. Lukic et al. (2023) °	Dispositional - global	Daily diary: - 1 entry/day - 8 consecutive weeks	Fixed emotion labels (n = 13) on a 7-point Likert scale (1 = not at all; 7 = a lot) Positive (n = 8): *awe, amusement, compassion, pride, calm, contentment, joy, gratitude* Negative (n = 5): *anger, annoyance, anxiety, fear, sadness*	English (USA)	ICC-based ** - ICCs for absolute agreement - no cases with negative ICCs - no-variance cases: //
59. Lv et al. (2024) °	Dispositional - negative	ED task: - 20 standardized images (OASIS; Kurdi et al., 2017) - valence: negative - online	Fixed emotion labels (n = 5) on a 10-point scale (1 = not at all; 10 = extremely) Negative (n =5): *anger, shame, disgust, sadness, fear*	Chinese (China)	ICC-based - ICCs method: // - negative ICCs: // - no-variance cases: //
60. Mankus et al. (2016)	Dispositional - negative	ED task: - 10 standardized images (IAPS; Lang et al., 1995) - valence: negative - online	Fixed emotion labels (n = 10) on a 7-point Likert scale (0= not at all; 6=very much) Negative (n =10): *fearful, worried, lonely, sad, guilty, ashamed, jealous, embarrassed, angry, disgusted*	English (USA)	ICC-based - ICCs with absolute agreement - negative ICCs: // - no-variance cases: //
61. Matt et al. (2024)	Dispositional - negative	EMA: - 5 prompts/day - 7 consecutive days	Fixed emotion labels (n = 7) on an 8-point Likert scale (0 = none; 7 = strongly) Negative (n = 7): *fear, sadness, distress, guilt, anger, disgust, shame*	English (USA)	ICC-based - ICCs with absolute agreement - negative ICCs: // - exclusion of no-variance cases
62. Matyi & Spielberg (2023)	Dispositional - negative	ED task: - 20 standardized images (Nook et al., 2018) - valence: negative - laboratory-based setting	Fixed emotion labels (n = 5) on a 21-point slider scale (from 0 to 20) Negative (n = 5): *scared, sad, angry, upset, disgust*	English (USA)	ICC-based - ICCs method: // - negative ICCs: // - no-variance cases: //

63. Mehak et al. (2024)	Dispositional - negative	EMA: - 7 prompts/day - 10 consecutive days	Fixed emotion labels (n = 23) on a 5-point Likert scale (1 = very slightly or not at all; 5 = extremely) Negative (n = 23): *guilty, ashamed, blameworthy, angry at self, disgusted with self, dissatisfied with self, sad, blue, downhearted, alone, lonely, afraid, scared, frightened, nervous, jittery, shaky, angry, hostile, irritable, scornful, disgusted, loathing*	English (Canada, USA)	ICC-based - ICCs for absolute agreement - exclusion of cases with negative ICCs - no-variance cases: //
64. Mikhail et al. (2020)	Dispositional - positive - negative	Daily diary: - 1 entry/day - 45 consecutive days	Fixed emotion labels (n = 20) on a 5-point Likert scale (1 = very slightly or not at all; 5 = extremely) Positive (n = 10): *interested, excited, strong, enthusiastic, proud, alert, inspired, determined, attentive, active* Negative (n = 10): *distressed, upset, guilty, scared, hostile, irritable, ashamed, nervous, jittery, afraid*	English (USA)	1. ICC-based - ICCs for absolute agreement - negative ICCs: // - no-variance cases: // 2. VAR-method - no-variance cases: //
65. Mikkelsen et al. (2021)	Dispositional - positive - negative	ED task: - 6 autobiographical recalls - valence: 3 positive, 3 negative - online	Fixed emotion labels (n = 6) Positive (n = 3): *happiness, interest, peacefulness* Negative (n = 3): *sadness, anger, anxiety*	Danish (Denmark)	ICC-based - ICCs method: // - negative ICCs: // - no-variance cases: //
66. Mikkelsen et al. (2020)	Dispositional - negative	ED task: - 34 standardized images (NAPS; Marchewka et al., 2014) - valence: negative - online	Fixed emotion labels (n = 4) on a 7-point Likert scale (1 = not at all; 7 = very intensely) Negative (n = 4): *anger, sadness, disgust, fear*	Danish (Denmark)	1. ICC-based - ICCs with consistency - negative ICCs coded as missing values - no-variance cases: // 2. PCA-based - no-variance cases: //

67. O'Toole et al. (2014)	Dispositional - positive - negative - global	Daily diary: - 1 entry/day - 11 consecutive days	Fixed emotion labels (n = 10) on a 5-point rating scale Positive (n = 5): *happiness, enthusiasm, amusement, curiosity, pride* Negative (n = 5): *shame, nervousness, anger, sadness, guilt*	Danish (Denmark)	AIC-based * - no-variance cases: //
68. O'Toole et al. (2021)	Dispositional - negative Daily - negative	EMA: - 3 (sample1) or 4 (sample 2) prompts/day - 10 consecutive days	Fixed emotion labels (n = 7) on a 5-point Likert scale (1 = not at all; 5 = very much) Negative (n = 7): *guilty, ashamed, nervous, sad, disgusted, angry, frustrated*	Danish (Denmark)	ICC-based - ICCs method: // - negative ICCs coded as missing values - no-variance cases: //
69. Oh & Tong (2020)	Dispositional - negative	Daily diary: - 1 entry/day - 8 consecutive days	Fixed emotion labels (n = 14) on a 5-point Likert scale (0 = none of the time; 4 = all of the time) Negative (n = 14): *so sad no one could cheer you up, nervous, restless, everything was an effort, hopeless, worthless, lonely, afraid, jittery, irritable, ashamed, upset, angry, frustrated*	English (USA)	ICC-based - ICCs method: // - negative ICCs coded as missing values - no-variance cases: //
70. Ottenstein & Lischetzke (2020), Study 1	Dispositional - negative	Daily diary: - 1 entry/day - 3 consecutive weeks	Natural affective language Freely generated emotion labels related to negative daily events - use of existing lexicons to identify emotional vocabulary: LIWC)Pennebaker et al., 2015); RIOT Scans (Boyd, 2014) - criteria for valence classification:// - criteria for specific-general classification of the vocabulary: drew on the LEAS (Lane et al., 1990)	German (Germany)	SI
71. Ottenstein & Lischetzke (2020), Study 2	Dispositional - negative	Daily diary: - 1 entry/day - 3 consecutive weeks	▪ Natural affective language Freely generated emotion labels related to negative daily events	German (Germany)	1. SI 2. ICC-based - ICCs for consistency

			- use of existing lexicons to identify emotional vocabulary: LIWC)Pennebaker et al., 2015); RIOT Scans (Boyd, 2014) - criteria for valence classification:// - criteria for specific-general classification of the vocabulary: drew on the LEAS (Lane et al., 1990) ▪ Fixed emotion labels (n = 6) on a 5-point Likert scale (0 = not at all; 4 = very intense) Negative (n =6): *fear, anger, frustration, sadness, embarrassment, boredom*		- negative ICCs: // - no-variance cases: //
72. Petagna & Wormwood (2025)	Dispositional - positive - negative	EMA: - 8 prompts/day - 7 consecutive days	Fixed emotion labels (n = 16) on a 5-point Likert scale (0 = not at all; 4 = very much) Positive (n = 7): *happy, excited, relaxed, focused, content, proud, grateful* Negative (n = 8): *tired, sad, nervous, frustrated, stressed, annoyed, angry, afraid* Other (n = 1): *neutral*	English (USA)	ICC-based - ICCs for consistency - negative ICCs: // - no-variance cases: //
73. Plonsker et al. (2017)	Dispositional - Within-category (negative)	ED task: - 44 standardized images (IAPS; Lang et al., 2008) - valence: negative - laboratory-based setting	Fixed emotion labels (n = 8 + 5 positive labels unrelated to the present study) on a 5-point Likert scale (1 = not at all felt; 5 = extremely felt) Positive (n = 5, unrelated to the present study): *interest, love, joy, happiness, amusement* Negative (n = 8): *shame, guilt, fear, anxiety, disgust, anger, sadness, embarrassment*	Hebrew (Israel)	MECA index
74. Pond Jr. et al. (2012), Study 1	Dispositional - negative	Diary: - 3 entries/week - 25 days	Fixed emotion labels (n = 10) on a 5-point Likert scale (from very slightly or not at all to extremely)	English (USA)	ICC-based - ICCs for absolute agreement

			Negative (n = 10): *distressed, upset, guilty, scared, hostile, irritable, ashamed, nervous, jittery, afraid*		- negative ICCs: // - no-variance cases: //
75. Pond Jr. et al. (2012), Study 2	Dispositional - negative	Daily diary: - 1 entry/day - 3 consecutive weeks	Fixed emotion labels (n = 5) on a 7-point Likert scale (from not at all to very much) Negative (n = 5): *embarrassed, disappointed, bored, anxious/nervous, sad*	English (USA)	ICC-based - ICCs for absolute agreement - negative ICCs: // - no-variance cases: //
76. Pond Jr. et al. (2012), Study 3	Dispositional - negative	Diary: - 3 entries/week - 25 days	Fixed emotion labels (n = 10) on a 5-point Likert scale (from very slightly or not at all to extremely) Negative (n = 10): *distressed, upset, guilty, scared, hostile, irritable, ashamed, nervous, jittery, afraid*	English (USA)	ICC-based - ICCs for absolute agreement - negative ICCs: // - no-variance cases: //
77. Potthoff et al. (2023)	Dispositional - positive - negative	ED task: - 12 standardized film-clips (E.Vids set; Blechert et al., 2015) - valence: 6 positive, 6 negative - laboratory-based setting	Natural affective language Freely generated emotion labels related to each emotion film-clip - use of existing lexicons to identify emotional vocabulary: // - criteria for valence classification: positive and negative terms were classified based on self-report valence ratings - criteria for specific-general classification of the vocabulary: //	German (Austria)	SI
78. Pugach et al. (2023)	Dispositional - negative	EMA: - 17 prompts/day - 3 consecutive days	Fixed emotion labels (n = 10) on a 7-point Likert scale (1 = not at all; 7 = very much) Negative (n = 10): *afraid, worried, horrified, helpless, guilty, numb, ashamed, sad, angry, disgusted*	English (USA)	ICC-based - ICCs method: // - no cases with negative ICCs - no-variance cases: //
79. Qiu et al. (2023)	Dispositional - positive - negative	ED task:	Fixed emotion labels (n = 10) on a 10-point Likert scale (1 = not at all; 10 = extremely)	Chinese (China)	ICC-based † - ICCs method: // - negative ICCs: //

		- 40 standardized images (OASIS; Kurdi et al., 2017) - valence: 20 positive, 20 negative - online	Positive (n = 5): *calm, excitement, happiness, inspiration, interested* Negative (n = 5): *anger, ashamed, disgust, sadness, scared*		- no-variance cases: //
80. Racine et al. (2024)	Momentary - negative	EMA: - 7 prompts/day - 10 consecutive days	Fixed emotion labels (n = 23) on a 5-point Likert scale (1 = very slightly or not at all; 5 = extremely) Negative (n = 23): *afraid, scared, frightened, nervous, jittery, shaky, angry, hostile, irritable, scornful, disgusted, loathing, guilty, ashamed, blameworthy, angry at self, disgusted with self, dissatisfied with self, sad, blue, downhearted, alone, lonely*	English (Canada, USA)	PROC VARCOMP - numerator equals zero: // - denominator equals zero: // - no-variance cases coded as complete differentiation, complete undifferentiation, or left missing
81. Ready et al. (2019)	Dispositional - positive - negative - global - within-arousal (positive) - within-arousal (negative) - within-arousal (global)	Correspondence rating task: - correspondence ratings of 16 emotion items - online	Fixed emotion labels (n = 16) on a correspondence ratings of items using a 10-point Likert scale (0 = completely different; 9 = completely similar) Positive (n = 8): *serene, relaxed, resting, at ease* (low arousal); *elated, delighted, excited, euphoric* high arousal) Negative (n = 8): *down, lethargic, droopy, and sluggish* (low arousal); *annoyed, nervous, worried, anxious* (high arousal)	English (USA)	Sum of the correspondence ratings of items **
82. Schmitt et al. (2024)	Momentary - positive - negative	EMA: - 8 prompts/day - 14 consecutive days	Fixed emotion labels (n = 27) on a 101-point slider scale (0 = not at all; 100 = very much) Positive (n = 12): *joyful, glad, happy, interested, alert, curious, love, closeness, trust, proud, confident, self-assured* Negative (n = 15): *angry, irritated, annoyed, sad, downhearted, unhappy, scared, fearful, afraid, ashamed, humiliated, disgraced, guilty, repentant, blameworthy*	German (Germany)	LMFA-based - no-variance cases: //

83. Seah, Almahmoud, et al. (2022)	Dispositional - negative	Weekly diary: - 1 entry/week - 10–12 months	Fixed emotion labels (n = 6 + 6 positive labels unrelated to the present study) on a 7-point Likert scale (1 = none; 7 strong) Positive (n = 6, unrelated to the present study): *happiness, enjoyment, affection, surprise, amusement, relief* Negative (n = 6): *fear, sadness, guilt, distress, anger, disgust*	English (USA)	ICC-based - ICCs for consistency - negative ICCs coded as zero - no-variance cases: //
84. Seah, Sidney, et al. (2022)	Dispositional - positive - negative	Daily diary: - 1 entry/day - 10 consecutive days	Fixed emotion labels (n = 12) on a 5-point Likert scale (1 = not at all; 5 = extremely) Positive (n = 6): *relief, enjoyment, amusement, happiness, affection, joy* Negative (n = 6): *fear, sadness, distress, anger, disgust, guilt*	English (USA)	ICC-based - ICCs with absolute agreement - negative ICCs coded as missing values - no-variance cases: //
85. Seah & Coifman (2024)	Dispositional - positive - negative Momentary - positive - negative	EMA: - 8 prompts/day - 7 consecutive days	▪ Fixed emotion labels (n = 12) on a 7-point Likert scale (1 = none; 7 = strongly). Positive (n = 6): *happiness, excited, affection, satisfaction, amusement, relief* Negative (n = 6): *fear, sadness, guilt, distress, anger, disgust* ▪ Natural affective language Freely generated emotion labels related to a negative daily event - use of existing lexicons to identify emotional vocabulary: LIWC)Pennebaker et al., 2015) - criteria for valence classification: // - criteria for specific-general classification of the vocabulary: //	English (USA)	1. ICC-based - ICCs with absolute agreement - negative ICCs coded as missing values - no-variance cases: // 2. SI 3. Derived from ICC - numerator equals zero: // - denominator equals zero: // - no-variance cases: //
86. Seah et al. (2020), Study 1	Dispositional - negative	Daily diary: - 1 entry/day - 14 consecutive days	Fixed emotion labels (n = 6 +6 positive labels unrelated to the present study) on a 5-point Likert scale (1 = not at all; 5 = extremely)	English (USA)	ICC-based - ICCs for absolute agreement

			Positive (n = 6, unrelated to the present study): *happiness, enjoyment, affection, satisfaction, amusement, relief* Negative (n = 6): *fear, sadness, guilt, distress, anger, disgust*		- negative ICCs coded as zero - no-variance cases: //
87. Seah et al. (2020), Study 2	Dispositional - negative	Daily diary: - 1 entry/day - 10 consecutive days	Fixed emotion labels (n = 6 + 6 positive labels unrelated to the present study) on a 5-point Likert scale (1 = not at all; 5 = extremely) Positive (n = 6, unrelated to the present study): *happiness, enjoyment, affection, satisfaction, amusement, relief* Negative (n = 6): *fear, sadness, guilt, distress, anger, disgust*	English (USA)	ICC-based - ICCs for absolute agreement - negative ICCs coded as zero - no-variance cases: //
88. Sels et al. (2024), Study 1	Momentary - negative	Daily diary: - 1 entry/day - 7 consecutive days	Fixed emotion labels (n = 8) on a 7-point Likert scale Negative (n = 8): *sad, angry, depressed, nervous, fearful, guilty, ashamed, irritated*	English (USA)	Derived from ICC - numerator equals zero: // - denominator equals zero: // - no-variance cases: //
89. Sels et al. (2024), Study 2	Momentary - negative	EMA: - 10 prompts/day - 7 consecutive days	Fixed emotion labels (n = 4) on a 101-point Slider scale (from 0 to 100) Negative (n = 4): *sad, angry, depressed, anxious*	Dutch (Belgium)	Derived from ICC - numerator equals zero: // - denominator equals zero: // - no-variance cases: //
90. Sels et al. (2024), Study 3	Momentary - negative	EMA: - 10 prompts/day - 9 consecutive days	Fixed emotion labels (n = 6) on a 101-point Slider scale (from 0 to 100) Negative (n = 6): *sad, angry, depressed, anxious, ashamed, disappointed*	Dutch (Belgium)	Derived from ICC - numerator equals zero: // - denominator equals zero: // - no-variance cases: //

91. Sels et al. (2024), Study 4	Momentary - negative	EMA: - 10 prompts/day - 7 consecutive days	Fixed emotion labels (n = 4) on a 101-point Slider scale (from 0 to 100) Negative (n = 4): *sad, dull, anxious, irritated*	English (Australia)	Derived from ICC - numerator equals zero: // - denominator equals zero: // - no-variance cases: //
92. Sheets et al. (2015)	Dispositional - positive - negative	EMA: - 23 prompts/day - 1 day	Fixed emotion labels (n = 10) on a 5-point Likert scale (1 = none/not at all; 5 = severe/extremely) Positive (n = 4): *joyful, cheerful, energetic, lively* Negative (n = 6): *downhearted, discouraged, uneasy, anxious, irritability/frustration, impatience*	English (USA)	ICC-based - ICCs for absolute agreement - negative ICCs: // - no-variance cases: //
93. Springstein et al. (2023) °	Momentary - positive - negative	EMA: - 6 prompts/day - 10 consecutive days	Fixed emotion labels (n = 13) on a 7-point Likert scale (1 = not at all; 7 = extremely) Positive (n = 6): *excited, enthusiastic, happy, peaceful, relaxed, grateful* Negative (n = 7): *stressed, angry, nervous, disgusted, sad, sluggish, bored*	English (USA)	Derived from ICC - numerator equals zero: // - denominator equals zero: // - no-variance cases: //
94. Starr et al. (2017), Study 1	Dispositional - positive - negative	Daily diary: - 1 entry/day - 14 consecutive days	Fixed emotion labels (n = 14) Positive (n =7): *talkative, enthusiastic, confident, cheerful, energetic, satisfied, happy* Negative (n = 7): *tense, anxious, distracted, restless, irritated, depressed, guilty*	English (USA)	ICC-based - ICCs method: // - negative ICCs: // - no-variance cases: //
95. Thompson, Springstein, et al. (2021)	Dispositional - positive - negative	EMA: - 5 prompts/day - 14 consecutive days	Fixed emotion labels (n = 12) on a 5-point scale (0 = not at all; 4 = extremely) Positive (n = 6): *relaxed, content, calm, happy, excited, enthusiastic* Negative (n = 6): *bored, sluggish, sad, frustrated, nervous, angry*	English (USA)	ICC-based - ICCs for consistency - negative ICCs coded as zero - no-variance cases: //

96. Tong & Keng (2017)	Dispositional - negative	EMA: - up to 36 observations - 2 consecutive days	Fixed emotion labels (n = 8) on a 7-point Likert scale (1 = not at all; 7 = very much) Negative (n = 8): *anger, boredom, disgust, fear, frustration, guilt, sadness, shame*	English (Singapore)	ICC-based - ICCs method: // - negative ICCs: // - no-variance cases: //
97. Tugade et al. (2004), Study 2	Dispositional - positive	EMA: - 10 prompts/day - 28 consecutive days	Fixed emotion labels (n = 5) on a 7-point Likert scale (0 = not at all; 6 = a great deal) Positive (n = 5): *amusement, happiness, interest, joy, pride*	English (USA)	ICC-based - ICCs for absolute agreement - negative ICCs: // - no-variance cases: //
98. Van Der Gucht et al. (2019)	Dispositional - positive - negative	EMA: - 10 prompts/day - 4 consecutive days	Fixed emotion labels (n = 12) Positive (n = 6): *enjoyment, cheerfulness, happiness, satisfaction, relaxation, restfulness* Negative (n = 6): *anger, anxiety, depression, stress, sadness, grief*	Dutch (Belgium)	ICC-based - ICCs for consistency - negative ICCs: // - no-variance cases: //
99. Vandercammen et al. (2014), Study 1	Dispositional - positive - negative	Daily diary: - 1 entry/day - 10 consecutive days	Fixed emotion labels (n = 12) on a 6-point Likert scale (1 = totally disagree; 6 = totally agree) Positive (n = 6): *enthusiastic, cheerful, optimistic, contented, calm, relaxed* Negative (n = 6): *tense, gloomy, depressed, worried, miserable, uneasy*	Dutch (Belgium)	ICC-based - ICCs for absolute agreement - negative ICCs: // - no-variance cases: //
100. Vandercammen et al. (2014), Study 2	Dispositional - positive - negative	EMA: - 5 prompts/day - 4 consecutive days	Fixed emotion labels (n = 12) on a 7-point Likert scale (1 = totally disagree; 7 = totally agree) Positive (n = 6): *enthusiastic, cheerful, optimistic, contented, calm, relaxed* Negative (n = 6): *tense, gloomy, depressed, worried, miserable, uneasy*	Dutch (Belgium)	ICC-based - ICCs method: // - negative ICCs: // - no-variance cases: //

101. Vedernikova et al. (2021)	Dispositional - positive - negative	ED task: - 20 standardized scenarios (Dizén & Berenbaum, 2011) - valence: 10 positive, 10 negative - online	Fixed emotion labels (n = 12) on a 7-point Likert scale (0 = not at all; 6 = extremely strongly) Positive (n = 4): *love, joy, relief, satisfaction* Negative (n = 8): *anger, disgust, sadness, loneliness, fear, anxiety, shame, guilt*	English (miscellneaous: participants recruited via Prolific)	ICC-based - ICCs for consistency - negative ICCs coded as missing values - no-variance cases: //
102. Ventura-Bort et al. (2021) °	Dispositional - positive - negative	ED task: - 40 standardized images (IAPS; Lang et al., 2008) - valence: 10 positive, 10 negative - laboratory-based setting DRM: - recall of 15 episodes from the previous day - 2 days	Fixed emotion labels on a 101-point slider scale (0 = not at all; 100 = very much) for the ED task (n = 8); on a 7-point Likert scale (0 = not at all; 6 = very much) for the DRM (n = 19). Positive (n = 4 for the ED task; n = 10 for the DRM): *amusement, happiness, satisfaction, sympathy* (ED task); *amusement, awe, contentment, excitement, gratitude, happiness, love, pleasure, pride, serenity* (DRM) Negative (n = 4 for the ED task; n = 9 for the DRM): *fear, anger, disgust, sadness* (ED task); *anger, boredom, disgust, dissatisfaction, downheartedness, embarrassment, fear, sadness, fatigue* (DRM)	German (Germany)	ICC-based - ICCs method: // - exclusion of cases with negative ICCs - no-variance cases: //
103. Wabnegger et al. (2024)	Dispositional - negative	EMA: - 2 prompts/day - 7 consecutive days	Natural affective language Freely generated emotion labels related to a negative daily event - use of existing lexicons to identify emotional vocabulary: // - criteria for valence classification: positive and negative terms classified based on self-report valence ratings - criteria for specific-general classification of the vocabulary: //	German (Austria)	Modified SI

104. Walters et al. (2023)	Dispositional - positive - negative	EMA: - 4 prompts/day - 35 consecutive days	Fixed emotion labels (n = 7) on a 5-point Likert scale (1 = not at all; 5 = extremely) Positive (n = 3): *relaxed, cheerful, energized* Negative (n = 4): *stressed, sad, fidgety, irritable*	English (USA)	ICC-based - ICCs for consistency - negative ICCs: // - no-variance cases: //
105. Walukevich-Dienst et al. (2023)	Dispositional - negative	Daily diary: - 1 entry/day - 14 consecutive days	Fixed emotion labels (n = 5) on a 5-point Likert scale (1 = very slightly or not at all; 5 = extremely) Negative (n = 5): *distressed, upset, nervous, scared, afraid*	English (USA)	ICC-based - ICCs method: // - no cases with negative ICCs - no-variance cases: //
106. Wang, Liao, et al. (2020)	Dispositional - positive	ED task: - 10 standardized images (IAPS; Lang et al., 2008) - valence: positive - laboratory-based setting	Fixed emotion labels (n = 10) on a 7-point Likert scale (1 = completely absent; 7 = to a large extent) Positive (n = 10): *amused, content, excited, relaxed, enthusiastic, proud, grateful, happy, confident, fond*	Chinese (China)	ICC-based - ICCs method: // - negative ICCs: // - no-variance cases: //
107. Wang, Shangguan, et al. (2020) °	Dispositional - negative	ED task: - 20 standardized images (IAPS; Lang et al., 2008) - valence: negative - laboratory-based setting	Fixed emotion labels (n = 20) on a 5-point Likert scale (1 = completely absent; 5 = to a large extent) Negative (n = 20): *fear, anxiety, anger, disgust, depression, sadness, loneliness, shame, frustration, hopelessness, panic, irritation, guilt, rage, dreariness, worry, unhappiness, nervousness, embarrassment, regret*	Chinese (China)	ICC-based - ICCs for absolute agreement - negative ICCs: // - no-variance cases: //
108. Wang et al. (2024) °	Dispositional - negative	ED task: - 10 standardized images (IAPS; Lang et al., 2008) - valence: negative - laboratory-based setting	Fixed emotion labels (n = 10) on a 7-point Likert scale (0 = not at all; 6 = very much) Negative (n = 10): *fear, anxiety, anger, disgust, depression, sadness, loneliness, shame, frustration, guilt*	Chinese (China)	ICC-based - ICCs method: // - negative ICCs: // - no-variance cases: //

109. Williams & Uliaszek (2022)	Dispositional - negative	Autobiographical narrative of emotional experience In-the-moment ratings of emotional experience over 7 time points	▪ Natural affective language Affective lexicon extrapolated from open-ended descriptions of negative events - use of existing lexicons to identify emotional vocabulary: corpus by Johnson-Laird and Oatley (1989) - criteria for valence classification: // - criteria for specific-basic-general classification of the vocabulary: drew on the corpus by Johnson-Laird and Oatley (1989) ▪ Fixed emotion labels (n = 10) on a 9-point Likert scale (from none to extremely) Negative (n = 10): *anxiety, sadness, fear, disappointment, guilt, anger, disgust, jealousy, shame*	English (Canada)	1. SI 2. NS 3. ICC-based - ICCs for consistency - negative ICCs coded as missing values - no presence of no-variance cases
110. Williams-Kerver & Crowther (2020)	Dispositional - positive - negative	EMA: - 4 prompts/day - 7 consecutive days	Fixed emotion labels (n = 13) on a 5-point Likert scale (1 = very slightly or not at all; 5 = extreme) Positive (n = 7): *calm, enthusiastic, excited, happy, relaxed, satisfied, alert* Negative (n = 6): *angry, ashamed, bored, guilty, nervous, sad*	English (USA)	ICC-based - ICCs for absolute agreement - negative ICCs: // - no-variance cases: //
111. Willroth et al. (2020)	Dispositional - positive - negative - within-category (negative)	Daily diary: - 1 entry/day - 14 consecutive days	Fixed emotion labels (n = 16) on a 5-point Likert scale (1 = very slightly or not at all; 5 = extremely) Positive (n = 5): *happy, excited, optimistic, strong, proud* Negative (n = 11): *sad, hopeless, guilty, ashamed, distressed, anxious, nervous, worried, angry, hostile, irritable*	English (USA)	ICC-based - ICCs for absolute agreement - negative ICCs: // - no-variance cases: // -

112.Yang (2022)	Dispositional - positive - negative	Daily diary: - 1 entry/day - 7 consecutive days	Fixed emotion labels (n = 10) on a 5-point Likert scale (1 = not at all; 5 = extremely) Positive (n = 5): *excited, enthusiastic, inspired, determined, alert* Negative (n = 5): *distressed, sad, irritated, angry, anxious*	English (USA)	ICC-based - ICCs method: // - negative ICCs: // - no-variance cases: //
113.Yang (2023)	Dispositional - negative	Daily diary: - 1 entry/day - 7 consecutive days	Fixed emotion labels (n = 5) on a 9-point Likert scale (from 1 to 9) Negative (n = 5): *distressed, sad, irritated, angry, anxious*	English (USA)	ICC-based - ICCs method: // - negative ICCs: // - no-variance cases: //
114.Yue et al. (2024)	Dispositional - negative	EMA: - 5 prompts/day - 10 consecutive days	Fixed emotion labels (n = 20) on a 7-point Likert scale (1 = not at all; 7 = very intense) Positive (n = 10): *interested, excited, strong, enthusiastic, proud, inspired, determined, active, attentive, alert* Negative (n = 10): *distressed, upset, guilty, scared, hostile, irritable, ashamed, nervous, jittery, afraid*	Chinese (China)	ICC-based - ICCs method: // - negative ICCs: // - no-variance cases: //
115.Zhang et al. (2021)	Dispositional - positive	ED task: - 11 or 12 standardized film-clips - online	Fixed emotion labels (n = 16) on a 9-point Likert scale (1 = not at all; 9 = a great deal) Positive (n = 16): *family affection, reverence, pride, love, inspiration, friendship, interest, sympathy, aesthetics, respect, liberation, wishful, adore, humor, hope, appreciation*	Chinese (China)	ICC-based - ICCs for absolute agreement - negative ICCs coded as missing values - no-variance cases: //

Note: AIC = Average Interitem Correlation; DRM = Day Reconstruction Method; ED task = Emotion Differentiation task; EG = Emotional Granularity; EMA = Ecological Momentary Assessment; IAPS = International Affective Picture System; ICC = Intraclass Correlation; LEAS = Levels of Emotional Awareness Scale; LIWC = Linguistic Inquiry and Word Count; LMFA = Latent Markov Factor Analysis; MECA = Multiple Emotion Co-Activation; MSD = Mean-Standard-Deviation; NAPS = Nencki Affective Picture System; NS = Nuance Score; OASIS = Open Affective Standardized Image Set; PCA = Principal Component Analysis; PROC VARCOMP = Variance Components Procedure; SI = Specificity Index; VAR = Average Variance.
° indicates that the study is explicitly grounded in a constructionist account of emotion; // indicates missing information in the article; -- indicates information not applicable; † indicates that the authors did not specify whether the Fischer's *r*-to-*z* *t*ransformation was applied; * indicates that the global index was derived by averaging separate indices for negative and positive emotion granularity; ** indicates that the global index was derived across both negative and positive emotion labels.

2.4. Table S4: Overview of the Main Aims, Methodological Characteristics, and Key Findings of the Reviewed Studies

Table S4. Overview of the main aims, methodological characteristics, and key findings of the reviewed studies.

Autor(s) (Year)	Main Topic	Objectives and Hypothesis	Study Design	Sample	EG correlates
1. Aaron et al. (2018)	Emotion experience	(1) Divergent patterns of affect labeling relate most strongly to difficulty identifying feelings (2) EG and dialecticism relate most strongly to difficulty describing feelings	Quasi-experimental	Sample size: n = 108 Population: undergraduates Age: M(SD) = 19.3(0.88) Sex/gender: 67.6% women	*Correlational analysis*: correlation between negative EG and alexithymia (-)*, affect labeling (+)*, intensity of primary emotions (-), arousal (-), negative dialectism (+), positive dialectism (+); correlation between positive EG and alexithymia (-), affect labeling (-), intensity of primary emotions (+), arousal (-), negative dialectism (+), positive dialectism (+) *Regression analysis*: negative EG predicts difficulty describing feelings (-)* but not difficulty identifying feelings (-); positive EG does not predict difficulty identifying feelings (-) nor externally-oriented thinking (+)
2. Barrett et al. (2001)	Emotion experience	(1) Individuals with high EG have better ER than individuals with poor EG (2) This effect is stronger for negative emotional experience	Longitudinal intensive	Sample size: n = 53 Population: // Age: M (SD) = // Sex/gender: 19 men	*Moderation analysis*: negative EG is related to negative ER (+)**, particularly at higher levels of emotional intensity (+)*; neither positive EG (+) nor its interaction with emotional intensity (-) are related to positive ER
3. Berman et al. (2022)	Wellbeing and mental health	(1) Greater impact from COVID-19 is positively associated with obsessive-compulsive symptom severity (2) This association is explained by trait (poor ER and EG) and state	Cross-sectional	Sample size: n = 841 Population: college students Age: M(SD) = 18.8(1.5)	*Mediation analysis*: negative EG mediates the association between COVID-19 impact-apprehension (-)** and obsessive-compulsive symptom severity (-)*, but not the one between COVID-19 impact- social distress (-) and obsessive-compulsive symptom severity (-)**

			risk factors (poor sleep quality, less exercise frequency, less social support, thwarted sense of belonging, and greater loneliness)		Sex/gender: 67.6% female	
4.	Bicaker et al. (2022)	Eating behaviors and body image	(1) To investigate the relationship between EG and loss of control over eating at both the between-persons and within-person levels (2) To investigate the relationship between self-compassion and negative EG (3) To explore whether lower negative emotional intensity and enhanced negative EG independently mediate the relationship between self-compassion and loss of control eating frequency	Longitudinal intensive	Sample size: n = 192 Population: undergraduates Age: M(SD) = 20.6(2.26) Sex/gender: 51.6% women	*Correlational analysis*: correlation between negative EG and loss of control over eating (-), self-compassion (+ for women,–for men) *, negative emotion intensity (- for women) * (- for men) ***, and loss of control over eating (-) *Multilevel analysis*: negative ED does not predict loss of control over eating neither in women nor in men, neither within-persons nor between-persons *Mediation analysis*: negative EG does not mediate the association between self-compassion (+ for women) ** (- for men) * and loss of control eating (+ for women, - for men)
5.	Boden et al. (2013), Study 1	Emotion experience	(1) To examine the relation between emotional clarity and EG (2) To examine whether they demonstrate unique relations to affect intensity and affect variability	Cross-sectional	Sample size: n = 210 Population: undergraduates Age: 16–33, M(SD) = 19.4(2.3) Sex/gender: 57.9% female	*Correlational analysis*: correlation between negative EG and positive EG (+) **, emotional clarity (+), trait affect intensity (-) **, trait affect variability (-) **, and scenario-response task affect intensity (-) **; correlation between positive EG and negative EG (+) **, emotional clarity (-), trait affect intensity (-) **, trait affect variability (-), and scenario-response task affect intensity (-) ** *Path analysis*: negative EG predicts trait affect variability (-) * and scenario-response task affect intensity (-) ** ; positive EG predicts trait affect intensity (-) ** and scenario-response task intensity (-) **
6.	Boden et al. (2013), Study 2	Emotion experience	(1) To examine the relation between emotional clarity and EG	Longitudinal intensive	Sample size: n = 99	*Correlational analysis*: correlation between negative EG and emotional clarity (+), positive EG (+) **, ESM–PA intensity (-), ESM–NA

			(2) To examine whether they demonstrate unique relations to affect intensity and affect variability		Population: undergraduates Age: 18–24, M(SD) = 19.1(1.2) Sex/gender: 60.6% female	intensity (-)**, trait affect intensity (-)**, ESM–NA variability (-)**, ESM–PA variability (-)**, trait variability (-)*; correlation between positive EG and emotional clarity (+), negative EG (+)**, ESM–PA intensity (-), ESM–NA intensity (-)**, trait affect intensity (-)**, ESM–NA variability (-)**, ESM–PA variability (-)**, trait variability (-) *Path analysis*: negative EG predicts ESM–NA variability (-)**, trait affect intensity (-)*, and ESM–NA intensity (-)**; positive EG predicts ESM–PA variability (-)**, trait affect intensity (-)**, and ESM–PA intensity (-)**
7.	Bonar et al. (2023)	Wellbeing and mental health	(1) To test whether negative EG (but not necessarily positive EG) is associated with less intense self-reported stress responses (2) To examine the links between negative EG and SNS responding (3) To examine whether participants' appraisals about the task covary with the effect of negative EG on self-reported stress	Longitudinal intensive + Quasi-experimental	Sample size: n = 195 Population: university students Age: M(SD) = 19.2(1.29) Sex/gender: 55% female	*Correlational analysis*: correlation between negative EG and positive EG (+), NA (-)**, PA (-), negative high arousal emotions (-)*, external Trier Social Stress Test (-), internal Trier Social Stress Test (-), SNS reactivity (+)*; correlation between positive EG and negative EG (+), NA (-)**, PA (-)**, negative high arousal emotions (-), external Trier Social Stress Test (-), internal Trier Social Stress Test (-)*, SNS reactivity (+) *Regression analysis*: negative EG (-)* but not positive EG (-), predicts negative, high arousal emotion during the stressor; this effect does not remain statistically significant when covariates are added to the model; negative EG (+)* but not positive EG (+), is associated with cardiac SNS reactivity when controlling for model covariates
8.	Brown et al. (2021)	Emotion experience	(1) The relationship between the intensity of daily events and the disengagement strategies (i.e., avoidance, substance use, distraction) chosen to regulate distress is mediated by low negative EG	Longitudinal intensive	Sample size: n = 574 Population: college students Age: M(SD) = 18.77(1.08)	*Correlational analysis*: correlation between negative EG and between-person stress intensity (-)*, between-person use of avoidance (-)***, between-person substance use (-)***, between-person distraction (-)***, between-person problem-solving (-), between-person social-support (-)***,

			(2) The relationship between the intensity of daily events and the engagement strategies (i.e., problem-solving and social support seeking) chosen to regulate distress is mediated by high negative EG		Sex/gender: 52.8% women	between-person emotion intensity (-)***, and within-person emotion intensity (+)*** *Generalized linear mixed-effects model:* negative EG does not moderate the relationship between between-person stress intensity and the use of avoidance (-), distraction (-), problem-solving (-), social support (-), and substance use (-); negative EG does not moderate the relationship between within-person stress intensity and the use of avoidance (-), problem-solving (-), social support (-), and substance use (-), but moderates the relationship between within-person stress intensity and the use of distraction (-)***; negative EG predicts the use of avoidance (-)***, distraction (-)***, and substance use (-)***, while it does not predict problem-solving (+), social support (-)
9.	Cameron et al. (2013), Study 1	Cognitive processes	(1) Incidental disgust influences moral judgments (2) This association is moderated by high EG	Experimental	Sample size: n = 130 Population: university students Age: M (SD) = // Sex/gender: 91 females	*Repeated-measures general linear model*: negative EG is associated with lenient moral judgments (+)*; significant interaction between negative EG and incidental disgust on moral judgments (+)*: low negative EG × incidental disgust increased the strength of moral judgments (+)*, for low negative EG × incidental disgust this influence disappeared (+)
10.	Dawel et al. (2023)	Wellbeing and mental health	(1) To investigate the relationships between affective indices and psychosocial functioning (2) To test which of the eight affective indices uniquely predicted change in psychosocial functioning from wave 1 to wave 7 of COVID-19 (3) To explore whether EG, co-occurrence, and positive–negative ratios explained a significant	Repeated measure	Sample size: n = 613 Population: general population Age: 19–87, M(SD) = 51.0(16.1) Sex/gender: 47.3% female	*Correlational analysis*: correlation between negative EG and stress wave-1 (-)*, stress wave-7 (-)*, loneliness wave-1 (-)*, loneliness wave-7 (-)*, impairment wave-1 (-)*, impairment wave-7 (-)*, wellbeing wave-1 (-)*, wellbeing wave-7 (-)*, coping wave-1 (-)*, coping wave-7 (+)*; correlation between positive EG and stress wave-1 (-)*, stress wave-7 (-)*, loneliness wave-1 (-)*, loneliness wave-7 (-)*, impairment wave-1 (-)*, impairment wave-7 (-)*, wellbeing wave-1 (+)*,

		amount of the wave 1-to-7 change over and above emotion intensity and variability			wellbeing wave-7 (+)*, coping wave-1 (+)*, coping wave-7 (+)* *Partial correlations*: correlation between negative EG and stress wave-1 (-), stress wave-7 (-), loneliness wave-1 (-), loneliness wave-7 (-)*, impairment wave-1 (-), impairment wave-7 (+), wellbeing wave-1 (+), wellbeing wave-7 (+)*, coping wave-1 (+), coping wave-7 (+); correlation between positive EG and stress wave-1 (-)*, stress wave-7 (-)*, loneliness wave-1 (-)*, loneliness wave-7 (-)*, impairment wave-1 (-), impairment wave-7 (-), wellbeing wave-1 (+)*, wellbeing wave-7 (+)*, coping wave-1 (+), coping wave-7 (+) *Linear regression analysis*: adjusting for both negative and PA intensity and variability, negative EG does not predict change in stress (-), loneliness (-), impairment (+), wellbeing (-), and coping (+); adjusting for both NA and PA intensity and variability, positive EG does not predict change in stress (-), loneliness (-), impairment (+), wellbeing (+), and coping (+)
11.	Decker et al. (2008)	Emotion experience	(1) Individuals with general anxiety disorder have higher momentary intensity of emotion relative to control participants (2) Individuals with general anxiety disorder have less EG than controls (3) Individuals with general anxiety disorder use a narrower range of ER strategies compared to control participants	Longitudinal intensive	Sample size: n = 105 (+ 33 diagnosed with general anxiety disorder) Population: undergraduate and graduate students Age: M(SD) = 27.3(10.3) ° Sex/gender: 79% female among healthy controls	*T-Test*: participants with and without general anxiety disorder do not differ in both negative and positive EG levels

12. Eckland et al. (2021)	Wellbeing and mental health	(1) Depression and rumination are negatively associated with EG (2) Worry is positively associated with unpleasant EG	Longitudinal intensive	Sample size: n = 614 (tot); n = 277 (sample 1); n = 140 (sample 2); n =197 (sample 3) Population: undergraduates Age: 18–27, M(SD) = 19.1(1.3) (sample1); 18–23, M(SD) = 19.3(1.2) (sample 2); 18–25, M(SD) = 19.3(1.3) (sample 3) Sex/gender: 68% female (sample 1); 64% female (sample 2); 60% female (sample 3)	*Generalized linear mixed-effects regressions*: depression (-)†, worry (-)†, and rumination (-)† marginally predict both positive and negative EG
13. Edwards & Wupperman (2017)	Maladaptive behaviors	(1) Alexithymia and difficulties in EG positively correlate with one another and independently contribute to the prediction of ER and impulsive aggression (2) The relationship between restricted access to emotional information (i.e., alexithymia and EG) and impulsive aggression is mediated by ER	Cross-sectional	Sample size: n = 96 Population: college students Age: 18–38, M(mode) = 20.0(18) Sex/gender: 76% female	*Correlational analysis*: correlation between negative EG and alexithymia (-), positive EG (+)*, global EG (+)***, difficulties in ER (+), impulsive aggression (+); correlation between positive EG and alexithymia (+), negative EG (+)*, global EG (+)***, difficulties in ER (+), impulsive aggression (+) *Mediation analysis*: global EG has a direct effect on impulsive aggression (+)**, but this direct effect is no longer significant when controlling for ER; indirect effect of global EG (+)** on impulsive aggression (+)*** via difficulties in ER
14. Edwards et al. (2020)	Emotion experience	(1) Alexithymic trait severity is positively associated with use of negative emotion words and	Cross-sectional in laboratory setting	Sample size: n = 96	*Correlational analysis*: correlation between negative EG and NA (+)**, PA (-), negative emotion language (+)*, positive emotion language

		inversely associated with use of positive emotion words across contexts (2) Poor EG is positively associated with use of negative emotion words in unpleasant contexts and use of positive emotion words in pleasant contexts (3) No hypotheses were about participants' use of non-emotion words (e.g., references to self, others, and cognitive processes)		Population: undergraduates Age: 18–38, M(SD) = 20.0(4.06) Sex/gender: 76% female	(-), negative emotion language bias (+)**, self-oriented language (+), social language (-), and cognition language ()*; correlation between positive EG and NA (+)**, PA (-)**, negative emotion language (+), positive emotion language (-), negative emotion language bias (+)*, self-oriented language (-), social language (-), and cognition language (-)
15. Emery et al. (2014)	Maladaptive behaviors	(1) Urgency mediates the relationship between EG and alcohol-related problems	Longitudinal intensive	Sample size: n = 102 Population: undergraduates Age: 18–24, M(SD) = 20.34(1.5) Sex/gender: 52% female	*Correlational analysis*: correlation between negative EG and gender (+), negative urgency (-)*, positive urgency (-), positive EG (+)**, and alcohol-related problems (-)*; correlation between positive EG and gender (+), negative urgency (-), positive urgency (-), negative EG (+)**, and alcohol-related problems (-)* *Path analysis*: negative urgency mediates the association between negative EG (-)** and alcohol-related problems (+)**; positive EG does not mediate the relationship between positive EG (-) and alcohol-related problems (+); positive EG directly impacts alcohol-related problems (-)**; negative and positive EG are correlated (-)***
16. Erbas et al. (2019)	Wellbeing and mental health	(1) To test how different types of EG (i.e., between-category, within-category, cross-category) are related to wellbeing	Cross-sectional (dataset 1, 2, 4, 5, 6) + Experimental (dataset 3)	Sample size: n = 1074 (tot); n = 170 (dataset 1); n = 18 (dataset 2); n = 167 (dataset 3); n = 399 (dataset 4); n = 142 (dataset 5); n = 178 (dataset 6)	*Correlational analysis:* correlations (+)*** between cross-, between- and within-category EG, as well as separate within-category EG for the anger, fear, shame, and sadness categories; correlation between NA (-)*** and cross-, between- and within-category EG, as well as separate within-category EG for the anger, fear, shame, and sadness categories; correlation between alexithymia (difficulties identifying

				Population: college students (dataset 1, 3, 4, 6); general population (dataset 5); secondary school students (dataset 2) Age: M(SD) = 18.0(1.13) (dataset 1); M(SD) = 17.0(.78) (dataset 2); M(SD) = 19.0(3.1) (dataset 3); M(SD) = 19.0(2.63) (dataset 4); M(SD) = 23.0(3.39) (dataset 5); M(SD) = 19.0(1.0) (dataset 6) Sex/gender: 18.8% male (dataset 1); 66.7% male (dataset 2); 17.8% male (dataset 3); 29.8% male (dataset 4); 50% male (dataset 5); 29.8% male (dataset 6)	emotions) and cross- (-)***, between- (-)* and within-category (+) EG, as well as separate within-category EG for the anger (+), fear (+), shame (-), and sadness (+) categories; correlation between depression and cross- (-)*, between- (-) and within-category (+) EG, as well as separate within-category EG for the anger (-), fear (+), shame (-), and sadness (+) categories; correlation between self-esteem and cross- (+)**, between- (+) and within-category (-) EG indices, as well as separate within-category EG for the anger (+), fear (+), shame (-), and sadness (-) categories; correlations, controlling for NA, between depression and integral EG (-), between- (+) and within-category (+)* EG; correlations, controlling for NA, between alexithymia (difficulties identifying emotions) and cross-category EG (-)**, between- (-) and within-category (+)*** EG; correlations, controlling for NA, between self-esteem and cross- (+)*, between- (+) and within-category (-) EG
17. Erbas et al. (2018)	Wellbeing and mental health	(1) To examine whether higher levels of stress on one day predict lower levels of EG on the next day, but not vice versa	Longitudinal intensive	Sample size: n = 200 (wave 1); n = 190 (wave 2); n =177 (wave 3) Population: students about to start their first year at university Age: M(SD) = 18.32(.97) (wave 1);	*Multilevel model of EG predicted by stress*: stress predicts EG at the daily level (-)***, at the wave level–ESM (-)**, and at the wave level–trait (-)** *Multilevel model of EG predicted by lagged stress while controlling for lagged EG*: lagged stress predicts EG at the daily level (-)*, but not at the wave level–ESM (+), and at the wave level–trait (-); lagged EG predicts EG at the daily level (-)***,

M(SD) = 18.64(1.03) (wave 2); M(SD) = 19.28(1) (wave 3) Sex/gender: 90 males (wave 1), 84 males (wave 2), 79 males (wave 3)	at the wave level–ESM (-)***, and at the wave level–trait (-)*** *Multilevel model of EG predicted by lagged stress while controlling for stress and lagged EG*: stress (-)**, lagged stress (-)**, and lagged EG (-)*** predict EG at the daily level *Multilevel model of stress predicted by lagged EG while controlling for lagged stress*: lagged EG does not predict stress at the daily level (+), nor at the wave level–ESM (-), or at the wave level–trait (-); lagged stress predicts stress at the daily level (+)*, at the wave level–ESM (-)***, and at the wave level–trait (-)*** *Regression analysis in the concurrent day-level model*: anger, anxiety, sadness, depression, loneliness predicts EG (-)*** *Regression analysis prospective day-level model*: anger, anxiety, sadness, depression, loneliness does not predict EG (-) *Concurrent multilevel model*: day-level EG is predicted by stress (-)***, time (+), and the interaction between stress × time (+)* *Prospective multilevel models*: day-level EG is predicted by lagged EG (-)***, lagged stress (-)**, time (+), and the interaction between lagged stress × time (+)* *Concurrent multilevel model*: day-level EG is predicted by stress at level 1, and as a moderator at level 2 by depression (+)*, neuroticism (+), alexithymia (difficulties identifying emotions sub-scale) (+)*, personality disorders (borderline scale) (-), updating capacity (-) *Prospective multilevel model*: day-level EG is predicted by lagged stress and lagged EG at level

					1, and as a moderator at level 2 by depression (+), neuroticism (-), alexithymia (difficulties identifying emotions sub-scale) (+), personality disorders (borderline scale) (-), updating capacity (+) *Concurrent multilevel model*: while controlling for stress, and the moderator, week-level EG is predicted by the interaction between ESM stress × depression (-), ESM stress × neuroticism (+), ESM stress × alexithymia (difficulties identifying emotions sub-scale) (-), ESM stress × personality disorders (borderline scale) (-), ESM stress × updating capacity (+) *Concurrent multilevel model*: while controlling for stress, and the moderator, week-level EG is predicted by the interaction between trait stress × depression (+), trait stress × neuroticism (+), trait stress × alexithymia (difficulties identifying emotions sub-scale) (-), trait stress × personality disorders (borderline scale) (-), trait stress × updating capacity (+).
18. Erbas et al. (2015), Study 1	Emotion experience	(1) To test whether EG is negatively related to valence focus (2) To test whether EG higher levels of EG are related to smaller overlap in appraisal patterns of like valenced emotions. (3) To examine how EG is related to appraisal overlap between different-valenced emotions (4) To examine whether both valence focus and appraisal overlap are uniquely related to EG	Longitudinal intensive	Sample size: n = 79 Population: community sample Age: M(SD) = 23.52(7.82) Sex/gender: 29 males	*Correlational analysis*: correlation between positive EG and negative EG (+)**, valence focus (-)**, appraisal overlap concerning positive emotions (+)**, appraisal overlap concerning negative emotions (+), and appraisal overlap concerning different-valenced emotions (-)**; correlation between negative EG and positive EG (+)**, valence focus (-)**, appraisal overlap concerning positive emotions (+)*, appraisal overlap concerning negative emotions (+)**, and appraisal overlap concerning different-valenced emotions (-)**. After controlling for valence focus, the relationship between appraisal overlap of different valenced emotions and EG decreases for

						positive emotions (-)* and increases negative emotions (+). REGRESSION ANALYSIS: after controlling for one another, positive EG is predicted by both valence focus (-)*** and appraisal overlap between positive emotions (+)***; negative EG is predicted by both valence focus (-)*** and appraisal overlap between negative emotions (+)***
19.	Erbas et al. (2015), Study 2	Emotion experience	(1) To test whether EG is negatively related to valence focus (2) To test whether EG higher levels of EG are related to smaller overlap in appraisal patterns of like valenced emotions. (3) To examine how EG is related to appraisal overlap between different-valenced emotions (4) To examine whether both valence focus and appraisal overlap are uniquely related to EG	Longitudinal intensive	Sample size: n = 95 Population: undergraduates Age: M(SD) = 19.06(1.28) Sex/gender: 36 males	*Correlational analysis*: correlation between positive EG–ESM and negative EG–ESM (+)**, positive EG–ED task (+)*, negative EG–ED task (+)*, valence focus (-)**, appraisal overlap concerning positive emotions (+)**, appraisal overlap concerning negative emotions (+)†, and appraisal overlap concerning different-valenced emotions (-)**. Correlation between negative EG–ESM and positive EG–ED task (+), negative EG–ED task (+)*, valence focus (-)**, appraisal overlap concerning positive emotions (+)†, appraisal overlap concerning negative emotions (+)**, and appraisal overlap concerning different-valenced emotions (-)**. Correlation between positive EG–ED task and negative EG–ED task (+)**, valence focus (-)†, appraisal overlap concerning positive emotions (+)**, appraisal overlap concerning negative emotions (+), and appraisal overlap concerning different-valenced emotions (-)†. Correlation between negative EG–ED task and valence focus (-)**, appraisal overlap concerning positive emotions (+), appraisal overlap concerning negative emotions (+)*, and appraisal overlap concerning different-valenced emotions (-)*. Both positive (+) and negative (+) EG–ESM are not related to larger overlap in appraisal patterns between different-valenced emotions after controlling for valence focus. Both positive (-) and negative (+) EG–ED task are not related to

					larger overlap in appraisal patterns between different-valenced emotions after controlling for valence focus *Regression analysis:* after controlling for one another, positive EG–ESM is related to both valence focus (-)*** and appraisal overlap between positive emotions (+)***, while negative EG–ESM is related to both valence focus (-)*** and appraisal overlap between negative emotions (+)*. After controlling for one another, negative EG–ED task is related to appraisal overlap between negative emotions (+)**, but not anymore to valence focus (-). Positive EG–ED task is related to appraisal overlap between positive emotions (+)* and marginally to valence focus (-)†
20. Erbas et al. (2014), Study 1	Personality traits	(1) Lower intensity of negative emotions is related to higher levels of negative EG (2) Neuroticism is related to lower levels of negative EG (3) Self-esteem is positively related to negative EG	Longitudinal intensive	Sample size: n = 50 Population: adults recruited via the Careers & Employment Service of the university Age: M(SD) = 21.58(3.87) Sex/gender: 24 males	*Correlational analysis*: correlation between negative EG and emotion intensity (-)†, neuroticism (-), extraversion (+), openness, (-), agreeableness (+), conscientiousness (+), self-esteem (+)*
21. Erbas et al. (2014), Study 2	Personality traits	(1) Negative EG is related to well established dimensions of individual differences in terms of experienced emotional intensity, personality traits, self-esteem, depression and alexithymia	Cross-sectional	Sample size: n = 131 Population: undergraduates Age: M(SD) = 18.48(1.74) Sex/gender: 20 males	*Correlational analysis*: correlation between negative EG and emotion intensity (-)**, neuroticism (-)†, extraversion (+), openness, (+), agreeableness (-), conscientiousness (-), self-esteem (+)*, alexithymia–difficulties describing feeling (+), alexithymia–difficulties identifying feeling (-)*, alexithymia–externally oriented thinking (+), depression (-)*

22.	Erbas et al. (2014), Study 3	Wellbeing and mental health	(1) Individuals who have a high motivation to avoid negative emotions generalize across emotions and hence show lower negative EG (2) EG correlates with alexithymia and depression	Cross-sectional	Sample size: n = 170 Population: undergraduates Age: M(SD) = 18.42(1.13) Sex/gender: 32 males	*Correlational analysis*: correlation between negative EG and emotion intensity (-)**, alexithymia–difficulties describing feeling (-)*, alexithymia–difficulties identifying feeling (-)**, alexithymia–externally oriented thinking (+), depression (-)*, need for affect–approach (-)**, and need for affect–avoidance (-)*
23.	Erbas et al. (2022), Study 1	Wellbeing and mental health	(1) Momentary EG correlates with self-esteem, stress, rumination, and emotion-focused coping, and to momentary levels of positive and negative emotion (2) Momentary EG relates to momentary wellbeing after accounting for its shared variance with the mean and standard deviation of momentary emotions (3) Momentary well-being outcome measures relate to person-level EG	Longitudinal intensive	Sample size: n = 200 Population: secondary-school students about to start their first year at university Age: M(SD) = 18.64(1.45) Sex/gender: 90 males	*Concurrent multilevel analysis with momentary EG*: momentary negative EG predicts momentary negative emotions (-)***, momentary positive emotions (+)***, momentary stress (-)***, momentary rumination (-)***, and momentary self-esteem/coping (+)***; momentary positive EG predicts momentary negative emotions (-)***, momentary positive emotions (+)***, momentary stress (-)***, momentary rumination (-)***, and momentary self-esteem/coping (+)***. While controlling for the momentary person-centered mean and standard deviation of negative emotions, momentary negative EG predicts momentary positive emotions (+)***, momentary rumination (+)**, and momentary self-esteem/coping (+)***, but not momentary stress (-). While controlling for the momentary person-centered mean and standard deviation of positive emotions, momentary positive EG predicts momentary negative emotions (-)***, momentary stress (-)*, momentary rumination (+)***, and momentary self-esteem/coping (+)*** *Concurrent multilevel analysis with dispositional EG*: dispositional negative EG predicts momentary negative emotions (-)**, but not momentary positive emotions (+), momentary stress (-), momentary rumination (-), and momentary self-esteem/coping (+); dispositional positive EG predicts momentary self-

						esteem/coping (+)*, but not momentary negative emotions (-), momentary positive emotions (+), momentary stress (-), momentary rumination (-). While controlling for the momentary person-centered mean and standard deviation of negative emotions, dispositional negative EG does not predict momentary positive emotions (-), momentary rumination (+), and momentary self-esteem/coping (+), and momentary stress (-). While controlling for the momentary person-centered mean and standard deviation of positive emotions, dispositional positive EG predicts and momentary self-esteem/coping (+)**, but not momentary negative emotions (-), momentary stress (+), momentary rumination (-)
24.	Erbas et al. (2022), Study 2	Wellbeing and mental health	(1) Momentary EG correlates with self-esteem, stress, rumination, and emotion-focused coping, and to momentary levels of positive and negative emotion (2) Momentary EG relates to momentary wellbeing after accounting for its shared variance with the mean and standard deviation of momentary emotions (3) Momentary well-being outcome measures relate to person-level EG	Longitudinal intensive	Sample size: n = 100 Population: college students Age: M(SD) = 18.32(.97) Sex/gender: 14 males	*Concurrent multilevel analysis with momentary EG*: momentary negative EG predicts momentary negative emotions (-)***, momentary positive emotions (+)*, momentary stress (-)***, momentary rumination (-)***, and momentary self-esteem/coping (+)***; momentary negative EG predicts momentary negative emotions (-)***, momentary stress (-)*, momentary rumination (-)***, and momentary self-esteem/coping (+)**, but not momentary positive emotions (+). While controlling for the momentary person-centered mean and standard deviation of negative emotions, momentary negative EG predicts momentary positive emotions (+)**, momentary rumination (-)***, and momentary self-esteem/coping (+)***, but not momentary stress (-). While controlling for the momentary person-centered mean and standard deviation of positive emotions, momentary positive EG predicts momentary rumination (+)*** and momentary self-esteem/coping (+)***, but not momentary negative emotions (-) and momentary stress (+)

					Concurrent multilevel analysis with dispositional EG: dispositional negative EG does not predict momentary negative emotions (-), momentary positive emotions (+), momentary stress (-), momentary rumination (-), and momentary self-esteem/coping (-); dispositional negative EG predicts momentary rumination (-)** and momentary self-esteem/coping (-)†, but does not predict momentary negative emotions (+), momentary stress (-), or momentary positive emotions (+). While controlling for the momentary person-centered mean and standard deviation of negative emotions, dispositional negative EG does not predict momentary positive emotions (+), momentary stress (-), momentary rumination (-), momentary self-esteem/coping (-). While controlling for the momentary person-centered mean and standard deviation of positive emotions, dispositional positive EG predicts momentary stress (-)* and momentary rumination (-)*, but not momentary negative emotions (-) and momentary self-esteem/coping (-)***
25. Erbas et al. (2016)	Romantic relationship	(1) Individuals who have a higher level of EG are more accurate when making inferences about their partners' feelings (2) Individuals with high EG tend to be more sensitive to changes or fluctuations in their partners' emotions	Longitudinal intensive	Sample size: n = 98 (49 heterosexual couples) Population: heterosexual couples from community and relationship therapy centers Age: 18–70, M(SD) = 27.52(10.36) Sex/gender: 49 males	*Correlational analysis*: correlation between negative EG and positive EG (+), valence accuracy (+)**, and arousal accuracy (+); correlation between positive EG and valence accuracy (-) and arousal accuracy (+) *Multilevel analysis*: male × negative EG in predicting valence accuracy (+)*, but not arousal accuracy (+); female × negative EG in predicting valence accuracy (+)*, but not arousal accuracy (+). Male × positive EG does not predict neither valence accuracy (-), nor arousal accuracy (+); female × positive EG does not predict valence accuracy (+), nor arousal accuracy (-)

					Contrasts test: the relation between negative EG and empathic accuracy does not change as a function of the partners being together or not at the time of the accuracy judgment *Multilevel analysis:* the target's own ratings about empathic accuracy are predicted by the actor's ratings × positive EG in males (+)**, but not in females; the target's own ratings about empathic accuracy are not predicted by the actor's ratings × negative EG neither in males nor in females
26. Fayn et al. (2018)	Cognitive processes	(1) Knowledge of the arts and curiosity is associated with greater EG (2) These relationships are mediated by greater comprehension of the art works	Cross-sectional	Sample size: n = 214 Population: college students Age: 18–56, M(SD) = 20.56(4.91) Sex/gender: 69% female	*Correlational analysis*: correlation between negative EG and positive EG (-), curiosity (+)**, curiosity (stretching sub-scale) (+)*, curiosity (embracing sub-scale) (+)**, aesthetic fluency (+)**, and comprehension of the art works (+)**; correlation between positive EG and negative EG (-), curiosity (+)**, curiosity (stretching sub-scale) (+)*, curiosity (embracing sub-scale) (+)**, aesthetic fluency (+)**, and comprehension of the art works (+)** *Regression analysis:* negative EG is predicted by art expertise (+)** and curiosity (+) *Multilevel SEM:* the association between art expertise and negative EG (+)** at level 2 (between-person) is mediated by comprehension at level 1 (within-person); art expertise predicts comprehension (+)***, which is predicted by negative EG (+)*
27. Fogarty et al. (2015)	Mindfulness	(1) To examine the links between trait mindfulness and recovery from negative experience, as distinct from reduced emotional reactivity (2) To explore whether mindfulness is associated with greater EG	Experimental	Sample size: n = 80 Population: general population Age: // Sex/gender: 40 males	*Paired contrast comparison*: high mindful individuals marginally show greater negative EG† compared to low mindful individuals; no differences between high and low mindful individuals emerges as regard to positive EG. Participants differentiate less in the emotional condition* than in the neutral condition. In the

					emotion condition, but not in the neutral condition, high mindful women show greater negative EG** than low mindful women. In the emotion condition, high mindful men marginally show greater negative EG† than low mindful men; in the neutral condition, no differences emerge between high and low mindful men
28. Grossmann et al. (2016), Study 2	Emotion experience	(1) Country-level differences in the prevalence of dialectical belief systems and interdependence would be related to EC, with a greater association between EC and interdependence (2) Emotional dialecticism and EG (markers of EC) would be positively related to each other (3) Cultural differences in EG would be comparable to cultural differences in emotional dialecticism	Cross-sectional	Sample size: n = 1,396 (tot); n = 123 (Germany); n = 267 (India); n = 623 (Japan); n = 70 (Russia); n = 126 (UK); n = 187 (USA) Population: college students Age: M= 26.84 (Germany); M = 18.48 (India); M = 18.58 (Japan); M = 20.14 (Russia); M = 21.06 (UK); M = 18.84 (USA) Sex/gender: 68.29% female (Germany); 84.27% female (India); 33.71% female (Japan); 74.29% female (Russia); 76.98% female (UK); 69.52% female (USA)	*Correlational analysis* (Germany): correlation between positive EG and negative EG (+), positive emodiversity (+)*, negative emodiversity (+)*; correlation between negative EG and positive emodiversity (-), negative emodiversity (+) *Correlational analysis* (India): correlation between positive EG and negative EG (+)***, positive emodiversity (+)*, negative emodiversity (+); correlation between negative EG and positive emodiversity (+)*, negative emodiversity (+) *Correlational analysis* (Japan): correlation between positive EG and negative EG (+)***, positive emodiversity (-), negative emodiversity (+); correlation between negative EG and positive emodiversity (-)*, negative emodiversity (-)* *Correlational analysis* (Russia): correlation between positive EG and negative EG (+)*, positive emodiversity (+), negative emodiversity (+); correlation between negative EG and positive emodiversity (+), negative emodiversity (+) *Correlational analysis* (UK): correlation between positive EG and negative EG (+), positive emodiversity (+), negative emodiversity (+); correlation between negative EG and positive emodiversity (+), negative emodiversity (+)* *Correlational analysis* (USA): correlation between positive EG and negative EG (+)*,

						positive emodiversity (-), negative emodiversity (); correlation between negative EG and positive emodiversity (-), negative emodiversity (+) *Correlational analysis*: interdependence is predicted by both positive (+)** and negative EG (+)***. Prevalence of Dialectical Belief is not predicted either by positive (+) nor by negative EG (+)
29.	Grossmann et al. (2016), Study 3	Wellbeing and mental health	(1) To replicate the findings of Study 2, adding 10 individual-level measures of dialectical thinking and independence-interdependence, to examine which of these constructs accounts for group differences across the four operationalizations of EC (2) To extend our explorations of Study 2 to include a more diverse population of respondents	Cross-sectional	Sample size: n = 403 (Japan); n = 226 (USA) Population: community-dwelling adults Age: 25–40 = 40.9%, 41–59 = 35.5%, 60 –79 = 24.6%, M(SD) = 49.4(13.87) (Japan); 25– 40 = 39.8%, 41–59 = 32.3%, 60 –79 = 27.9%, M(SD) = 47.33(14.67) (USA) Sex/gender: 49.4% female (Japan); 51.3% female (USA)	*Correlational analysis*: correlation between positive EG and Dialectical thinking-Prediction of change (-), Dialectical thinking-Proverbs (-), Interdependence-Self-construal index (-), Interdependence-Interpersonal index (-), Emotional dialecticism-Intra-individual correlations (+)***, Emotional dialecticism-Mixed emotions (+)**, negative EG (+)**, positive emodiversity (+), negative emodiversity (-); correlation between negative EG and Dialectical thinking-Prediction of change (+), Dialectical thinking-Proverbs (-), Interdependence-Self-construal index (+), Interdependence-Interpersonal index (+), Emotional dialecticism-Intra-individual correlations (+)***, Emotional dialecticism-Mixed emotions (+), positive emodiversity (-), negative emodiversity (+) *Correlational analysis* (Japan only): correlation between positive EG and dialectism for mixed emotions (+), negative EG (+)**, positive emodiversity (+), negative emodiversity (-); correlation between negative EG and dialectism for mixed emotions (-), positive emodiversity (-)**, negative emodiversity (-) *Correlational analysis* (USA only): correlation between positive EG and dialectism for mixed emotions (+)***, negative EG (+), positive emodiversity (+), negative emodiversity (-);

						correlation between negative EG and dialectism for mixed emotions (+), positive emodiversity (-), negative emodiversity (+) *Mediation analysis*: EG-anger (+)*, EG-fear (+)*, EG-disgust (+)* and EG-sadness (+)* mediate the association between cognitive fusion and depression *Mediation analysis*: EG-fear (+)*, EG-disgust (+)* and EG-sadness (+)*, but not EG-anger (+), mediate the association between cognitive fusion and panic symptoms.
30.	Grühn et al. (2013)	Emotion experience	(1) Time-based indicators of EC would be associated with adaptive functioning	Longitudinal intensive	Sample size: n = 109 Population: community sample Age: 23–90, M(SD) = 55.4(15.9) Sex/gender: 69 women	*Correlational analysis: 1) Emotion complexity*: correlation between global EG and positive EG (+)**, between global EG and negative EG (+)**, between negative and positive EG (+); correlation between covariation score (i.e., a person's intraindividual correlation between the broader dimensions of PA and NA over time) and global EG (-)**, positive EG (+), and negative EG (+); correlation between PCA component score 1 (i.e., number of principal PCA components) and global EG (+)**, positive EG (+)**, and negative EG (+); correlation between the PCA component score 2 (i.e., amount of unshared variance) and global EG (+)**, positive EG (+)**, and negative EG (+); correlation between variability in PA and global EG (-)**, positive EG (-)**, and negative EG (-); correlation between variability in NA and global EG (-)**, positive EG (+), and negative EG (-)**. *2) Subjective wellbeing:* correlation between global EG and life satisfaction (-), PA (+) NA (-), and depression (+)**; correlation between positive EG and life satisfaction (-), PA (-) NA (+), and depression (+); correlation between negative EG and life satisfaction (+), PA (+) NA (-), and depression (-). correlation between PCA

component 1 and life satisfaction (-)*, PA (-) NA (+)*, and depression (+)*; correlation between PCA component 2 and life satisfaction (+)*, PA (-) NA (+), and depression (+)*. *3) Psychological wellbeing*: correlation between global EG and autonomy (-), environmental mastery (+), personal growth (-), relations with others (+), purpose in life (+), self-acceptance (+); correlation between positive EG and autonomy (-), environmental mastery (+), personal growth (-)**, relations with others (-), purpose in life (-), self-acceptance (-); correlation between negative EG and autonomy (+), environmental mastery (+), personal growth (+), relations with others (+), purpose in life (+), self-acceptance (+)*; correlation between PCA component 1 and autonomy (-)*, environmental mastery (-), personal growth (-), relations with others (-), purpose in life (-), self-acceptance (-)*; correlation between PCA component 2 and autonomy (-), environmental mastery (-), personal growth (-), relations with others (-), purpose in life (-), self-acceptance (-). *4) Personality*: correlation between global EG and neuroticism (-), extraversion (-), conscientiousness (+), agreeableness (+), openness (-); correlation between positive EG and neuroticism (+), extraversion (+), conscientiousness (-), agreeableness (-), openness (-); correlation between negative EG and neuroticism (-)*, extraversion (+), conscientiousness (+), agreeableness (+), openness (-); correlation between PCA component 1 and neuroticism (+)*, extraversion (-), conscientiousness (-)**, agreeableness (-)*, openness (-); correlation between PCA component 2 and neuroticism (+), extraversion (-), conscientiousness (-)*, agreeableness (-), openness (-). 5) S*elf complexity*:

					correlation between global EG and ego level (-), and self-representation (+); correlation between positive EG and ego level (-)**, and self-representation (-); correlation between negative EG and ego level (-), and self-representation (-); correlation between PCA component 1 and ego level (-)*, and self-representation (-); correlation between PCA component 2 and ego level (-)*, and self-representation (-)*
31. Hill & Updegraff (2012)	Mindfulness	(1) Higher mindfulness is associated with higher levels of EG (2) Mindfulness is associated with less negative, positive, and individual emotion lability (3) EG and ER mediate the relationship between mindfulness and emotion lability (4) ER affects EG directly, so that ER mediates the relationship between mindfulness and EG	Longitudinal intensive	Sample size: n = 96 Population: university students Age: M(SD) = 19.19(2.21) Sex/gender: 70 females	*Correlation analysis*: correlation between negative EG and age (+), compliance (-), gender (+), and ethnicity (-); correlation between negative EG and age (-), compliance (-), gender (-), and ethnicity (+) *Mediation analysis*: positive EG is predicted by mindfulness (-)*, and consequently impact positive emotional lability (+)**. Positive EG mediated the relationship between nonreactivity (sub-scale of mindfulness) and positive emotion lability (-)**. *Mediation analysis*: negative EG mediates the relationship between mindfulness and positive emotional lability (-)*: negative EG is predicted by mindfulness (-)*, and consequently impact positive emotional lability (+)**. Negative EG mediated the relationship between nonreactivity (sub-scale of mindfulness) and negative emotion lability (-)*. *Mediation analysis*: ER difficulties mediate the relationship between mindfulness and positive EG (-)***, as well as marginally mediate the relationship between mindfulness and negative EG (-)†

32. Hoemann, Barrett, et al. (2021)	Emotion experience	(1) To test whether both positive and negative EG progressively increase over time (2) To explore whether the seven selected methodological and individual factors (i.e., the number of ambulatory assessment days completed by each participant, the mean number of experience sampling prompts responded to each day, the mean length of entries, the mean percentage of affective language used in these entries, participants' mean self-reported positive and NA, resting RSA) influence on any increase in EG over time	Longitudinal intensive	Sample size: n = 52 Population: community sample Age: 18–36, M(SD) = 22.8(4.4) Sex/gender: 54% female	*Person-specific regression analysis*: both positive (+)*** and negative (-)* EG increased over the course of ambulatory assessment *T-test*: the estimated effect sizes are d = 0.50*** for positive EG and d = 0.32* for negative EG, indicating that experience sampling has a medium treatment effect and that this is larger for positive than negative EG *Regression fitted with Bayesian estimation*: increase of positive EG is influenced by the mean number of experience sampling prompts per day (+)* and resting RSA (+)*, but not by the number of days of ambulatory assessment included (+), the mean length of event descriptions provided in end-of-day diaries (-), the mean percentage of affective language used in event descriptions (-), or mean self-reported positive (-) or negative (+) affect. Increase of negative EG is influenced by the mean number of experience sampling prompts per day (-)* and the mean length of event descriptions (-)†, but not by the number of days of ambulatory assessment included (-), the mean percentage of affective language used in event descriptions (+), mean self-reported positive (+) or negative (-) affect, or resting RSA (+)
33. Hoemann, Khan, et al. (2021)	Emotion experience	(1) EG positively associated with resting respiratory sinus arrhythmia (2) Higher EG is related to a greater number of patterns (i.e., clusters) in cardiorespiratory physiological activity during seated rest (3) EG is related to how distinctly patterns in autonomic nervous system activity map onto the words used to label emotional events, such	Longitudinal intensive	Sample size: n = 50 Population: community sample Age: 18–36, M(SD) = 22.8(4.4) Sex/gender: 55% female	*Regression analysis*: relationship between EG and resting respiratory sinus arrhythmia when controlling for respiration rate and multivariate outliers (+); relationship between interbeat interval and EG when adjusting respiratory sinus arrhythmia for interbeat interval (+) *Clustering analysis*: relationship between EG and the number of clusters discovered (i.e., patterns of cardiorespiratory physiological activity during seated rest) when controlling for the number of

		that participants with higher EG have patterns of change in cardiorespiratory physiological activity during emotional events that can be more accurately classified			seated rest periods submitted and removing multivariate outliers (+)* *Classification analysis*: relationship between EG and mean classifier performance (i.e., patterns of cardiorespiratory physiological activity during emotional events that are accurately matched to their corresponding emotion label) after outliers are removed (+)†
34. Hoemann et al. (2023), Study 1	Emotion experience	(1) Experiential diversity (i.e., a more varied and balanced set of contexts and activities) is positively associated with EG	Longitudinal intensive	Sample size: n = 50 Population: community sample Age: 18–36, M(SD) = 22.5(4.5) Sex/gender: 62% women	*Regression analysis*: experiential diversity predicts negative EG (+)** controlling for the number of event descriptions and mean NA; among 27 estimates of experiential diversity, the effect of experiential diversity is not significant in two of the 27 regression models. Experiential diversity predicts positive EG (+)* controlling for the number of event descriptions and mean PA; among 27 estimates of experiential diversity, the effect of experiential diversity is not significant in four of the 27 regression models
35. Hoemann et al. (2023), Study 2	Emotion experience	(1) Experiential diversity (i.e., a more varied and balanced set of contexts and activities) is positively associated with EG	Longitudinal intensive	Sample size: n = 76 Population: undergraduates Age: M(SD) = 19.29(1.28) Sex/gender: 61% female	*Regression analysis*: experiential diversity predicts negative EG (+)** controlling for the number of event descriptions and mean NA. Experiential diversity does not predict positive EG (+) controlling for the number of event descriptions and mean PA
36. Hoemann et al. (2023), Study 3	Emotion experience	(1) Experiential diversity (i.e., a more varied and balanced set of contexts and activities) is positively associated with EG	Longitudinal intensive	Sample size: n = 49 Population: community sample Age: M(SD) = 21.53(1.84)	*Regression analysis*: experiential diversity predicts negative EG (+)* controlling for the number of event descriptions and mean NA. Experiential diversity does not predict positive EG (+) controlling for the number of event descriptions and mean PA

				Sex/gender: 72% female	
37. Huggins et al. (2019)	Personality traits	(1) Greater motor cognition is associated with greater emotional intensity and more refined EG	Cross-sectional	Sample size: n = 160 Population: undergraduates and general population Age: 17–59, Median = 20, IQR = 3 Sex/gender: 140 females	*Correlational analysis*: correlation between positive and negative EG (+)*. Neither positive (+) nor negative (-) EG correlates with motor empathy. Autistic traits correlated with global EG (-)**, positive EG (-)*, and negative EG (-)* *T-test*: difference** between positive and negative, indicating that participants tended to differentiate more between negative than positive emotional terms *ANOVA*: No gender differences emerged either in positive or negative EG *Regression analysis*: negative emotional intensity marginally predicts negative EG (-)†, while it does not predict positive EG (-). Global EG is predicted by autistic traits–aloof subscale (-)***, but not by autistic traits–pragmatic language difficulties (-) or autistic traits–rigidity (+)
38. Huggins et al. (2023)	Emotion experience	(1) Japanese participants show high scores on the TAS-20, but no differences in emotional self-awareness on the EC task and positive EG task	Cross-sectional	Sample size: n = 29 (Japan); n = 43 (UK) Population: community sample Age: 29–50, M = 22.0, IQR = 4 (Japan); 17–59, M = 23.0, IQR = 3 (UK) Sex/gender: 14 women (Japan); 33 women (UK)	*T-test*: no differences among cultural groups in terms of positive or negative differentiation *MANCOVA*: controlling for age and gender, no significant effect for nationality and no effects for either age or gender

39. Ikeda (2023)	Wellbeing and mental health	(1) To examine the relationship between emotional vocabulary size and EG (2) To explore the relationship between emotional vocabulary size and mental health with a focus on stress, subjective happiness, and life satisfaction	Cross-sectional	Sample size: n = 397 Population: participants form the GMO Research Age: 18–59, M(SD) = 39.52(11.07) Sex/gender: 196 females	*Correlational analysis*: correlation between EG and stress (-), happiness (+), satisfaction with life (+), emotional vocabulary (+)*
40. Israelashvili et al. (2019), Study 1	Emotion experience	(1) Negative EG is positively related to negative emotion recognition	Cross-sectional	Sample size: n = 368 Population: university students Age: M(SD) = 19.0(2.63) Sex/gender: 32% men	*Correlational analysis*: correlation between negative EG and the verbal IQ test (+)* *Regression analysis*: controlling for emotional intensity levels, emotion recognition is predicted by negative EG (+)*** and is higher when participants have completed the emotion recognition task before, rather than after the ED task***
41. Israelashvili et al. (2019), Study 2	Emotion experience	(1) Negative EG is positively related to negative emotion recognition (2) Individuals make more use of emotion knowledge when there is less emotion information available, that is, when expressive cues are minimal	Cross-sectional	Sample size: n = 217 Population: recruited via Mturk Age: M(SD) = 37.0(12.0) Sex/gender: 47% men	*Correlational analysis*: correlation between negative EG and the verbal IQ test (+)* *Regression analysis*: controlling for emotional intensity levels, emotion recognition is predicted by negative EG (+)*** *Paired contrast comparison*: negative EG is not associated with accurate emotion recognition in front of scarce emotion information, compared with condition with most elaborate emotional stimuli
42. Jacobson et al. (2023)	Wellbeing and mental health	(1) EG, qualitative idiographic EC (i.e., the self-reported number of emotional building blocks identified by participants), and quantitative idiographic EC correlate positively	Longitudinal intensive	Sample size: n = 117 Population: students from personality psychology courses	*Correlational analysis*: correlation between negative EG and qualitative idiographic (+), quantitative idiographic (-), and positive EG (+)*; correlation between positive EG and qualitative idiographic (-), quantitative idiographic (-)*

			(2) Higher scores on each index would predict lower anxiety, depression, and self- and observer-rated personality pathology levels		Age: 18–31, M = 19.9 Sex/gender: 18% male; 81% female; 1% transgender	*T-test*: the average participant has significantly more than 1 factor on average, averaging approximately 5 factors each *Commonality analysis*: negative EG predicts antagonism (-)* and detachment personality (+)*, but not anxiety (-), depression (+), personality functioning-observed report (-), personality functioning-self report (-), NA personality (-), psychotic personality (-), and disinhibition personality (-). Positive EG predicts disinhibition personality (-)*, but not antagonism (-), detachment personality (+), anxiety (-), depression (+), personality functioning-observed report (-), personality functioning-self report (-), NA personality (-), psychotic personality (-)
43.	Jeong et al. (2023), Study 1	Social behaviors	(1) Negative EG moderates the relationship between negative emotions and helping, such that the negative relationship is mitigated for individuals with high negative EG	Cross-sectional	Sample size: n = 220 Population: recruited through online survey company Age: M(SD) = 30.9(5.92) Sex/gender: 55% female	*Correlational analysis*: correlation between negative EG and helping behavior (+)*, negative emotions (-)**, gender (-), depression (-)**, and time spent on survey (-)* *Regression analysis:* negative EG does not predict helping behavior (+); the interaction negative emotions × negative EG predict helping behavior (+)*
44.	Jeong et al. (2023), Study 2	Social behaviors	(1) Negative EG moderates the relationship between feeling sympathetic and helping, such that the positive relationship is stronger for individuals with high negative EG	Quasi-experimental	Sample size: n = 91 Population: undergraduates Age: M = 18.5 Sex/gender: 31% male	*Correlational analysis*: correlation between negative EG and helping behavior (-), feeling sympathetic (-), gender (-), business major (-), depression (-), and NA (-)* *Regression analysis*: negative EG does not predict helping behavior (-); the interaction feeling sympathetic × negative EG predict helping behavior (+)*
45.	Jones & Herr (2018)	Eating behaviors	(1) Lower positive EG is associated with higher caloric intake after a	Experimental	Sample size: n = 103	*Correlational analysis*: correlation between negative EG and caloric intake (-)**, positive EG

	and body image	positive, and not negative, mood induction (2) Caloric intake is related to self-reported emotional eating when in the congruent mood state (i.e., increased food intake when experiencing negative and/or positive moods) (3) EG mediates the relationship between ER difficulties and caloric intake		Population: college students Age: 18–31, M(SD) = 19.3(1.4) Sex/gender: 83% female	(+)**, difficulties in ER (-)*, negative emotional eating (-), and positive emotional eating (-); correlation between positive EG and caloric intake (-), difficulties in ER (-), negative emotional eating (+), and positive emotional eating (-) *Regression analysis:* main effect of negative EG (-)***, but not of positive EG (-), on caloric intake regardless of group (negative vs. positive mood induction) Moderation analysis: neither negative (+) nor positive (+) EG does not moderate the relationship between group (negative vs. positive mood induction) and caloric intake *Mediation analysis*: negative EG mediates the relationship between ER difficulties and caloric intake (+): ER difficulties predict negative EG (-)*, which conversely predict caloric intake (-)** when controlling for ER difficulties. Positive EG does not mediate the relationship between ER difficulties and caloric intake (+). ER difficulties do not mediate the relationship between negative EG and caloric intake (-): negative EG predicts ER difficulties (-)*, which conversely does not impact caloric intake (+)
46. Kalokerinos et al. (2019), Study 1	Emotion experience	(1) EG is positively associated with reappraisal and acceptance, and negatively associated with suppression and rumination (2) Among low differentiators, all strategies are associated with increased negative emotion (3) Among high differentiators, reappraisal, acceptance, distraction, and sharing are associated with	Longitudinal intensive	Sample size: n = 560 (tot); n = 198 (wave 1); n = 185 (wave 2); n = 177 (wave 3) Population: university students Age: M(SD) = 18.32(.96) (wave 1); M(SD) = 18.64(1.04)	*Linear mixed-effects models*: negative EG predicts cognitive reappraisal (-)*** and social sharing (-)**, but not rumination (+), distraction (+), and expressive suppression (+). Negative EG interacts with all strategies (i.e., cognitive reappraisal, social sharing, rumination, distraction, and expressive suppression) in predicting negative emotions (-)***

		decreased negative emotion and the effects of suppression and rumination on negative emotion is attenuated		(wave 2); M(SD) = 19.28(1.0) (wave3) Sex/gender: 90 men (wave 1); 83 men (wave 2); 79 men (wave 3)	
47. Kalokerinos et al. (2019), Study 2	Emotion experience	(1) EG is positively associated with reappraisal and acceptance, and negatively associated with suppression and rumination (2) Among low differentiators, all strategies are associated with increased negative emotion (3) Among high differentiators, reappraisal, acceptance, distraction, and sharing are associated with decreased negative emotion and the effects of suppression and rumination on negative emotion is attenuated	Longitudinal intensive	Sample size: n = 101 Population: first-year psychology students Age: M(SD) = 18.64(1.45) Sex/gender: 14 men	*Linear mixed-effects models*: negative EG predicts rumination (-)* and social sharing (-)*, and expressive suppression (-)*, but not distraction (+), acceptance (+), and cognitive reappraisal (-). Negative EG interact with rumination (-)***, distraction (-)***, acceptance (+)***, and social sharing (-)***, but not with cognitive reappraisal (-) and expressive suppression (-) in predicting negative emotions
48. Kashdan & Farmer (2014)	Social behaviors	(1) Participants with social anxiety disorder display less negative EG than healthy controls across random, social, and end-of-day contexts (2) These effects are not attributed to group differences in average emotion intensity and variability over the 14-day assessment period (3) Negative EG deficits are linked specifically to social anxiety severity, controlling for comorbid conditions	Longitudinal intensive	Sample size: n = 42 (+ 43 diagnosed with social anxiety disorder) Population: community sample Age: M(SD) = 28.5(8.6) ° ° Sex/gender: 27 women °	*T-test*: participants with social anxiety disorder report lower dispositional negative EG** and lower dispositional EG concerning social interactions; no differences in negative EG at the end of the day, positive EG at the end of the day, dispositional positive EG, or positive EG concerning social interactions *ANOVA:* participants with social anxiety disorder demonstrate poorer negative EG compared to healthy controls; there is no difference in positive EG

49. Kashdan et al. (2014)	Wellbeing and mental health	(1) Low self-esteem predicts heightened activation in distress-related neural responses (i.e., dorsal anterior cingulate cortex and anterior insula) (2) This relationship is moderated by negative EG	Experimental + Longitudinal intensive	Sample size: n = 25 Population: undergraduates Age: M(SD) = 20.94(5.24) Sex/gender: 16 females	*Moderation analysis*: interaction self-esteem × negative EG in predicting dorsal anterior cingulate cortex activity (+)* in response to social rejection: among low emotion differentiators lower self-esteem is strongly associated with greater dorsal anterior cingulate cortex activation (-)***, while among high emotion differentiators self-esteem is not associated with greater dorsal anterior cingulate cortex activation (+). Interaction self-esteem × negative EG in predicting both right (+)** and left ()** anterior insula in response to social rejection: among low emotion differentiators lower self-esteem predicts higher right (+)*** and left (-)*** anterior insula activation (-), while among high emotion differentiators self-esteem is not associated with greater anterior insula activation (+). No main effect of EG on right (-) and left (+) anterior insula activation
50. Kashdan et al. (2010)	Maladaptive behaviors	(1) People with high EG are better equipped to manage negative emotions and less likely to drink to cope compared with people with low EG	Longitudinal intensive	Sample size: n = 106 Population: community sample Age: 18–31, M(SD) = 19.3(.79) Sex/gender: 57 women	*Hierarchical regression model*: negative EG does not predict alcohol consumption (-), but interacts with NA intensity in predicting alcohol consumption (-)*: people with high EG are relatively immune to the effects of intense NA on alcohol use, whereas people with low EG are vulnerable to excessive alcohol use when they feel intense NA *Hierarchical linear model*: negative EG predicts alcohol consumption (-)*, but this effect disappears when adding average alcohol consumption to the model. Negative EG interacts with pre-drinking NA in predicting alcohol consumption (-)*: greater tendency to differentiate emotions leads to less alcohol intake when people are confronted with intense pre-drinking negative emotions

51.	Kimhy et al. (2014)	Wellbeing and mental health	(1) Individuals with schizophrenia display significantly poorer social functioning and lower EG compared to healthy controls (2) Among individuals with schizophrenia, higher EG predicts better social functioning	Longitudinal intensive	Sample size: n = 26 (+ 77 diagnosed with schizophrenia) Population: individuals from a medical center Age: M(SD) = 23.95(5.01) ° Sex/gender: 63% female °	*T-test*: individuals with schizophrenia reports lower global EG** than healthy controls; there are no differences for negative EG *ANOVA*: individuals with schizophrenia report lower global EG* than healthy controls controlling for age, emotional intensity and variability; there are no differences for negative EG controlling for age, emotional intensity and variability
52.	Lazarus et al. (2022)	Romantic relationship	(1) Actors' negative and positive EG is associated with their own relationship quality ratings both concurrently and prospectively (2) Partners' negative and positive EG is associated with the actors' relationship quality ratings both concurrently and prospectively (3) The association between the actors' negative and positive EG and relationship quality is higher for actors whose partners' negative and positive EG is lower, both concurrently and prospectively	Longitudinal intensive	Sample size: n = 200 (100 heterosexual couples) Population: heterosexual couples expecting their first child Age: 18–46; M(SD) = 28.7(4.3) (women); M(SD) = 30.3(4.1) (men) Sex/gender: 100 women	*Correlational analysis*: in women, correlation between negative EG and positive EG (+), NA (-)***, PA (+)*, pre-partum couple satisfaction (+)*, 3-month couple satisfaction (+)***, 6-month couple satisfaction (+)**, pre-partum perceived partner responsiveness (+)***, 3-month perceived partner responsiveness (+)***, 6-month perceived partner responsiveness (+)***. In women, correlation between positive EG and NA (-)*, PA (+), pre-partum couple satisfaction (+), 3-month couple satisfaction (+)*, 6-month couple satisfaction (+), pre-partum perceived partner responsiveness (+)*, 3-month perceived partner responsiveness (+)*, 6-month perceived partner responsiveness (+)†. In women, correlation between positive EG and NA (-)*, PA (+), pre-partum couple satisfaction (+), 3-month couple satisfaction (+)*, 6-month couple satisfaction (+), pre-partum perceived partner responsiveness (+)*, 3-month perceived partner responsiveness (+)*, 6-month perceived partner responsiveness (+)†. In men, correlation between negative EG and positive EG (+)***, NA (-)**, PA (+)***, pre-partum couple satisfaction (+)**, 3-month couple satisfaction (+)**, 6-month couple satisfaction (+)**, pre-partum perceived partner

					responsiveness (+)**, 3-month perceived partner responsiveness (+)**, 6-month perceived partner responsiveness (+)**. In men, correlation between negative EG and NA (-)**, PA (+), pre-partum couple satisfaction (+)**, 3-month couple satisfaction (+)**, 6-month couple satisfaction (+)*, pre-partum perceived partner responsiveness (+)*, 3-month perceived partner responsiveness (+)**, 6-month perceived partner responsiveness (+)*** *Concurrent multilevel analysis*: couple satisfaction is predicted by actor × partner negative EG (-)*, actor positive EG (+)*, and partner positive EG (+)*, but not by actor negative EG (+), partner negative EG (+), and actor × partner positive EG (+). Perceived partner responsiveness is predicted by actor negative EG (+)*, partner negative EG (+)*, and actor positive EG (+)†, but not by actor × partner negative EG (-), partner positive EG (+), and actor × partner positive EG (-) *Prospective multilevel analysis*: couple satisfaction is predicted by partner negative EG (+)* and partner positive EG (+)*, but not by actor negative EG (+), actor positive EG (+), actor × partner negative EG (-), and actor × partner positive EG (+). Perceived partner responsiveness is marginally predicted by partner negative EG (+)†, but not by actor negative EG (+), actor × partner negative EG (-), actor positive EG (+), partner positive EG (+), and actor × partner positive EG (+)
53. Lee et al. (2017)	Emotion experience	(1) To investigate the effects of individual differences in EG on electroencephalography-based brain	Cross-sectional	Sample size: n = 33 Population: university students	*Regression analysis*: main effect of granularity on ERP is significant between 60–90 ms (+)**, 270-300 ms (+)***, and 540-570 ms (+)*: more negative early ERPs in the lowly granular group, a

		activity during the experience of emotion		Age: M(SD) = 21.52(2.11) Sex/gender: 11 females	more negative N2 peak of the highly granular group, and a fast ERP drop after the LPP of the highly granular group. No interaction effect between granularity and brain regions or the interaction between emotion and brain regions in any time bin. Interaction effect between granularity and emotion (+)***: an individual's level of granularity has an early- to mid-time frame moderating effect on brain signals responding to the experience of different emotion categories
54. Li & Ashkanasy (2019)	Cognitive processes	(1) The number of wrong risk-taking decisions at Time 1 is negatively related to increased risk-taking behavior at Time 2 (2) The number of missed opportunities at Time 1 is positively related to increased risk-taking behavior at Time 2 (3) The positive relationship between risk-taking and return is strengthened when there is a high probability that risky choices will result in successful outcomes (4) Under the high risk-taking favorability (80%) condition, negative EG is positively related to decision-making performance (5) Under the low risk-taking favorability (20%) condition, negative EG is positively related to decision-making performance (6) Under the equivocal condition of risk-taking, negative EG is not	Experimental	Sample size: n = 175 Population: undergraduates Age: 17–37, M = 21.0 Sex/gender: 51% female	*Correlational analysis*: correlation between negative EG and age (+)**, gender (+), income (+), race (-), risk-taking T1 (-), opportunity missed T2 (-), increased risk taking (T2-T1), (-), decision performance change (T2-T1) (-)*, decision performance T2 (-) *Regression analysis*: there is a relationship between negative EG and decision-making performance in terms of the monetary amount ear negative EG in the decisions (+)†, the effect of negative EG on decision-making performance is moderated by the favorability of the risk making environment: For the high-favorability condition (where decision-makers have relatively more opportunities for risky choice success), participants win more money when they has higher awareness of their negative emotions elicited by wrong decision-making *Regression analysis*: no significant impact in the low favorability condition *Regression analysis:* under the condition of medium risk-taking favorability condition (equivocal condition), there is no significant effect between negative EG and decision performance

		related to decision-making performance			
55. Liao et al. (2025)	Emotion experience	(1) Individuals with higher negative EG demonstrate more changes in their ER endorsement in response to changes in contextual factors on a day-to-day basis (2) Negative EG is positively associated with within-strategy variability at the person level, and with between-strategy variability at both levels	Longitudinal intensive	Sample size: n = 101 Population: university students Age: M(SD) = 20.24(1.54) Sex/gender: 54% female	*Correlational analysis*: correlation between negative EG and within strategy variability (+)†, between strategy variability (+)**, NA (-)**, mean ER endorsement (-)**, average of ΔER endorsement (+) *Multilevel analysis* (with change in each of the contextual factors as Level 1 predictor, respectively): negative EG moderates the association between day-to-day change in ER endorsement and change in event type (+)* and ER goal (+)* above and beyond NA. Negative EG does not moderate the association between change in event intensity and change in ER use (-). Participants with higher levels of negative EG report higher levels of average ΔER use when the event type (+)*** or goal (+)* change. In contrast, among the participants with lower level of negative EG, the association between the change in event type or ER goal and average ΔER use is not significant *Regression analysis*: negative EG is associated with the between strategy variability (+)*** as well as within strategy variability (+)* *Multilevel analysis* (the Level 2 predictor and daily between-strategy variability as the Level 1 outcome): association between negative EG and between-strategy variability at the day level (+)**
56. Lischetzke et al. (2021)	Wellbeing and mental health	(1) Daily stress has an indirect effect on poorer subjective sleep quality through calmness in the evening	Longitudinal intensive	Sample size: n = 313 Population: general population	*Correlational analysis*: correlation between daily negative EG and calmness in the morning (+), daily stress (-)***, calmness in the evening (+)***, nightly sleep quality (+)*, daily rumination (-)***, daily NA (-)***; correlation between dispositional

(2) Negative EG moderates the within-person relation between daily stress and calmness in the evening such that at higher (vs. lower) levels of negative EG, higher daily stress is less strongly associated with a more tense mood in the evening	Age: 15–82, M(SD) = 30.1(14.9) Sex/gender: 74.1% women	negative EG and depressive symptoms (-), calmness in the morning (+)*, daily stress (-), calmness in the evening (+)**, nightly sleep quality (+), daily rumination (-), daily NA (-)*** *Moderated multilevel mediation model*: dispositional negative EG (L2) predicts calmness in the evening (L1) (+)* and interacts with daily stress (L1) in eliciting calmness in the evening (+)**: The within-person relation between daily stress and less calmness in the evening is stronger at low than high dispositional EG. Controlling for NA and depressive symptoms at L2, the main effect of dispositional EG on calmness in the evening is no longer significant, while the cross-level interaction of dispositional EG and daily stress on calmness in the evening is retained. Calmness in the evening mediates the relationship between daily stress and sleep quality: For individuals with low dispositional EG, the estimated within-person indirect effect is significant, while for individuals with high EG, the estimated within-person indirect effect is non-significant *Moderated multilevel mediation model*: the interaction stress × daily EG is significant on days with higher EG (+)**: the stress-calmness link is less negative than on days with lower EG. However, when daily NA is added to the model as a Level 1 predictor, the Level 1 interaction term is no longer significant *Multilevel model*: daily EG significantly predicts daily rumination (-): on days with lower EG, the probability to ruminate is higher. However, when added daily NA as an additional predictor of daily rumination, this effect vanishes

57. Liu et al. (2020)	Wellbeing and mental health	(1) Elevated trait rumination is associated with and predicts onset of major depressive disorder (2) Negative EG, but not positive EG, moderates the rumination-depression association, such that rumination would only predict increases in depression when negative emotions are less, not more, differentiated	Repeated measure + Longitudinal intensive	Sample size: n = 65 Population: community sample Age: 20–71, M(SD) = 38.4(14.5) Sex/gender: 60% female	*Correlational analysis*: correlation between negative EG and positive EG (+)***, global EG (+)***, NA (-), PA (+), T1 rumination (-)***, T1 depressive symptoms (-)*, T2 depressive symptoms (-); correlation between positive EG and global EG (+), NA (-), PA (+), T1 rumination (-)***, T1 depressive symptoms (-), T2 depressive symptoms (-); correlation between global EG (+) and NA (-), PA (+), T1 rumination (-)***, T1 depressive symptoms (-)*, T2 depressive symptoms (-) *Regression analysis*: controlling for T1 depressive symptoms, negative and PA, negative EG (+), and T1 rumination, negative EG moderates the impact of T1 rumination on T2 depressive symptoms (-)** *Regression analysis*: controlling for T1 depressive symptoms, negative and PA, positive EG (-), and T1 rumination, positive EG moderates the impact of T1 rumination on T2 depressive symptoms (-)* *Post-hoc regression analysis*: controlling for T1 depressive symptoms, negative and PA, negative EG (+)*, positive EG (-) and T1 rumination, neither negative (-) nor positive (+) EG moderate the impact of T1 rumination on T2 depressive symptoms *Regression analysis*: controlling for T1 depressive symptoms, negative and PA, global EG (+), valence discrepancy of EG (+) and T1 rumination, global EG (-)*, but not valence discrepancy of EG (+), moderates the impact of T1 rumination on T2 depressive symptoms
58. Lukic et al. (2023)	Emotion experience	(1) Participants with higher EG have greater cortical thickness in inferior frontal cortex, a region that may support the controlled selection	Intervention (RCT)	Sample size: n = 58	*Regression analysis*: global EG predicts cortical thickness both in the left (+)* and right (+)* lateral orbitofrontal cortex, with both global EG indices

		of emotion concepts during experience reporting		Population: volunteers in the Hillblom Healthy Aging Network Age: 62–84, M(SD) = 74.7(4.3) Sex/gender: 38 females	*Follow-up analysis*: there are no differences between the intervention and control groups in their mean levels of overall EG
59. Lv et al. (2024)	Wellbeing and mental health	(1) Chronic stress affects fatigue and the higher the chronic stress, the higher the fatigue (2) Depression and anxiety play a mediating role between chronic stress and fatigue (3) Negative EG affects the relationship between chronic stress and fatigue by moderating the anxiety and depression caused by chronic stress (4) Compared with those with low negative EG, individuals with high negative EG are less likely to be affected by the chronic stress that results in anxiety and depression, and then affects fatigue	Cross-sectional	Sample size: n = 288 Population: employees Age: 18–34, M(SD) = 23.14(3.79) Sex/gender: 13.89% female	*Correlational analysis*: correlation between negative EG and chronic stress (-), fatigue (-), depression (-), anxiety (-) *Moderated mediation analysis*: anxiety, but not depression, mediate the relationship between stress and fatigue, and anxiety mediates the association between stress and depression; EG does not predict depression (+), while the interaction anxiety × EG predicts anxiety (-)*: when negative EG is low, anxiety has a significant positive effect on depression, while when negative EG is high, the positive predictive effect of anxiety on depression decreased
60. Mankus et al. (2016)	Emotion experience	(1) Older age is associated with higher type clarity, source clarity, negative EG, and voluntary attention and lower involuntary attention (2) Gender is not associated with type clarity or source clarity, but that women report higher voluntary attention and involuntary attention than would men	Cross-sectional	Sample size: n = 919 Population: recruited via Mturk Age: M(SD) = 35.4(13.1) Sex/gender: 66.9% female	*Correlational analysis*: correlation between EG and age (+)*, gender (men=0; women=1) (+)**, socioeconomic status (+), type clarity (i.e., the extent to which people unambiguously identify, label, and represent the type of emotion experienced) (+)**, source clarity (i.e., the extent to which people unambiguously identify, label, and represent the source of their emotional experiences) (+)**, voluntary attention (+)**, involuntary attention (-)

		(3) Socioeconomic status is related to individual variation in emotional awareness facets			*Path-analysis*: EG is predicted by age (+)*, gender (men=0; women=1) (+)**, but not by socioeconomic status (+)
61. Matt et al. (2024)	Wellbeing and mental health	(1) Exposure to an online training targeting emotion word knowledge (vs. a control condition) is associated with improvements in negative EG and emotional self-efficacy, as well as reductions in psychological symptoms and distress (2) Changes in negative EG or emotional self-efficacy mediate the effects of the training on levels of psychological distress one week and two-months post-intervention (3) Individual differences in levels of engagement with the word learning task influence the associations described above	Intervention (RCT)	Sample size: n = 118 Population: university students Age: M(SD) = 20.52(3.9) (neutral condition); M(SD) = 19.74(2.33) (emotion condition) Sex/gender: 80% female (neutral condition); 82.76% female (emotion condition)	*Correlational analysis*: correlation between baseline EG and age (-), total diaries (+), verbal intelligence (-), baseline distress (-), post-task distress (-)**, two months distress (-)*, baseline emotional self-efficacy (-), post-task emotional self-efficacy (-); correlation between post-task EG and age (+), total diaries (+)**, verbal intelligence (-), baseline distress (+), post-task distress (-), two months distress (-), baseline emotional self-efficacy (-), post-task emotional self-efficacy (+), baseline EG (+)* *T-test:* control and experimental group do not differ for baseline EG or post-task EG *Mediation analysis*: controlling for baseline verbal intelligence and distress, pre-task negative EG, and post-task NA, post-task negative EG does not mediate the relationship between group (control vs. experimental) and post-task distress (-): it does not predict post-task distress (-) and is not predicted by group (+). Controlling for baseline verbal intelligence and distress, pre-task negative EG, and post-task NA, post-task negative EG does not mediate the relationship between group (control vs. experimental) and two-months distress (-): it does not predict two-months distress (-) and is not predicted by group (+)
62. Matyi & Spielberg (2023)	Emotion experience	To examine how five major white matter pathways (i.e., anterior thalamic radiation, uncinate fasciculus, inferior fronto-occipital fasciculus, and peri-genual and dorsal cingulum bundle) relate to	Cross-sectional	Sample size: n = 66 Population: community sample Age: 20–26, M(SD) = 22.8(1.7)	*Correlational analysis*: negative EG is related to left peri-genual cingulum bundle (-)*, to right anterior thalamic radiation (-)*, right inferior fronto-occipital fasciculus (-)*, and left peri-genual cingulum bundle (-)*. Looking at these patterns within the anterior, middle, and posterior

		individual differences in negative EG		Sex/gender: 53 females	subdivisions of these tracts, negative EG is related to right anterior thalamic radiation in the anterior (-)*, middle (-)*, and posterior (-)* subdivisions and right inferior fronto-occipital fasciculus in the middle subdivision (-)***
63. Mehak et al. (2024)	Eating behaviors and body image	(1) Greater momentary negative emotion predicts greater momentary 'feeling fat' (2) This effect is moderated by dispositional negative EG, such that the relationship between negative emotion and 'feeling fat' is stronger in those with lower EG	Longitudinal intensive	Sample size: n = 198 Population: undergraduates Age: 18–37, M(SD) = 20.6(2.24) Sex/gender: 52.24% female	*Correlational analysis*: correlation between negative EG and negative affect (-)***, fear (-)***, hostility (-)***, guilt (-)***, sadness (-)***, within-person "feeling fat" (-), between-person "feeling fat" (-)*** *Multilevel analysis–concurrent model*: both at the within (+) and between (-) level, controlling for NA, the interaction NA × negative EG on "feeling fat" is not significant. The effect is not significant either when inserting the NA subscales as predictors (instead of global NA) *Multilevel analysis–prospective model:* at the within level, but not at the between level (-), controlling for NA, the interaction NA × negative EG on "feeling fat" is significant (+)*. These effects are not significant when inserting the NA subscales as predictors (instead of global NA)
64. Mikhail et al. (2020)	Eating behaviors and body image	(1) Women who experience greater emotional eating or have a history of clinically significant binge eating have lower EG	Longitudinal intensive	Sample size: n = 475 Population: twin women from a twin registry Age: 15–25, M(SD) = 17.86(1.82) Sex/gender: 100% female	*Correlational analysis:* correlation between negative EG–ICC and positive EG–ICC (+)***, negative EG-AIC (+)***, positive EG-AIC (+)***, negative EG-VAR (-)**, positive EG-VAR (-), NA (-)***, PA (-), emotional eating (-)***, binge eating (-)**, BMI (-), age (+). Correlation between positive EG–ICC and negative EG-AIC (+)***, positive EG-AIC (+)***, negative EG-VAR (+), positive EG-VAR (+)***, NA (-), PA (-)**, emotional eating (-), binge eating (-)*, BMI (-)*, age (-). Correlation between negative EG-AIC (+)*** and positive EG-AIC (+)***, negative EG-VAR (-), positive EG-VAR (+), NA (-)***, PA (-),

						emotional eating (-)*, binge eating (-)*, BMI (-), age (+). Correlation between positive EG-AIC and negative EG-VAR (+)*, positive EG-VAR (+)***, NA (+)*, PA (-)*, emotional eating (-), binge eating (-), BMI (-), age (-). Correlation between negative EG-VAR and positive EG-VAR (+)***, NA (+)***, PA (+)***, emotional eating (+)***, binge eating (+), BMI (-), age (-). Correlation between positive EG-VAR and NA (+)***, PA (+)***, emotional eating (-), binge eating (-), BMI (-), age (-) *Linear mixed model*: controlling for BMI and negative and PA, emotional eating predicted by positive EG–ICC (-), positive EG-AIC (-), positive EG-VAR (-)***, while binge eating episodes (BEs) predicted by positive EG–ICC (+)**, positive EG-AIC (+)*, positive EG-VAR (+). Controlling for BMI and negative and PA, emotional eating predicted by negative EG–ICC (-), negative EG-AIC (+), negative EG-VAR (-)***, while binge eating is predicted by negative EG–ICC (+), negative EG-AIC (+), negative EG-VAR (+)* *Linear mixed model*: controlling for BMI and negative and PA, emotional eating is predicted by negative EG–ICC (+), positive EG–ICC (-), negative EG-AIC (+), positive EG-AIC (-), negative EG-VAR (-)**, positive EG-VAR (-)*. Controlling for BMI and negative and PA, binge eating are predicted by negative EG–ICC (+), positive EG–ICC (+)*, negative EG-AIC (+), positive EG-AIC (+), negative EG-VAR (+)*, positive EG-VAR (+)
65.	Mikkelsen et al. (2021)	Wellbeing and mental health	(1) ER therapy tailored to distressed caregivers of cancer patients leads to significant improvements in EG	Intervention (RCT)	Sample size: n = 81	*T-test*: no statistically significant differences in baseline negative EG or baseline EG between the ER therapy condition and the waitlist condition

		in distressed caregivers of cancer patients (2) Improvements in EG are associated with reduced distress		Population: caregivers to patients with cancer Age: M(SD) = 45.15(15.77) Sex/gender: 74.1% women	*ANOVA*: greater increase in negative EG in the ER therapy condition compared to the waitlist condition (+)*, while there is no difference for positive EG. Improvements in negative EG are not associated with changes in distress symptoms from pre-treatment to post-treatment or 6-months follow-up
66. Mikkelsen et al. (2020)	Emotion experience	(1) There are no age-group differences in EG between young and older adults	Cross-sectional	Sample size: n = 246 (tot); n = 114 (young adults); n = 132 (older adults) Population: recruited via Qualtrics Panel Age: 18–30, M(SD) = 22.95(3.45) (young adults); 60–84, M(SD) = 66.58(4.97) (older adults) Sex/gender: 54.4% female (young adults); 50.8% female (older adults)	*T-test*: no significant differences between men and women for the PCA based indicator of EG overall, within the young group, or within the older group; no significant differences between men and women for the ICC based indicator of EG overall, within the young group, or within the older group
67. O'Toole et al. (2014)	Emotion experience	(1) High levels of social anxiety are associated with less adaptive (cognitive reappraisal) and more maladaptive (emotion suppression strategies) ER, as well as with diminished PA and poorer satisfaction with social life (2) These associations are moderated by trait social anxiety and daily positive and negative EG	Longitudinal intensive	Sample size: n = 131 (+ 130 with high social anxiety) Population: first-year college students with very low social anxiety Age: M(SD) = 23.4(7.0) ° Sex/gender: 38% women °	*T-test*: individuals with low social anxiety report higher global EG(***) than those with high social anxiety; no differences are found for negative or positive EG *Interaction analysis*: positive EG is not associated with expressive suppression in individuals with high social anxiety, while those with low social anxiety are more likely to use expressive suppression when they score lower on positive EG (-)*; positive EG is not associated with experiential avoidance or cognitive reappraisal either in high or low social anxiety. Negative EG

		(3) Trait social anxiety and daily expressive suppression interact in the prediction of daily PA (4) This interaction term also predicts daily social satisfaction			is associated with cognitive reappraisal in both high and low social anxiety (+)*: individuals with good negative EG used more cognitive reappraisal, those with high social anxiety are more likely to use daily cognitive reappraisal if they reported good negative EG but this difference is larger for those with low social anxiety; negative EG is not associated with experiential avoidance or expressive suppression either in high or low social anxiety
68. O'Toole et al. (2021)	Emotion experience	(1) Higher negative EG is positively associated with putatively adaptive ER strategies and negatively associated with putatively maladaptive ER strategies, above and beyond negative emotions	Longitudinal intensive	Sample size: n = 90 (tot); n = 51 (sample 1); n = 39 (sample 2) Population: college students Age: 20–57, M(SD) = 23.7(1.7) (sample 1), M(SD) = 25.4(6.02) (sample 2) Sex/gender: 82.2% women (tot); 88.2% women (sample 1); 74.4% women (sample 2)	*Correlational analysis*: without controlling for NA, correlation between dispositional negative EG and positive emotions (+), negative emotions (-)**, reflection (-), distancing (+)*, non-reactivity (+)**, reappraisal (+), rumination (-)**, experiential avoidance (-), expressive suppression (-), worry (-)**; controlling for NA, correlation between dispositional negative EG and positive emotions (+), negative emotions (-)**, reflection (-), distancing (+), non-reactivity (+), reappraisal (+), rumination (-), experiential avoidance (-), expressive suppression (-), worry (-) *Multilevel analysis* (association between daily ER strategies as a continuous measure and dispositional negative EG [without/with daily negative emotions as a covariate]): dispositional negative EG predicts reflection (+)/(+), distancing (+)**/(+), non-reactivity (+)*/(+), reappraisal (+)/(-), rumination (-)**/(-), experiential avoidance (-)*/(-), expressive suppression (-)/(+), worry (-)***/(-) *Multilevel analysis* (association between daily ER strategies as a continuous measure and mean-centered daily negative EG [without/with daily negative emotions as a covariate]): daily negative EG predicts reflection (-)/(-), distancing (+)***/(+),

					non-reactivity (+)**/(+), reappraisal (-)/(+), rumination (-)**/(-), experiential avoidance (-)*/(-), expressive suppression (-)*/(-)†, worry (-)***/(-) *Multilevel analysis* (association between daily ER strategies as a categorical [present/not present] measure and dispositional negative EG [without/with daily negative emotions as a covariate]): dispositional negative EG predicts reflection (+)/(+), distancing (+)**/(+), non-reactivity (+)*/(+), reappraisal (+)/(-), rumination (-)**/(+), experiential avoidance (-)*/(-), expressive suppression (-)/(+), worry (-)***/(-) *Multilevel analysis* (association between daily ER strategies as a categorical (present/not present) measure and mean-centered daily negative EG (without/with daily negative emotions as a covariate)): daily negative EG predicts reflection (+)/(+), distancing (+)/(-), non-reactivity (+)*/(+), reappraisal (-)/(+), rumination (-)*/(+), experiential avoidance (-)/(+), expressive suppression (-)/(-), worry (-)*/(+)
69. Oh & Tong (2020)	Wellbeing and mental health	(1) There are long-term associations between negative EG and physical health (2) The benefits of negative EG are moderated by trait neuroticism	Multiphase longitudinal	Sample size: n = 1,010 Population: participants from the MIDUS study Age: 34–83, M(SD) = 55.53(11.2) Sex/gender: 577 females	*Regression analysis*: negative EG does not predict neither subjective health at T2 (+) nor objective health at T2 (+); the interaction neuroticism × negative EG predicts both subjective health at T2 (-)** and objective health at T2 (-)**: when neuroticism is 1SD below the mean, there is a significant and positive conditional effect of negative EG on T2 subjective health (+)** as well as T2 objective health (+)*, however, when neuroticism is at mean levels, the conditional effect of negative EG is not significant for both T2 subjective health (+) and T2 objective health (+), while when neuroticism is 1SD above the mean, the conditional effect of negative EG on T2

						subjective health (-) and T2 objective health (-) is also nonsignificant *Path model for SEM*: negative EG does not predict T2 health (+), while the latent variable interaction term is statistically significant (-)**: controlling for baseline health and all other covariates, negative EG has a significant and positive conditional effect on T2 health when neuroticism is 1SD below the mean (+)**; however, the conditional effect of negative EG on T2 health is nonsignificant when neuroticism is at mean levels (+) or at 1SD above the mean (-)
70.	Ottenstein & Lischetzke (2020), Study 1	Wellbeing and mental health	(1) Momentary time pressure has an influence on the number of emotion adjectives reported (2) Negative EG is more closely related to daily well-being on days that presented a challenge to individuals' well-being (i.e., days with a negative event) compared with less challenging days (i.e., days without a negative event)	Longitudinal intensive	Sample size: n = 111 Population: general population Age: M(SD) = 34.95(15.72) Sex/gender: 73% female	*Correlational analysis*: correlation between EG–self-report and EG–SI (+), alexithymia–difficulties identifying feelings (-)***, alexithymia–difficulties describing feelings (-)***, reappraisal (+)*, suppression (-)*, daily life satisfaction (+), momentary pleasant−unpleasant mood (+); correlation between EG–SI and alexithymia–difficulties identifying feelings (+), alexithymia–difficulties describing feelings (-), reappraisal (+), suppression (-), daily life satisfaction (+)*, momentary pleasant−unpleasant mood (+)* *Multilevel analysis* (Daily life satisfaction): Daily life satisfaction is predicted by negative EG–SI (+)** but not by the interaction negative EG–SI × negative event during the day (+) *Multilevel analysis* (momentary pleasant−unpleasant mood): momentary pleasant−unpleasant mood is predicted by negative EG–SI (+)** but not by the interaction negative EG–SI × negative event during the day (+)

						Regression analysis: Momentary time pressure is unrelated to the number of adjectives *T-test*: There are no sex differences in the specificity index of negative EG–SI
71.	Ottenstein & Lischetzke (2020), Study 2	Wellbeing and mental health	(1) Momentary time pressure has an influence on the number of emotion adjectives reported (2) Negative EG is more closely related to daily well-being and ER on days that presented a challenge to individuals' well-being (i.e., days with a negative event) compared with less challenging days (i.e., days without a negative event)	Longitudinal intensive	Sample size: n = 190 (EG computed only for 64 participants) Population: general population Age: M(SD) = 40.36(16.01) Sex/gender: 74% female	*Regression analysis*: Momentary time pressure is unrelated to the number of adjectives *T-test*: There are no sex differences in negative EG–SI *Correlational analysis*: correlation between EG–self-report and negative EG–SI (-), alexithymia–difficulties identifying feelings (-)*, alexithymia–difficulties describing feelings (-)***, reappraisal (+)***, aggregated daily reappraisal (+), aggregated daily suppression (-), daily suppression (-), daily life satisfaction (-), momentary pleasant–unpleasant mood (-); correlation between negative EG–SI and alexithymia–difficulties identifying feelings (-)**, alexithymia–difficulties describing feelings (-), reappraisal (+), aggregated daily reappraisal (+)*, aggregated daily suppression (-), daily suppression (+), daily life satisfaction (+), momentary pleasant–unpleasant mood (+) *Correlation analysis between EG measures*: EG–ICC and EG–self-report (-); EG–ICC and EG–SI (-); EG–self-report and SI (-) *Multilevel analysis*: neither suppression (+) nor reappraisal (+) are predicted by negative EG–SI. Daily life satisfaction is not predicted by negative EG–SI (+) but is predicted by the interaction negative EG–SI × negative event (+)**. Momentary P-U mood is not predicted by negative EG–SI (+), but is predicted by the interaction negative EG–SI × negative event (+)**

72. Petagna & Wormwood (2025)	Emotion experience	(1) The accuracy of people's predictions about their future emotions is related to the ways they experience their emotions throughout daily life, including individual differences in EG, emotional complexity, emotional intelligence, and emodiversity	Repeated measure + Intensive longitudinal	Sample size: n = 126 Population: university students Age: 18–31, M(SD) = 19.22(1.96) Sex/gender: 75.4% female/women, 23% male/man, 1.6% non-binary or agender	*Correlational analysis* (affective forecasting): correlation between positive EG and positive emotion forecasting error (-), negative emotion forecasting error (-), emotion pattern consistency (-); correlation between negative EG and positive emotion forecasting error (-), negative emotion forecasting error (-)*, emotion pattern consistency (+) *Correlational analysis* (predicted and experienced emotions): correlation between positive EG and predicted positive emotions (-), experienced positive emotions (-), predicted negative emotions (-)*, experienced negative emotions (-); correlation between negative EG and predicted positive emotions (-), experienced positive emotions (-), predicted negative emotions (-)*, experienced negative emotions (-) *Regression analysis*: negative emotion forecasting error is predicted by negative EG (+)***. Emotion pattern consistency is predicted by negative EG (-)*
73. Plonsker et al. (2017)	Wellbeing and mental health	(1) Cognitive fusion correlates with reduced EG but does not correlate with specific emotion intensity (2) Lower levels of EG, but not specific emotion intensity, correlated with greater depression and panic symptoms (3) EG mediates expected associations between cognitive fusion and depression and panic symptoms	Cross-sectional	Sample size: n = 55 Population: community-dwelling adults Age: M(SD) = 26.8(3.9) Sex/gender: 50.9% women	*Correlational analysis* (cluster = anger): correlation between EG and specific emotion intensity (+)**, depression (+)**, panic symptoms (+)** *Correlational analysis* (cluster = fear): correlation between EG and specific emotion intensity (+)**, depression (+)**, panic symptoms (+)** *Correlational analysis* (cluster = disgust): correlation between EG and specific emotion intensity (+)*, depression (+)**, panic symptoms (+)** *Correlational analysis* (cluster = sadness): correlation between EG and specific emotion

					intensity (+)**, depression (+)**, panic symptoms (+)**
74. Pond Jr. et al. (2012), Study 1	Maladaptive behaviors	(1) Individuals with high negative EG are less susceptible to aggression when they felt angry, compared to people who have lower EG	Longitudinal intensive	Sample size: n = 199 Population: undergraduates Age: M(SD) = 19.42(1.54) Sex/gender: 76% women	*Multilevel analysis*: daily anger intensity did not vary as function of EG (+) *Multilevel analysis with moderation* (negative EG as a Level 2 predictor, daily anger intensity as a Level 1 predictor, a cross-level interaction term between negative EG and daily anger intensity, and daily aggressive tendencies as the outcome): negative EG × anger intensity predicts aggressive tendencies (-)*: among participants low in EG, anger intensity predicted increased daily aggressive tendencies (+)**, however, among participants who expressed a greater tendency to differentiate their emotions, there is not a significant association between anger intensity and aggression (-); the main effect of EG on aggressive tendencies is not significant (+)
75. Pond Jr. et al. (2012), Study 2	Maladaptive behaviors	(1) Individuals with high negative EG are less susceptible to aggression in response to being provoked to feel angry by another person, compared to people who have lower EG	Longitudinal intensive	Sample size: n = 187 Population: undergraduates Age: M(SD) = 29.99(9.14) Sex/gender: 62% women	*Multilevel analysis*: inverse relationship between negative EG scores and frequency of provocation episodes (-)* *Multilevel analysis with moderation* (negative EG as a Level 2 predictor, daily anger intensity as a Level 1 predictor, a cross-level interaction term between negative EG and daily anger intensity, and daily aggression as the outcome of interest): the interaction negative EG × anger intensity predicts aggressive behavior (-)**: among participants low in EG, there is a strong positive association between anger and aggression (+)***, while among participants who expressed greater EG, there is a weaker, positive association between anger and aggression (+)*; main effect of negative EG (-)** and of anger (+)***

76. Pond Jr. et al. (2012), Study 3	Maladaptive behaviors	(1) Individuals with high negative EG are less susceptible to aggression when they felt angry, compared to people who have lower EG (2) This interaction is mediated by higher levels of daily emotional control	Longitudinal intensive	Sample size: n = 243 Population: undergraduates Age: M(SD) = 19.34(2.27) Sex/gender: 78% women	*Multilevel analysis*: main effect for negative EG predicted daily anger intensity (-)*** *Multilevel analysis with moderation* (negative EG as a Level 2 predictor, daily anger intensity as a Level 1 predictor, a cross-level interaction term between negative EG and daily anger intensity, and daily aggressive tendencies as the outcome): negative EG × anger intensity predicts aggressive tendencies (-)**: among participants low in EG, anger intensity predicted increased daily aggression (+) ***, among participants who expressed a greater tendency to differentiate their emotions, the association between anger and aggression is a weaker, positive association (+)***; main effect of anger intensity (+)*** and EG (-)†
77. Potthoff et al. (2023)	Cognitive processes	(1) High EG is associated with longer viewing times (i.e., less avoidance) of emotion-eliciting videos (2) There is a significant relationship between EG and attention reallocation from the distractor image to the video	Quasi-experimental	Sample size: n = 156 Population: university students (n = 152) and white-collar workers (n = 4) Age: 18–35, M(SD) = 22.4(2.8) Sex/gender: 107 females	*Multilevel analysis* (dwell time): Neither the specificity index for negative videos (+) nor EG–self-report (+) is associated with the dwell time percentage on negative videos. The same is the case for the dwell time percentage on positive videos *Multilevel analysis* (revisits): a higher number of negative video revisits is predicted by a higher specificity index (+)**. Neither EG–self-report differentiation (+) nor the same models for positive trial revisits (+) are statistically significant *Multilevel analysis* (valence, dwell time, revisits): there is a significant effect of video type on all dependent variables, with higher valence for positive compared to negative videos (+)***, a higher percentage of dwell time on negative videos than positive videos (+)***, and more revisits on positive videos than negative videos (-)***

					Regression analysis: EG–self-report differentiation is a significant predictor of the specificity index in NA trials (+)*, but not in PA trials (+)
78. Pugach et al. (2023)	Wellbeing and mental health	(1) Negative EG is reduced in people with PTSD (2) Negative EG is associated with momentary PTSD symptoms (3) Negative EG moderates the effects of trauma-related avoidance on momentary PTSD symptoms	Longitudinal intensive	Sample size: n = 41 Population: trauma-exposed community members Age: M(SD) = 22.22(5.06) ° Sex/gender: 75.6% female °	*T-test*: those with PTSD report lower levels of negative EG than trauma-exposed controls***
79. Qiu et al. (2023)	Wellbeing and mental health	(1) Chronic stress affects an individual's smartphone addiction, and the higher the chronic stress, the higher the smartphone addiction (2) The influence of chronic stress on smartphone addiction is not entirely direct, and intolerance of uncertainty plays a mediating role in the relationship between them (3) EG regulates the relationship between chronic stress and smartphone addiction and its mediating mechanism	Cross-sectional	Sample size: n = 286 Population: employees Age: 17–39, M(SD) = 22.88(3.77) Sex/gender: 13.64% female	*Correlational analysis*: correlation between negative EG and chronic stress (-), smartphone addiction (+), intolerance of uncertainty (+); correlation between positive EG and chronic stress (-), smartphone addiction (+), intolerance of uncertainty (+)*, negative EG (+)*** *Moderated mediation analysis* (positive EG): positive EG does not impact Smartphone addiction, but its interaction with Intolerance of uncertainty does (-)*; the interaction between positive EG and chronic stress has no significant predictive effect on intolerance of uncertainty (-) and smartphone addiction (+) *Moderated mediation analysis* (negative EG): the interaction between negative EG and Intolerance of uncertainty does not impact Smartphone addiction (-); the interaction between positive EG and chronic stress has no significant predictive effect on intolerance of uncertainty (-) and smartphone addiction (-)

80.	Racine et al. (2024)	Maladaptive behaviors	(1) Momentary low EG predicts impulsive behavior, even after controlling for negative emotion intensity (2) Individuals with greater trait negative urgency exhibit stronger momentary associations between low EG and impulsivity (3) Being assigned to NA induction with instructions to focus on the nuances in emotions results in less behavioral impulsivity (4) The impact of differentiated versus undifferentiated NA on behavioral impulsivity is stronger for individuals with high negative urgency	Longitudinal intensive + Experimental	Sample size: n = 100 Population: undergraduates Age: 18–37, M(SD) = 20.61(2.23) Sex/gender: 99 females	*Correlational analysis* (within-person correlation): correlation between momentary low EG and NA (+), momentary impulsivity (+)***, impulsivity–work (+)**, impulsivity -relationships (+), impulsivity–food (+), impulsivity–exercise (+)***, impulsivity–finance (+) *Correlational analysis* (between-person correlation): correlation between momentary low EG and negative urgency (+), NA (+)***, momentary impulsivity (+)***, impulsivity–work (+)***, impulsivity–relationships (+)***, impulsivity–food (+)***, impulsivity–exercise (+)*, impulsivity–finance (+)*** *Multilevel analysis* (low EG and the interaction between undifferentiated NA and negative urgency as a predictor of general impulsivity): controlling for within and between NA, low EG between person (+)*** and negative urgency (+)*** predict impulsivity, while neither low EG within person (+) nor the interaction low EG within person × negative urgency (+) predict impulsivity *Multilevel SEM* (low EG and the interaction between undifferentiated NA and negative urgency as a predictor of domain-specific forms of impulsivity):controlling for both within and between NA, and negative urgency (+)*, impulsivity–work/school is predicted by low EG within person (+)**, low EG between person (-), and the interaction low EG within person × negative urgency (+); controlling for both within and between NA, and negative urgency (+), impulsivity–relationships is predicted by low EG within person (+)*, low EG between person (+)**, and the interaction low EG within person × negative urgency (+); controlling for both within and between NA, and negative urgency (-)*,

					impulsivity–drugs is predicted by low EG within person (-), low EG between person (+)**, and the interaction low EG within person × negative urgency (+); controlling for both within and between NA, and negative urgency (+), impulsivity–food is predicted by low EG within person (+), low EG between person (+)**, and the interaction low EG within person × negative urgency (+); controlling for both within and between NA, and negative urgency (-)*, impulsivity–exercise is predicted by low EG within person (+), low EG between person (+), and the interaction low EG within person × negative urgency (+); controlling for both within and between NA, and negative urgency (-)*, impulsivity–finance is predicted by low EG within person (+), low EG between person (+)***, and the interaction low EG within person × negative urgency (+)
81. Ready et al. (2019)	Emotion experience	(1) Older adults have higher EG than younger persons	Cross-sectional	Sample size: n = 83 (tot); n = 56 (younger adults); n = 27 (older adults) Population: undergraduates (younger adults); general population (older adults) Age: 18–32, M(SD) = 20.21(2.19) (younger adults); 60–92, M(SD) = 71.33(8.11) (older adults) Sex/gender: //	*T-test*: Older adults differentiate more between low arousal NA and high arousal NA items than younger individuals*. In contrast, older adults differentiated significantly less among high arousal PA items than younger individuals* *ANCOVA*: depressive symptoms are correlated with low and high arousal NA correspondence ratings (+)**, low and high arousal PA correspondence ratings (+)*, and high arousal PA and NA correspondence ratings (+)*. Alexithymia does not show significant correlations. Verbal IQ is significantly associated with greater correspondence among high arousal PA items (+)*

82. Schmitt et al. (2024)	Emotion experience	(1) Qualitatively distinct EG states based on state-specific measurement models of emotion ratings can be identified using LMFA (2) Momentary stress is related to the probability of transitioning between EG states (3) Individuals differ in the transitions between EG states (4) Neuroticism and dispositional mood regulation (negative mood repair and positive mood maintenance) predict latent class membership of individuals who differ in transitions between EG states	Longitudinal intensive	Sample size: n = 139 Population: university students and general population Age: M(SD) = 30.52(9.03) Sex/gender: 81% female, 17% male, 2% nonbinary	*LMFA* (identifying latent EG states): three latent EG states for the negative emotions (State 1 = High negative intensity, low EG; State 2 = Low EG between anger and sadness: State 3 = High EG between anger and sadness) and three for the positive emotions (State 1 = High positive intensity, high EG; State 2 = high EG between love, joy, and confidence; State 3 = High positive intensity, high EG) *LMFA* (momentary stress as a predictor of transitions between EG states): higher momentary stress is associated with a higher probability of transitioning from the “high EG between anger and sadness” state to the “high negative intensity, low EG” and “low EG between anger and sadness” states and a lower probability of transitioning from the “high negative intensity, low EG” and “low EG between anger and sadness” states to the “high EG between anger and sadness” state *MIXTURE LMFA* (identifying and predicting latent classes of individuals who differ in state transitions): Class C1_neg is characterized by lower probabilities of remaining in a particular state than Class C2_neg. Class C2_neg showed a very high overall probability of transitioning to or remaining in the “high negative intensity, low EG” state, a low to moderately high probability of transitioning to or remaining in the “low EG between anger and sadness” state, and low probabilities of transitioning to or remaining in the “high EG between anger and sadness” and “no negative emotions” states. Each between-person covariate significantly predicts class membership. Individuals with low neuroticism scores has a very high probability of being in the “variability in negative EG” class, but this probability

					decreases as neuroticism increases (while the probability of being in the "high negative intensity, low EG" class increases). In contrast, individuals with low scores on negative mood repair or positive mood maintenance have high probabilities of being in the "high negative intensity, low EG" class, and these probabilities decrease as scores on either of these variables increase
83. Seah, Almahmoud, et al. (2022)	Adaptive behaviors	(1) Negative EG moderates the association between NA and medication adherence	Longitudinal intensive	Sample size: n = 27 Population: multiple sclerosis sufferers Age: M(SD) = 36.11(8.88) Sex/gender: 74.1% female	*Correlational analysis*: correlation between negative EG and medication adherence (+)* and NA (-) *Regression analysis*: controlling for NA, negative EG does not predict medication adherence (+) *Moderation analysis*: NA interacts with negative EG in predicting medication adherence (+)*: among individuals with low negative EG, mean NA predicted poorer adherence
84. Seah, Sidney, et al. (2022)	Maladaptive behaviors	(1) Negative EG and polarity are negatively associated with substance use and binge eating (2) This association is not hypothesized for positive EG	Longitudinal intensive	Sample size: n = 199 Population: recruited via Qualtrics Panel Age: M(SD) = 50.42(16.06) Sex/gender: 55% female	*Correlational analysis*: correlation between negative EG and age (+)**, NA (-), PA (-), positive EG (+)**, emotion polarity (+)**, substance use (+), binge eating (-); correlation between negative EG and age (+)*, NA (-)*, PA (+), emotion polarity (+)*, substance use (+), binge eating (-) *ZINB mixed effects model–count of days engaging behavior model*: substance use is not predicted by neither negative (+) nor positive (+) EG, controlling for both positive and NA, and emotional polarity; binge eating is not predicted by neither negative (+) nor positive (+) EG, controlling for both positive and NA, and emotional polarity

					ZINB mixed effects model–likelihood of not engaging behavior at all model: substance use is predicted by negative EG (+)** but not by positive EG (-), controlling for both positive and NA, and emotional polarity; binge eating is predicted by negative EG (+)* but not by positive EG (+), controlling for both positive and NA, and emotional polarity
85. Seah & Coifman (2024)	Emotion experience	(1) Scaffolding emotion language use during affect labeling (i.e., initial provision of emotion word prompts followed by free response) impacts EG and psychological health	Crossover: Intervention (RCT) + Longitudinal intensive + Repeated measures	Sample size: n = 83 Population: college students Age: M(SD) = 19.75(1.55) Sex/gender: 86.7% female	*Correlational analysis*: correlation between dispositional negative EG–ICC and psychological symptoms at T0 (-), stress at T0 (+), trait anxiety (-), trait emotional clarity (+), mean affect valence at T1 (-), mean state emotional self-efficacy at T3 (+), mean affect valence at T3 (-), mean state ESE (-); correlation between dispositional positive EG–ICC and psychological symptoms at T0 (-), stress at T0 (-), trait anxiety (+), trait emotional clarity (-), mean affect valence at T1 (-), mean state emotional self-efficacy at T1 (-), mean affect valence at T3 (-), mean state emotional self-efficacy at T3 (-), dispositional negative EG–ICC (+); correlation between dispositional negative EG–SI and psychological symptoms at T0 (-), stress at T0 (-), trait anxiety (+), trait emotional clarity (+), mean affect valence at T1 (-)**, mean state emotional self-efficacy at T1 (-), mean affect valence at T3 (-)**, mean state emotional self-efficacy at T3 (-), dispositional negative EG–ICC (-), dispositional positive EG–ICC (-); correlation between dispositional positive EG–SI and psychological symptoms at T0 (-), stress at T0 (+)*, trait anxiety (+), trait emotional clarity (-), mean affect valence at T1 (+), mean state emotional self-efficacy at T1 (-), mean affect valence at T3 (+), mean state emotional self-efficacy at T3 (+), dispositional negative EG–ICC

						(-), dispositional positive EG–ICC (-), dispositional negative EG–SI (+) *T-test*: negative EG–SI scores are significantly higher in the Scaffolding than Control group*. There are no significant group differences in positive EG–SI, negative EG–ICC, positive EG–ICC *Multilevel analysis*: negative momentary EG–ICC is predicted by person-centered affect valence (-)***, group (+), mean affect valence (-), time × group (-). Positive momentary EG–ICC is predicted by person-centered affect valence (+)***, group (+), mean affect valence (-), time × group (-). Negative momentary EG–SI is predicted by person-centered affect valence (-), group (+), mean affect valence (-)**, word count (+)***, time × group (+). Positive momentary EG–SI is predicted by person-centered affect valence (+), group (+), mean affect valence (+), word count (+)*, time × group (+).
86.	Seah et al. (2020), Study 1	Social behaviors	(1) Negative EG moderates the positive association between rumination and social avoidance	Longitudinal intensive	Sample size: n = 23 (+ 31 diagnosed with social anxiety disorder) Population: general population and patients in clinics Age: M(SD) = 32.0(12.59) ° Sex/gender: 87% female °°	*Paired contrasts*: the clinical group reports lower negative EG compared to healthy controls*
87.	Seah et al. (2020), Study 2	Social behaviors	(1) Negative EG moderates the positive association between rumination and social avoidance	Longitudinal intensive	Sample size: n = 193 Population: college students	*Regression analysis*: negative EG predicts social avoidance (-)** controlling for NA and rumination

				Age: M(SD) = 20.07(2.39) Sex/gender: 79.3% female	*Moderation analysis*: negative EG predicts social avoidance (-)**, rumination interacts with negative EG in predicting social avoidance (-)** controlling for NA: for low differentiators, higher rumination predicts higher frequency of social avoidance
88. Sels et al. (2024), Study 1	Emotion experience	(1) Social sharing positively predicts EG (2) This relationship is moderated by rumination	Longitudinal intensive	Sample size: n = 90 Population: general population Age: M(SD) = 32.55(10.99) Sex/gender: 50% female	*Multilevel analysis*: controlling for NA (-)*** and lagged negative EG (-)**, momentary social sharing does not predict momentary negative EG (+) *Multilevel analysis with moderation*: controlling for NA (-)*** and lagged negative EG (-)**, momentary social sharing (+) and rumination (+) do not predict momentary negative EG, neither does the interaction social sharing × rumination (-)
89. Sels et al. (2024), Study 2	Emotion experience	(1) Social sharing positively predicts EG (2) This relationship is moderated by rumination	Longitudinal intensive	Sample size: n = 200 (wave 1); n =187 (wave 2); n =171 (wave 3) Population: university students Age: M(SD) = 35.23(11.87) Sex/gender: 55% female (wave 1); 56% female (wave 2); 55% female (wave 3)	*Multilevel analysis*: controlling for NA (-)*** and lagged negative EG (+), momentary social sharing does not predict momentary negative EG (-) *Multilevel analysis with moderation*: controlling for NA (-)*** and lagged negative EG (+), momentary social sharing (+) does not predict momentary negative EG, while both rumination (+)*** and the interaction social sharing × rumination (-)*** does
90. Sels et al. (2024), Study 3	Emotion experience	(1) Social sharing positively predicts EG (2) This relationship is moderated by rumination	Longitudinal intensive	Sample size: n = 100 Population: university students Age: M(SD) = 18.64(1.45)	*Multilevel analysis:* controlling for NA (-)*** and lagged negative EG (+)***, momentary social sharing predicts momentary negative EG (-)** *Multilevel analysis with moderation*: controlling for NA (-)*** and lagged negative EG (+)***, rumination (-)* predicts momentary negative EG, while momentary social sharing (+) and the

				Sex/gender: 86% female	interaction social sharing × rumination (-) does not
91. Sels et al. (2024), Study 4	Emotion experience	(1) Social sharing positively predicts EG (2) This relationship is moderated by rumination	Longitudinal intensive	Sample size: n = 197 Population: general population Age: M = 18.32 (wave 1); M = 18.64 (wave 2); M = 19.28 (wave 3) Sex/gender: 79% female	*Multilevel analysis*: controlling for NA (-)*** and lagged negative EG (+)***, momentary social sharing predicts momentary negative EG (-)*** *Multilevel analysis with moderation*: controlling for NA (-)*** and lagged negative EG (+)***, rumination (-)*** and the interaction social sharing × rumination (-)*** predict momentary negative EG, while momentary social sharing (-) does not.
92. Sheets et al. (2015)	Maladaptive behaviors	(1) Heavy smokers demonstrate poorer negative EG, as well as greater negative emotion intensity and emotion lability (2) No differences are expected in positive EG (3) Poorer differentiators are more likely to report smoking to regulate affect	Longitudinal intensive	Sample size: n = 30 Population: community sample Age: M = 37.47 Sex/gender: 30% female	*Correlational analysis*: correlation between negative EG and positive EG (+), NA (-)**, PA (+)*, negative emotion lability (-)***, positive emotion lability (-)**, smoking dependence–primary motives (-), smoking dependence–secondary motives (-)**, smoking dependence–negative reinforcement (-)*, smoking dependence–positive reinforcement (-)*; correlation between positive EG and NA (-), PA (-), negative emotion lability (-), positive emotion lability (-)***, smoking dependence–primary motives (-), smoking dependence–secondary motives (-), smoking dependence–negative reinforcement (-), smoking dependence–positive reinforcement (-) *T-test:* no differences in negative EG between heavy smokers and light smokers, no differences in positive EG between heavy smokers and light smokers
93. Springstein et al. (2023)	Emotion experience	(1) People are more differentiated and clearer about their emotions in social situations (vs. alone) (2) Older adults, people higher in extraversion, and those generally	Longitudinal intensive	Sample size: n = 277 Population: community sample	*Correlational analysis* (within person): correlation between momentary negative EG and momentary positive EG (+)**, clarity (-)*, negative emotions (-)**, positive emotions (+)**, social context (-), familiarity (+)**; correlation between

higher in social connectedness are more differentiated and clearer in their emotions in social situations than those who are younger, lower in extraversion, and lower in social connectedness (3) Results for effects of being with others (vs. alone) hold when accounting for familiarity of situations (4) Individuals experience more differentiated and clearer emotions when they are in familiar situations (5) These effects are stronger for older adults compared to younger adults (6) Different types of operationalizations of social context (i.e., only counting current social interactions, time since the last interaction), gender, and Big Five personality traits beyond extraversion play a role in how momentary EG and emotional clarity relate to social and familiar contexts (7) There are cross-lagged associations between EG or clarity, and social or familiar contexts (8) Contemporaneous effects emerge once cross-lagged effects were accounted for	Age: 25–84, M(SD) = 52.81(15.93) Sex/gender: 57.6% female	momentary positive EG and clarity (-)*, negative emotions (-)**, positive emotions (+), social context (-)**, familiarity of the situation (+)** *Correlational analysis* (between person): correlation between momentary negative EG and momentary positive EG (+)*, clarity (+), negative emotions (-)**, positive emotions (+)*, social context (-), familiarity of the situation (+), age (+), extraversion (+), social connectedness (+), loneliness (-), social support (+); correlation between momentary positive EG and clarity (-), negative emotions (-), positive emotions (+), social context (-), familiarity (+), age (+)*, extraversion (+), social connectedness (+), loneliness (-), social support (-) *Multilevel SEM* (association between social context and momentary negative EG on a within-person level, to test whether social context is associated with higher EG): being in a social situation is not related to momentary negative EG (+), while it is associated with momentary positive EG (-)*** *Multilevel SEM* (association between social context and momentary negative EG on a between-person level, to test whether social context is more strongly associated with higher EG for people who are older, more extraverted, or more socially connected): age (-/-), extraversion (-/-) or social connectedness (+/-) are associated with the strength of the association between social context and negative EG or positive EG *Multilevel SEM* (association between familiarity of the situation and momentary negative EG on a within-person level, to test to test whether familiarity of the situation is associated with higher EG): familiarity of the situation is not

					associated with momentary negative EG (+), but it is associated with momentary positive EG (+)*** *Multilevel SEM* (association between social context and momentary negative EG on a between-person level, to test whether familiarity of the situation is more strongly associated with higher EG for people who are older, more extraverted, or more socially connected): age is not associated with increased strength of the association between negative EG and familiarity of the situation (-), but it is associated with increased strength of the association between positive EG and familiarity of the situation (+)**
94. Starr et al. (2017), Study 1	Wellbeing and mental health	(1) Low negative EG predicts stronger associations between daily negative experiences and daily depressive symptoms (2) Low positive EG predicts stronger associations between daily positive experiences and reductions in daily depressive symptoms (3) Low negative EG predicts stronger associations between daily brooding and daily depressive symptoms (4) Low positive EG predicts stronger associations between daily savoring and reduced daily depressive symptoms	Longitudinal intensive	Sample size: n = 157 Population: undergraduates Age: M(SD) = 20.1(1.23) Sex/gender: 81% female	*Multilevel analysis*: controlling for negative experiences, negative EG does not predict daily depressive symptoms (-), neither does the interaction negative EG × negative experiences within-person (-), while the interaction negative EG × negative experiences between-person predicts depressive symptoms (+)* *Multilevel analysis*: controlling for positive experiences, positive EG does not predict daily depressive symptoms (+), neither does the interaction positive EG × positive experiences between-person (+), while the interaction positive EG × positive experiences within-person predicts depressive symptoms (+)**: negative association between daily uplifts and daily depressive symptoms is stronger when positive EG is low (-)***, in contrast, uplifts did not significantly predict reductions in depressive symptoms when positive EG is high (-) *Multilevel analysis*: controlling for daily brooding, negative EG does not predict depressive symptoms (-), neither does the interaction negative EG × brooding between-person (-), while

					the interaction negative EG × brooding within-person predicts depressive symptoms (-)*: reports of daily brooding are more predictive of same-day depressive symptoms at low levels of negative EG (+)*** as compared to high levels(+)*** *Multilevel analysis*: controlling for daily savoring, positive EG does not predict daily depressive symptoms (+), neither does the interaction positive EG × daily savoring between-person (-), while the interaction positive EG × savoring within-person predicts depressive symptoms (+)***: daily savoring more strongly predicted lower depressive symptoms for those with low positive EG (-)*** compared to those with high positive EG (-)**
95. Thompson, Springstein, et al. (2021)	Wellbeing and mental health	(1) To examine EG in conjunction with elevated negative and diminished positive emotional intensity, which are both cardinal symptoms of major depression disorder (2) To explore whether people low in EG use more general state terms (e.g., bad) and fewer emotion terms (e.g., anger) to describe their emotional experience	Longitudinal intensive	Sample size: n = 87 (+ 80 remitted from major depressive disorder, and 48 diagnosed with major depressive disorder) Population: // Age: 18–77, M(SD) = 44.3(16.1) °° Sex/gender: 66% women °°	*ANOVA*: healthy controls show higher negative EG compared to both remitted depressed and current depressed individuals*; healthy controls show higher positive EG compared to both remitted depressed and current depressed individuals*
96. Tong & Keng (2017)	Mindfulness	(1) To test the mediating role of both positive and negative ER in the relationship between trait mindfulness and negative EG (2) To test the mediating role of appraisal differentiation	Longitudinal intensive	Sample size: n = 395 Population: undergraduates Age: M(SD) = 22.08(1.36)	*Correlational analysis*: correlation between negative EG and mindfulness (+)*, appraisal differentiation (+)*, maladaptive ER (-)**, adaptive ER (+), understandability (+)**, predictability (+), perceived pleasantness (+)* *Mediation analysis*: controlling for personality traits, direct effect of mindfulness on negative EG (+), indirect effect of mindfulness on negative EG

(3) To test whether the Five-Factor Model domains render trait mindfulness redundant, and whether negative EG instead mediates the relationship between trait mindfulness and appraisal differentiation	Sex/gender: 61% female	via appraisal differentiation (+)** (the higher mindfulness, the higher appraisal differentiation, the higher negative EG), maladaptive ER (+)** (the higher mindfulness, the lower maladaptive ER, the higher negative EG), adaptive ER (-); concerning personality traits as covariates, extraversion predicted negative EG (-)*, while neuroticism (+), conscientiousness (-), agreeableness (-), and openness (+) do not *Mediation analysis*: negative EG does not mediate the association between mindfulness and appraisal differentiation (+), but it mediates the one between mindfulness and maladaptive ER (-)** (the higher mindfulness, the higher negative EG, the lower maladaptive ER) *Mediation analysis*: the direct effect of mindfulness on negative EG is not significant (+), while the effect of mindfulness on negative EG is mediated by self-appraisal (+)** (the higher mindfulness, the higher self-appraisal, the higher negative EG), other appraisal (+), and circumstances appraisal (+)** (the higher mindfulness, the lower circumstances appraisal, the higher negative EG) *Mediation analysis*: the direct effect of mindfulness on negative EG is not significant (+), while the effect of mindfulness on negative EG is mediated by appraisal differentiation (+)** (the more mindfulness, the more appraisal differentiation, the more negative EG), maladaptive ER (-)** (the more mindfulness, the less maladaptive ER, the more negative EG), adaptive ER (+), self-appraisal (+), other appraisal (-), and circumstances appraisal (+)

97. Tugade et al. (2004), Study 2	Wellbeing and mental health	(1) Positive EG is associated with useful coping styles to manage stress	Longitudinal intensive	Sample size: n = 130 Population: // Age: // Sex/gender: 53% female	*Correlational analysis*: correlation between positive EG and acceptance (+), active coping (-), behavioral disengagement $(+)^{*}$, denial (+), emotional support (+), humor (-), instrumental support (-), positive reframing (+), religion (-), self-blame (-), self-distraction $(-)^{**}$, substance use (+), venting (-), experiential ability $(-)^{*}$, experiential engagement $(-)^{*}$, rational ability (+), rational engagement (+)
98. Van Der Gucht et al. (2019)	Mindfulness	(1) After a mindfulness-based intervention participants show an improvement in negative and positive EG (2) This improvement in EG is mediated by an improvement in mindfulness skills (3) There is a mediating role of the different facets of mindfulness	Intervention	Sample size: n = 61 Population: adults from a stress clinic Age: 22–65, M(SD) = 42(9.9) Sex/gender: 68 females	*Correlational analysis*: at baseline, correlation between negative EG and positive EG $(-)^{**}$, mindfulness trait $(+)^{*}$, mindfulness state (+), NA $(-)^{**}$, PA (+), emotional distress $(-)^{*}$; at baseline, correlation between positive EG and mindfulness trait (+), mindfulness state (-), NA (-), PA (+), emotional distress (+) *Multilevel analysis*: negative EG improves from T1 to $T2^{*}$ and to $T3^{*}$, but these effects are no longer significant after controlling for NA; positive EG improves only from T1 to $T3^{*}$, and this effect remains significant* after controlling for PA *Multilevel analysis*: neither trait nor state mindfulness change mediates the change in positive EG; controlling for negative EG, both trait $(+)^{\dagger}$ and state $(+)^{**}$ mindfulness change mediates the change in negative EG *Multilevel analysis*: the facets of mindfulness state mediating the change in negative EG are acceptance/decentering** (no effect of attention/awareness), while the facets of mindfulness trait mediating the change in negative EG are accepting**, decentering**, and openness** (no effect of awareness of internal experiences,

					awareness of external experiences, acting with awareness, relativity, insightful understanding)
99. Vandercammen et al. (2014), Study 1	Cognitive processes	(1) To test the moderating role of EG on the relationship between twelve specific emotions and intrinsic motivation	Longitudinal intensive	Sample size: n = 71 Population: employees and trainees Age: M(SD) = 37.06(10.79) Sex/gender: 34 women	*Correlational analysis*: correlation between negative EG and enthusiastic (-), cheerful (-), optimistic (-), contented (-), calm (+), relaxed (+), tense (+), gloomy (+)* depressed (+)*, worried (-), miserable (+)**, uneasy (+), positive EG (+)**, and intrinsic motivation (-); correlation between positive EG and enthusiastic (-), cheerful (+), optimistic (+), contented (-), calm (+), relaxed (+), tense (+), gloomy (+), depressed (-), worried (+), miserable (-), uneasy (+), and intrinsic motivation (-) *Multilevel moderation analysis*: a negative moderation effect is found for tenseness (-)*, depression (-)**, worry (-)*, miserableness (-)** and uneasiness (-)**, while the moderation effect for gloominess is marginally significant (-)†. Positive EG positively moderates the relation between enthusiasm (+)**, cheerfulness (+)**, contentedness (+)**, calmness (+)** and relaxation (+)** on one hand and intrinsic motivation on the other hand, while the moderation effect for optimism is marginally significant (+)†
100. Vandercammen et al. (2014), Study 2	Cognitive processes	(1) To test the moderating role of EG on the relationship between twelve specific emotions and intrinsic motivation	Longitudinal intensive	Sample size: n = 34 Population: employees Age: M(SD) = 40.71(14.13) Sex/gender: 26 women	*Correlational analysis*: correlation between negative EG and enthusiastic (+), cheerful (+), optimistic (-), contented (+), calm (+), relaxed (+), tense (-), gloomy (-) depressed (-), worried (-), miserable (-), uneasy (-), positive EG (+), and intrinsic motivation (-); correlation between positive EG and enthusiastic (+), cheerful (+), optimistic (-), contented (+), calm (-), relaxed (-), tense (-), gloomy (-), depressed (-), worried (+), miserable (-), uneasy (+), and intrinsic motivation (+)**

					Multilevel moderation analysis: for negative EG, the moderation effect approached conventional levels of significance for gloominess (-)[†], miserableness (-)[†], and uneasiness (-)[†]. Positive EG, in turn, positively moderated the relationship between enthusiasm (+)[**], cheerfulness (+)[*], optimism (+)[*], and contentedness (+)[*] and intrinsic motivation. No moderation effect is found for calmness (+), relaxation (+), tenseness (-), depression (-), and worry (-)
101. Vedernikova et al. (2021)	Emotion experience	(1) The emotion knowledge intervention (vs. a control condition) leads to an increase in EG at the between-person level (2) Participants in the experimental condition have a larger increase in EG from T1 to T2 compared to the participants in the control condition (3) Intervention effects are still present at T3	Intervention (RCT)	Sample size: n = 60 Population: recruited via Prolific Platform Age: 18–74, M(SD) = 35.67(13.43) Sex/gender: 58 women	*ANOVA* (positive EG): There is no interaction between time and condition, meaning that the emotion knowledge manipulation did not produce any significant changes in the experimental condition as compared to the control condition *ANOVA* (negative EG): There is a significant[***] interaction between time and condition, meaning that the emotion knowledge manipulation produced significant changes in the experimental condition as compared to the control condition: participants in the experimental condition improved their negative EG more than participants in the control condition. The level of negative EG significantly differed between all three time points: T1 from T2[***], T1 from T3[**], and T2 from T3[*]; it increased from T1 to T2 and decreased from T2 to T3, however at T3 it is still higher than at T1. There is no effect of time for the control group
102. Ventura-Bort et al. (2021)	Emotion experience	(1) Individual differences in interoceptive sensibility and emotional conceptualization interact to moderate emotional intensity, arousal, and EG	Repeated measure	Sample size: n = 157 Population: university students Age: M(SD) = 25.92(8.39)	*Correlational analysis* (EG measured via ED task): correlation between negative EG and emotional intensity (+)[**], arousal (+), positive EG (+)**; correlation between positive EG and emotional intensity (+), arousal (-)

				Sex/gender: 135 women	*Correlational analysis* (EG measured via DRM): correlation between negative EG and emotional intensity (-), positive EG (+); correlation between positive EG and emotional intensity (+) *Multiple regression analysis*: negative EG is not predicted either by the sensibility score (i.e., sensibility toward perceiving physiological changes and emotion) (-), or by the monitoring score (i.e., perceptions about attentional resources devoted to physiological and emotional aspects) (-), or by their interaction (-). Positive EG is not predicted either by the sensibility score (i.e., sensibility toward perceiving physiological changes and emotion) (+), nor by the monitoring score (i.e., perceptions about attentional resources devoted to physiological and emotional aspects) (+), or by their interaction (+) *Multiple regression analysis*: positive EG is predicted by monitoring (-)*, but not by sensibility (-)* or their interaction (-). Negative EG is predicted by monitoring (-)**, sensibility (+)*, but not their interaction ()*
103. Wabnegger et al. (2024)	Cognitive processes	(1) Individuals with lower EG are more likely to endorse conspiracist ideation (2) Conspiracist ideation is differentially related to performance-based and self-reported measures of EG (3) There is a significant relationship between dysfunctional ER and conspiracist ideation	Longitudinal intensive	Sample size: n = 165 Population: university students and general population Age: M(SD) = 26.32(11.02) Sex/gender: 39 males, 122 females	*Regression analysis*: self-reported EG is predicted by age (+)***, clarity of own feelings ()***, but not by conspiracist ideation (+) *Multilevel analysis*: performance-based EG is predicted by depression (+)* and generic conspiracy beliefs (-)*, but not by gender (+), age (-), anxiety (-), emotional self-awareness(-), clarity of own feelings (+)
104. Walters et al. (2023)	Maladaptive behaviors	(1) Momentary PA and NA to are positively associated with	Longitudinal intensive	Sample size: n = 37	*Multilevel analysis*: Neither positive nor negative EG influence cigarettes craving. Negative EG

		momentary nicotine craving at the within-person level (2) Both positive and negative EG attenuate the associations between momentary PA and NA and craving		Population: young adults interested in quitting smoking or vaping Age: 18–25, M(SD) = 21.0(2.1) Sex/gender: 51% female	interact with NA (-)** and PA (-)* in predicting cigarette craving; the interaction between positive EG and NA is not significant (-), while the interaction between positive EG and PA is marginally significant (+)†
105. Walukevich-Dienst et al. (2023)	Maladaptive behaviors	(1) On days participants reported higher NA, participants with lower trait-levels of negative EG are more likely to report craving and use of cannabis, more intense cravings, and higher day-level coping motives, more hours high, and more negative consequences across cannabis use days	Longitudinal intensive	Sample size: n = 409 Population: general population Age: 18–25, M(SD) = 21.6(2.17) Sex/gender: 50.91% female	*Multilevel analysis*: negative EG does not predict cannabis use (-), number of hour high (-), or number of negative consequences (-); the interaction between negative EG and NA (between-person) does not predict cannabis use (+), number of hour high (-), or number of negative consequences (+); the interaction between negative EG and NA (within-person) does not predict cannabis use (-), number of hour high (+), or number of negative consequences (+) *Multilevel analysis*: cannabis craving across all sampled days is not predicted by negative EG (+), nor by the interaction between negative EG and NA (between person) (+) but is predicted by the interaction between negative EG and NA (within person) (+)***. Intensity of craving on days that craving is reported is not predicted by negative EG (+), nor by the interaction between negative EG and NA (between person) (-) but is predicted by the interaction between negative EG and NA (within person) (+)*. Coping motives is not predicted by negative EG (+), but is predicted by the interaction between negative EG and NA (between person) (+)***, and by the interaction between negative EG and NA (within person) (+)***

106. Wang, Liao, et al. (2020)	Emotion experience	(1) Positive EG modulates the parietal LPP amplitude difference between positive reappraisal and control conditions, such that individuals with high positive EG have more increased valence and arousal in the positive reappraisal condition compared to controls (2) Individuals with high positive EG display higher parietal LPP amplitude during positive reappraisal compared to controls in the late time windows (3) The generator of parietal LPP related to cognitive reappraisal also differs between the two groups	Cross-sectional	Sample size: n = 36 Population: undergraduates and postgraduates Age: 18–25, M(SD) = 22.81(1.70) Sex/gender: 26 women	*ANOVA* (valence and arousal ratings): no main effect of positive EG level or an interaction between trial type and positive EG level for the valence ratings or arousal ratings *ANOVA* (LPP amplitude): main effect of positive EG*, such that high positive EG individuals show larger LPP. Interaction positive EG × trial type: the high- positive EG group presented the regulation effect (+)* and the emotion effect (+)*, while for the low- positive EG group no effects are found. A three-way interaction effect among trial type, positive EG level, and time window (+)** is found
107. Wang, Shangguan, et al. (2020)	Emotion experience	(1) Negative EG positively predicts resting frontal alpha asymmetry and negatively predicts slow/fast wave ratio	Cross-sectional	Sample size: n = 40 Population: undergraduates and postgraduates Age: 18–26, M(SD) = 21.84(1.65) Sex/gender: 25 women	*Correlational analysis*: correlation between negative EG and FP2–FP1 (+)*, F4–F3 (+)*, F8–F7 (+)*, theta/beta-F3 (-)*, theta/beta-F4 (-)*, theta/beta-FZ (-)* *Multiple regression analysis* (frontal alpha asymmetry): negative EG significantly predicted the level of alpha asymmetry at prefrontal electrodes pairs (+)*, while indicators of parietal alpha asymmetry at CP2–CP1 (+), P4–P3 (+), and P8–P7 (-) are not predicted by negative EG *Multiple regression analysis* (Theta/Beta Ratios): negative EG significantly predicted TBR at F3 (-)* and FZ (-)* electrode sites, but the theta/beta ratio at F4 could not be significantly predicted by negative EG (-). Negative EG could not predict the theta/beta ratio at the P3 (-), P4 (-), or PZ (-) electrode sites

108. Wang et al. (2024)	Emotion experience	(1) Individuals with high negative EG present diminished parietal LPP amplitudes when using CR to alleviate negative emotions and exhibit higher frontal LPP amplitudes and stimulus-preceding negativity during the cognitive reappraisal process (2) The expected increase in frontal LPP amplitudes and SPNs corresponds to the cognitive demands of reappraisal	Experimental	Sample size: n = 38 Population: graduate students Age: 18–24, M(SD) = 22.68(1.73) (females); M(SD) = 22.62(1.93) (males) Sex/gender: 22 females	*ANOVA* (behavioral assessment: group × task): no group difference in either regulatory effect (-) or the emotional effect (-) of valence. Group difference* in the regulatory effect for arousal: individuals with high negative EG are more effective in reducing their arousal. No group difference in the emotional effect for arousal. No effect group (high negative EG vs. low negative EG) × task (unpleasant-view vs. unpleasant-reappraise vs. neutral-view vs. neutral-reappraise) on neither valence nor arousal *ANOVA* (ERP assessment: group × task × time): The high negative EG group show a regulation effect, characterized by lower LPP amplitude under unpleasant-reappraise conditions than under unpleasant-view conditions within T2*, T3*, T4*. The low negative EG group does not show any regulation effect. The high negative EG group show an emotional effect, characterized by a higher LPP amplitude in the unpleasant-view compared to the neutral-view condition, within T1* and T2**. The low negative EG group show an emotional effect, characterized by a higher LPP amplitude in the unpleasant-view compared to the neutral-view condition, within T2**. Group difference for regulatory effect within T2*, T3*, T4**, T5*, T6†: the high negative EG group exhibited a greater regulatory effect than the low negative EG group. No significant differences in the emotional effects between groups. Interaction effect group × task*: high negative EG individuals, but not negative EG individuals, presented a significantly lower LPP amplitude in the unpleasant-reappraise condition compared to unpleasant-view condition. For stimulus-preceding negativity, no significant three-way

					interaction is observed between group, task, and time
109. Williams & Uliaszek (2022)	Wellbeing and mental health	(1) EG is negatively associated with indices of psychopathological symptom severity (i.e., depression, stress, borderline personality disorder symptoms, anxiety) and ER difficulties	Repeated measure	Sample size: n = 307 Population: undergraduates and people recruited via Mturk Age: 18–65, M(SD) = 23.87(10.54) Sex/gender: 70.8% female	*Correlational analysis* (EG indices): correlation between SI-past and EG–NS-past (+)*, EG–SI-present (+), EG–NS-present (+), EG–ICC (+); correlation between NS-past and EG–SI-present (+), EG–NS-present (+), EG–ICC (-); correlation between EG–SI-present and EG–NS-present (+)*, EG–ICC (-); correlation between EG–NS-present and EG–ICC (+) *Correlational analysis* (EG indices and outcomes): correlation between ER difficulties and EG–SI (-), EG–NS (-), EG–ICC (-)*; correlation between depression and EG–SI (-), EG–NS (-), EG–ICC (-)*; correlation between anxiety and EG–SI (-), EG–NS (-), EG–ICC (-)*; correlation between stress and EG–SI (-), EG–NS (-), EG–ICC (-)*; correlation between borderline symptoms and EG–SI (-), EG–NS (-)*, EG–ICC (-)*; correlation between NA and EG–SI (-), EG–NS (-), EG–ICC (-)* *Regression with commonality analysis*: difficulties in ER is predicted by EG–ICC (-)***, but not by EG–SI (+) or EG–NS (-); when controlling for affect intensity, EG–SI (-), EG–NS (+), and EG–ICC (-) are not significant, while affect intensity is significant (+)**. Averaged depression, anxiety and stress scores are predicted by EG–NS (-)* and EG–ICC (-)**, but not by EG–SI (+); when controlling for affect intensity, EG–SI (+), EG–NS (-), and EG–ICC (-) are not significant, while affect intensity is significant (+)**. Borderline symptoms are predicted by EG–NS (-)* and EG–EG–ICC (-)**, but not by EG–SI (+); when controlling for affect intensity, EG–SI (-), EG–NS

					(-), and EG–ICC (-) are not significant, while affect intensity is significant (+)**
110. Williams-Kerver & Crowther (2020)	Eating behaviors and body image	(1) Low negative and positive EG are associated with more severe eating disorder symptomatology (2) These relationships are strengthened at higher levels of appearance schemas (3) Low negative and positive EG are associated with the engagement in daily disordered eating behaviors (4) Baseline scores for appearance schemas moderate these daily relationships	Longitudinal intensive	Sample size: n = 118 Population: undergraduates Age: M(SD) = 19.39(1.56) Sex/gender: 100% female	*Correlational analysis*: correlation between negative EG and positive EG (+)**, NA (-), PA (-), eating disorder symptoms (-)*, binge eating (-), compensatory behaviors (-)**, appearance schema (+); correlation between positive EG and NA (+), PA (+)**, eating disorder symptoms (-), binge eating (-), compensatory behaviors (-), appearance schema (-) *Hierarchical regression moderation analysis*: eating disorder symptoms are predicted by negative EG (-)* and its interaction with appearance schemas (-)*, but not by positive EG (+) and its interaction with appearance schemas (+) *Hierarchical regression moderation analysis*: frequency of binge eating is not predicted by negative EG (-), its interaction with appearance schemas (-), positive EG (+), its interaction with appearance schemas (+) *Hierarchical regression moderation analysis*: compensatory behaviors are predicted by negative EG (-) and positive EG (-)**, but not by their interaction (+)
111. Willroth et al. (2020)	Wellbeing and mental health	(1) Depressive symptoms and negative and positive EG are related above and beyond emotion intensity (2) Deficits in negative EG are specific to distinct categories of negative emotions (sadness, guilt, anger, and anxiety)	Longitudinal intensive	Sample size: n = 220 Population: community sample Age: M(SD) = 40.4(11.4) Sex/gender: 59% female	*Correlational analysis*: correlation between depressive symptoms and positive EG (+), negative EG (-)*, sadness-related negative EG (-)*, guilt-related negative EG (-)*, anxiety-related negative EG (-), anger-related negative EG (-)*; correlation between negative EG and negative EG (+), sadness-related negative EG (+), guilt-related negative EG (+), anxiety-related negative EG (+), anger-related negative EG (+), matched mean emotion intensity (-)†; correlation between

(3) Age and gender predict EG and its associations with depressive symptoms

negative EG and sadness-related negative EG (+)*, guilt-related negative EG (+)*, anxiety-related negative EG (+)*, anger-related negative EG (+)*, matched mean emotion intensity (-)*; correlation between sadness-related negative EG and guilt-related negative EG (+), anxiety-related negative EG (+)†, anger-related negative EG (+), matched mean emotion intensity (-)*; correlation between guilt-related negative EG and anxiety-related negative EG (+), anger-related negative EG (+)*, matched mean emotion intensity (-)*; correlation between anxiety-related negative EG and anger-related negative EG (+)*, matched mean emotion intensity (-)†; correlation between anger-related negative EG and matched mean emotion intensity (-)*

Regression analysis: depressive symptoms are associated with significantly lower negative EG (-)**, when controlling for mean negative emotion intensity. The association between depressive symptoms and positive EG remains not statistically significant when controlling for mean positive emotion in tensity (+)

Multiple regression analysis: depressive symptoms are predicted by sadness-related negative EG (-)**, guilt-related negative EG (-)*, the mean intensity of negative emotions (+)***, but not by negative EG (-), anxiety-related negative EG (+), anger-related negative EG (-)

T-test: After controlling for mean emotion intensity, men and women did not significantly differ on any of the EG variables. After controlling for mean emotion intensity, age is not significantly associated with any of the EG variables

					Regression moderation analysis: The interaction terms between age and negative EG are not statistically significant for any of the types of EG (+). The interaction between age and negative EG is marginally significant, such that the negative association between depressive symptoms and negative EG became weaker as age increased
112.Yang (2022)	Wellbeing and mental health	(1) Stressors and NA are associated with lower levels of state optimism (2) PA is associated with higher levels of state optimism (3) Negative EG mitigates the negative associations of stressors and NA to optimism (4) Positive EG strengthens the positive association of PA to optimism (5) The current day's stressor and NA are negatively associated with next day's optimism (6) The current day's PA is positively associated with next day's optimism (7) Negative EG mitigates the negative associations of current day's stressor and NA to next day's optimism (8) Positive EG strengthens the positive association of current day's PA to next day's optimism	Longitudinal intensive	Sample size: n = 248 Population: college students Age: M(SD) = 19.65(3.53) Sex/gender: 72% female	*Correlational analysis*: correlation between negative EG and positive EG (+)***, neuroticism (-), wellbeing (-), optimism (+)***, stressors (-), PA (+), NA (-)***; correlation between positive EG and neuroticism (+), wellbeing (+), optimism (+), stressors (-), PA (-), NA (-) *Multilevel concurrent analysis*: optimism predicted by negative EG (+)** and the interaction PA × positive EG (+)**, but not by positive EG (+), the interaction NA × negative EG (-), the interaction negative EG × stressor (+) *Multilevel lagged analysis*: optimism is predicted by negative EG (+)**, but not by positive EG (+), the interaction stressor × negative EG (+), the interaction lagged stressor × negative EG (+), NA × negative EG (-), PA × positive EG (+)
113.Yang (2023)	Maladaptive behaviors	(1) Daily stressors (a predictor), daily hurt feelings (a predictor), rejection sensitivity (a moderator),	Longitudinal intensive	Sample size: n = 248	*Correlational analysis*: correlation between negative EG and physical aggression (-)*, verbal aggression (-)*, somatic symptoms (-), general

and negative EG (a moderator) predict verbal aggression (2) Rejection sensitivity and negative EG, respectively, moderate the association between each predictor and verbal aggression such that high rejection sensitivity and low EG predict an association between each predictor and verbal aggression (3) Daily stressors, daily hurt feelings, rejection sensitivity, and negative EG predict physical aggression (4) Rejection sensitivity and negative EG, respectively, moderate the association between each predictor and verbal aggression such that high rejection sensitivity and low EG predict an association between each predictor and physical aggression (5) Daily stressors, daily hurt feelings, rejection sensitivity, and negative EG predict somatic symptoms (6) Negative EG moderates the association between each predictor and somatic symptoms such that rejection sensitivity and negative EG would predict an association of each predictor to somatic symptoms	Population: college students Age: M(SD) = 19.65(3.53) Sex/gender: 72% female	health (+), stressors (-), hurt (-)**, rejection sensitivity (-) *Multilevel analysis* (verbal aggression): verbal aggression is predicted by the interaction between negative EG and stressors (+)***, but not by negative EG or the interaction between negative EG and hurt *Multilevel analysis* (physical aggression): physical aggression is not predicted by the interaction between negative EG and stressors, nor by negative EG or the interaction between negative EG and hurt

114. Yue et al. (2024)	Emotion experience	(1) Negative EG is positively correlated with mental health (2) Negative EG positively predicts the affect labeling effect (3) The affect labeling effect mediates the relationship between negative EG and mental health	Experimental + Longitudinal intensive	Sample size: n = 100 Population: university students Age: M(SD) =// Sex/gender://	*ANOVA* (behavioral data): in the affect labeling task, the accuracy of the high negative EG group is significantly higher than that of the low negative EG group***. However, in the artificial or natural labeling task, there is no significant difference in accuracy between the high negative EG group and the low negative EG group. The main effect of the type of participant is not significant *ANOVA* (EEG): compared to the low negative EG group, the high negative EG group showed a significant decrease in the amplitude of LPP induced by affect labeling relative to artificial or natural labeling at the FC, FCZ, CZ, CPZ and PZ sites, indicating the presence of an affect labeling effect. However, in the low negative EG group, there is no significant difference in LPP amplitude between affect labeling and artificial or natural labeling at the FZ and FCZ sites, while at the CZ, CPZ and PZ sites, the LPP amplitude induced by affect labeling is significantly higher than that induced by artificial or natural labeling, and there is no affect labeling effect *Mediation analysis*: negative EG has not a direct effect on general health (-); affect labeling effect mediates this association***
115. Zhang et al. (2021)	Wellbeing and mental health	(1) Positive personality predict life satisfaction via social connectedness (2) Alexithymia predicts life satisfaction via social connectedness (3) EG predicts life satisfaction via social connectedness	Cross-sectional	Sample size: n = 318 Population: undergraduates Age: 18–38, M(SD) = 22.75(3.01) Sex/gender: 49.4% men	*Correlational analysis*: correlation between positive EG and relationship (-), vitality (-), conscientiousness (-), positive personality (-), difficulty in identifying feelings (-), externally oriented thinking (-), alexithymia (-) social connectedness (+), life satisfaction (-) *Regression analysis*: positive EG does not impact life satisfaction (-) or social connectedness (+)

	(4) EG predicts alexithymia	*Path analysis*: positive EG predicts alexithymia (-)**

Note: The results reported refer only to emotional granularity. In studies involving both clinical and nonclinical populations, only the results pertaining to the nonclinical population are presented.

AIC = Average Inter-item Correlation; BMI = Body Mass Index; DRM = Day Reconstruction Method; EC = Emotion Complexity; ED task = Emotion Differentiation task; EEG = Electroencephalogram; EG = Emotional Granularity; EMA = Ecological Momentary Assessment; ER = Emotion Regulation; ERP = Event-related Potential; ICC = Intraclass Correlation; LMFA = Latent Markov Factor Analysis; LPP = Late Positive Potential; NA = Negative Affect; NS = Nuance Score; PA = Positive Affect; PTSD = Posttraumatic Stress Disorder; RCT = Randomized Control Trial; SI = Specificity Index; SNS = Sympathetic Nervous System; VAR = Average Variance.

//indicates missing information in the article; ° indicates that data refers to nonclinical participants; °° indicates that data refers to the whole sample; (+) indicates a positive relationship between variables; (-) indicates a negative relationship between variables; × indicates an interaction effect; * $p < .05$; ** $p < .01$; *** $p < .001$; † $.05 < p < .08$

3. Figures

3.1. Figure S1: Network of Relationships Between Keywords Reported by Included Studies, Accounting for Years in Which the Studies Were Conducted

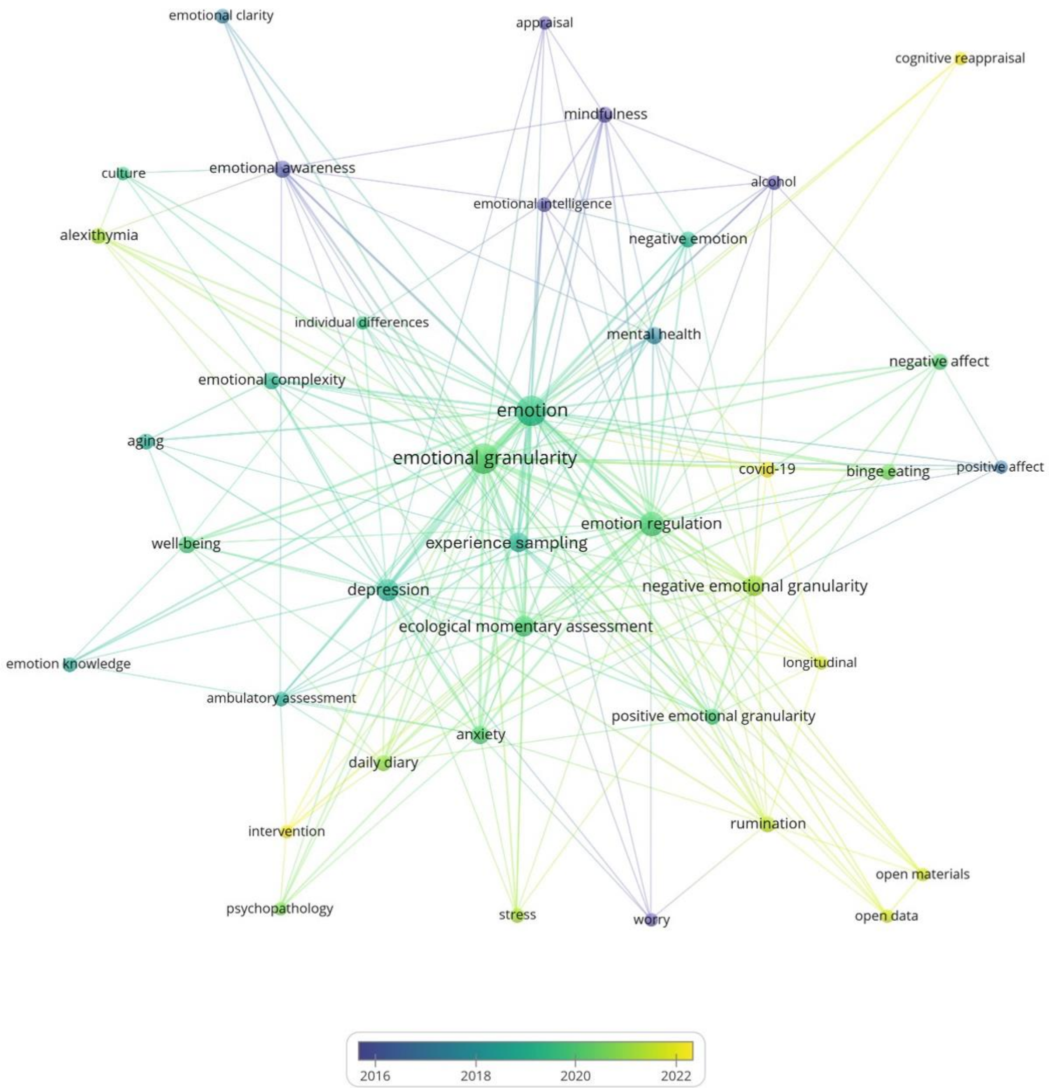

Figure S1. Network of relationships between keywords reported by included studies, accounting for years in which the studies were conducted.
Note: Nodes represent the keywords reported in the included studies. The larger the node size, the more frequently the construct was investigated across the literature. The thicker the edge, the higher the strength of the co-occurrence between two constructs. Node colors represent the time period during which the constructs were studied, allowing for a temporal visualization of research trends.

Chapter 2

Emotional Granularity and Emotion Regulation: Network Modeling of Within-Person Concurrent and Prospective Emotional Dynamics Across Distinct Latent Sleep Profiles

Ilaria Telazzi[1], Michela Zambelli[1], Semira Tagliabue[2], & Stefania Balzarotti[1,3]

[1]Università Cattolica del Sacro Cuore di Milano, Italy

[2]Università Cattolica del Sacro Cuore di Brescia, Italy

[3]Communication Psychology Lab, Università Cattolica del Sacro Cuore di Milano, Italy

Abstract

Emotional granularity (EG) has been theorized to both facilitate and being supported by emotion regulation (ER), yet empirical evidence remains scarce. The primary aim of this study was to investigate the bidirectional associations between positive and negative EG and five ER strategies, controlling for emotional intensity, both concurrently and prospectively. As a second research objective, we further examined these relationships across distinct sleep patterns, conceptualized as markers of allostatic regulation in emotional functioning.

In a 10-day experience sampling study involving 255 participants, multilevel network analysis was used to examine contemporaneous and lagged EG–ER associations. To investigate whether these associations differed as a function of sleep, we then estimated separate multilevel network models across latent sleep profiles, defined by daily sleep quality and hygiene using multilevel latent profile analysis.

Primary findings indicate a clear timescale-dependent pattern that was partially moderated by sleep. Among individuals with good sleep quality and good sleep hygiene, no prospective associations between EG and ER emerged. In contrast, among individuals characterized by poor sleep quality, regardless of sleep hygiene, maladaptive ER strategies predicted subsequent reductions in EG, and reciprocal effects were also observed. At the momentary level, EG–ER associations were largely consistent across sleep profiles and involved both adaptive and maladaptive strategies.

By integrating moment-to-moment emotional experience with daily sleep, this study moves beyond descriptive accounts of emotional functioning to elucidate how EG and ER dynamically relate to one another across multiple timescales and how these dynamics depend on sleep-related well-being. Overall, the results suggest that sleep quality and sleep hygiene exert a limited influence on in-the-moment EG–ER coupling, whereas prospective associations between EG and ER are primarily contingent on sleep quality, advocating its role in sustaining allostatic regulation within emotional functioning.

Keywords: emotional granularity, emotion differentiation, emotion regulation, emotions, sleep, network analysis, latent profile analysis, experience sampling

1. Introduction

The human body constantly regulates its metabolic and physiological resources to meet the demands of daily life. Within a predictive coding framework, this process is conceptualized as *allostatic regulation*, that is, the ongoing prediction and allocation of these resources, based on the integration of interoceptive signals (reflecting autonomic, visceral, hormonal, and immunological processes) and environmental demands (Kleckner et al., 2017; Sterling, 2012). According to the Theory of Constructed Emotion (TCE; Barrett, 2017a; Barrett et al., 2025), emotional experiences can be understood as an experiential correlate of ongoing allostatic regulation. Interoceptive signals generate a continuous background state known as *core affect*, which varies along the dimensions of valence (pleasant–unpleasant) and arousal (activated–deactivated) (Barrett & Bliss-Moreau, 2009; Russell, 2003; Russell & Barrett, 1999). Fluctuations in valence and arousal track the organism's moment-to-moment resource state, signaling the current balance of metabolic and physiological resources and the relative cost or benefit of ongoing conditions (Kleckner et al., 2017). Emotions emerge when the brain interprets and categorizes fluctuations in core affect as emotional states within a given context, drawing upon prior experience and conceptual knowledge (Barrett, 2017a; Barrett et al., 2025).

The precision of this categorization process depends on the individual's level of *emotional granularity* (or emotion differentiation), that is, the ability to differentiate and label distinct emotional experiences with fine-grained specificity (Barrett et al., 2001). Individuals with low emotional granularity (EG) tend to represent affective experiences in broad terms along valence and arousal dimensions, resulting in relatively undifferentiated categorizations of emotional states. Conversely, high EG enables a more nuanced and context-sensitive identification and labeling of emotions. Research has distinguished between positive and negative EG, depending on the valence of the experiences to which it applies, and between dispositional and state-level EG, depending on whether EG is conceptualized as a relatively stable or more transient construct (Thompson, Springstein, et al., 2021). Of note, EG is conceived as an ability: In other words, it not merely consists in the possession of emotion labels or concepts, but it also implies the capacity to apply such labels and concepts to lived experience (Hoemann et al., 2024). For this reason, EG has been assessed using behavioral or performance-based methods rather than standard self-report questionnaires (Kashdan et al., 2015). Most studies have employed intensive approaches such as ecological momentary assessment (EMA): Participants are repeatedly asked to rate their emotions in response to everyday events at random moments during the day (for more details regarding EG measurement, see Thompson, Springstein, et al., 2021).

A growing body of research has examined the implications of EG for the individual's psychological functioning, under the hypothesis of positive outcomes (Erbas et al., 2022; O'Toole et al., 2021; Tan et al., 2022; Thompson, Springstein, et al., 2021). Among such beneficial effects, emerging evidence suggests a relationship between EG and successful emotion regulation (ER), defined as "the efforts to influence which emotions one has, when one has them, and how one experiences or expresses these emotions" (Gross, 2024, p. 5). From a psychological constructionist perspective, emotion regulation cannot be sharply distinguished from emotion generation, as emotions are conceived as continuously constructed mental events rather than discrete, static states (Gross & Barrett, 2011). Within this framework, a key target of emotion regulation is the process by which internal bodily sensations are interpreted, categorized and rendered meaningful in a given context (Barrett et al., 2014; Gross & Barrett, 2011). It has been suggested that the distinction between emotion generation and regulation may lie primarily in the subjective experience of agency or volition. Specifically, emotion generation may refer to instances in which individuals experience little or no sense of agency in assigning meaning to affective states, whereas emotion regulation involves an experienced sense of agency in shaping that meaning (Gross & Barrett, 2011). The specific characteristics and conditions under which meaning of affective experience is constructed can therefore be articulated as distinct ER strategies, that are understood as situated transitions from one mental event to another (Barrett et al., 2014).

In the last decades, an extensive body of research has investigated individuals' habitual use of ER strategies (John & Gross, 2004). This literature has shown that ER strategies differ in their implications for individuals' affective well-being (e.g., experience of more positive and less negative affect), with some strategies (e.g., cognitive reappraisal or social sharing) that have been generally linked to more favorable consequences than others (e.g., suppression or rumination). More recently, experience sampling studies have revealed a similar pattern in within-person relationships between ER strategies and well-being in daily life, even though these relationships are moderated by individual and contextual variables (Brockman et al., 2017; Haines et al., 2016; Nezlek & Kuppens, 2008; Newman & Nezlek, 2022). In this regard, the intensity of emotional experience has emerged as a factor determining the selection of an ER strategy (Kozubal et al., 2023; Wylie et al., 2023).

1.1. The Relationship Between Emotion Granularity and Emotion Regulation

Theoretically, it has been suggested that higher levels of EG facilitate the selection of adaptive ER strategies, since finely differentiated emotional categories may offer more precise targets for regulatory processes (Kashdan et al., 2015; Thompson, Springstein, et al., 2021). Accordingly, it has been proposed that higher EG should be positively related to the use of putatively adaptive strategies (e.g., reappraisal and social sharing; Gross & John, 2003; Rimé et al., 2020) and negatively related to the use of putatively maladaptive strategies (e.g., suppression and rumination; Gross & John, 2003; Nolen-Hoeksema et al., 2008). Although current literature has primarily advanced the hypothesis of a causal link from EG to ER, the reverse direction has been also recently suggested (O'Toole et al., 2021; Sels et al., 2024): Adaptive ER may be employed with the purpose of gaining emotional understanding, thereby fostering higher EG; by contrast, maladaptive ER strategies may hinder emotional awareness, ultimately undermining a nuanced differentiation of emotional states. Of note, emotional intensity may play a non-trivial role in the interplay between EG and ER, as it signals the need to modulate one's current state or initiate goal-directed behaviors (Barrett et al., 2001). Finally, some EG theorists have even speculated that EG itself may function as an ER strategy, enabling individuals to distance themselves from their emotions (Thompson, Springstein, et al., 2021). This hypothesis aligns with a psychological constructionist conceptualization, according to which processes of emotion generation and emotion regulation substantially overlap (Gross & Barrett, 2011). From this perspective, accurately distinguishing among emotional states in a context-sensitive manner can be understood as a process of meaning-making applied to affective experience. As such, EG may constitute an active process through which affective states are interpreted, categorized, and rendered meaningful. Consequently, it may be conceptualized as an ER strategy insofar as it reflects an experienced sense of agency in shaping the meaning of affective experiences.

Although researchers have emphasized the need to clarify the mechanisms through which EG and ER intertwine (Kashdan et al., 2015; Thompson, Springstein, et al., 2021), to date empirical evidence in this regard remains scarce and mixed. A first bulk of studies have focused on dispositional EG (Barrett et al., 2001; Kalokerinos et al., 2019; O'Toole et al., 2021) under the assumption that high trait-level ability to differentiate emotions may provide more sophisticated instrumental knowledge that informs the downstream use of ER strategies (Thompson, Springstein, et al., 2021). For instance, in two experience-sampling studies, Kalokerinos et al. (2019) have examined the association between dispositional negative EG and the selection of momentary adaptive and maladaptive ER strategies. Each ER strategy was modeled separately as an outcome of EG while controlling for the intensity of negative emotions. Contrary to the hypothesis, however, few and inconsistent direct effects of EG were observed, with results varying across strategies and between studies: Granularity showed some associations with cognitive reappraisal, expressive suppression, and rumination; no association with distraction and acceptance; a significant negative association with social sharing. Nonetheless, negative EG moderated the effectiveness of ER strategies (rumination, distraction, acceptance, and social sharing) in downregulating negative emotions: ER strategies were more strongly related to increased negative emotional intensity among low EG compared to high EG individuals.

A smaller subset of studies has focused on state-level EG, claiming that individuals may deviate from their dispositional tendencies on a day-to-day or moment-to-moment basis. This line of research is grounded in the assumption that emotions are inherently situated and episodic phenomena (Frijda, 1986; Gross, 2014) and has emphasized the importance of investigating the EG–ER relationship in light of situation specificity (O'Toole et al., 2021). Along with this line of reasoning, both EG and ER are conceived to vary according to the particular situation (Demiralp et al., 2012; Grühn et al., 2013; Kashdan et al., 2015; O'Toole et al., 2021), and their relationship may therefore unfold within-persons over time (O'Toole et al., 2021). However, similar to research focusing on dispositional EG, results have been inconsistent. For instance, O'Toole et al. (2021) found that dispositional and state-level (daily) negative EG were unrelated to both habitual and daily ER strategy use (i.e., reappraisal, rumination, suppression, experiential avoidance, distancing, reflection, non-reactivity, worry) once the intensity of negative emotions was accounted for. Thus, within-individual daily variations in negative EG and daily ER were not significantly related after controlling for negative emotions. Using data from four daily life studies, Sels et al. (2024) tested whether ER (i.e., social sharing) is a predictor of state-level (momentary) negative EG while controlling for negative emotions. Unexpectedly, their results showed that social sharing predicted *reduced* momentary negative EG. Additionally, rumination moderated this effect: Social sharing was associated with less precision in negative EG when participants ruminated more than usual, whereas it was linked to higher precision in EG when they ruminated less than usual. Finally, the analyses also revealed a link between *lower* EG at a given time point and increased social sharing at the subsequent measurement occasion.

Some important limitations of current research concern the fact that state-level fluctuations in EG have so far received little attention compared to dispositional EG, despite growing emphasis on the view that both EG and ER vary over time and may covary in light of the situated, episodic nature of emotional intensity. Also, most of the existing literature has focused on negative EG, so that the relationship between ER and positive EG has been so far relatively unexplored (Decker et al., 2008; O'Toole et al., 2014; Wang, Liao, et al., 2020). Little self-report research has been conducted on non-clinical adult samples, yielding no significant evidence of a link between positive EG and ER (Barrett et al., 2001). Additionally, to our knowledge, previous studies have examined dispositional positive EG, whereas no evidence exists concerning the association between state-level positive EG and ER.

Overall, current research examining the relationship between EG and ER has mostly focused on dispositional (rather than state-level) and negative (rather than positive) EG, yielding mixed and often contradictory findings regarding its association with ER strategy use. It is thus necessary to further investigate the dynamic patterns of these constructs over time, including an analysis of their influence on each other.

1.2. Examining the Interplay of Emotional Granularity and Emotion Regulation through a Network Psychometric Approach

So far, state-level investigations have predominantly assessed the interplay between EG and ER at a concurrent level, that is, examining whether fluctuations in EG and ER co-occur within the same time frame. Nonetheless, EG and ER may be also prospectively linked, and thus transient changes in EG may shape subsequent ER strategy use (or vice versa) (Sels et al., 2024). Also, existing research has modeled ER strategies separately, precluding a comprehensive view of their simultaneous and interdependent associations with EG. Research would thus benefit from an integrative approach that considers *within-person variations* in both positive and negative EG and their relationships with multiple ER strategies in a multivariate model, while accounting for emotional intensity. Because current evidence suggests complex mutual influences between EG and ER, the adoption of an in-the-moment and prospective approach may enable to gain a better understanding of the temporal linkages between EG and ER and their direction, adding information about their potential (mal)adaptive function.

A suitable approach to investigate the complex interplay of temporal dynamics of EG and ER could be provided by the Network Psychometric Analysis (NPA). The network approach allows for the conceptualization of psychological processes as systems of interacting elements and allows for the examination of multivariate mutual associations among variables within a network structure (Borsboom et al., 2021). Within this framework, variables are conceptualized as *nodes* connected by *edges* representing partialized statistical relationships, enabling the simultaneous modeling of complex patterns of interdependence. Importantly, extensions of network models to panel and intensive longitudinal data make it possible to investigate *within-person dynamics*, by explicitly separating intra-individual variability from stable between-subject differences. Multilevel network models are based on estimating two within-person networks: A *temporal* network, encoding the lagged relationships from one time to the subsequent one, and the *contemporaneous* network, including within-person partial correlations in the same measurement occasion (Bringmann et al., 2016; Epskamp, Waldorp, et al., 2018).

The potential of the multilevel network psychometrics approach to uncover micro-level temporal dynamics in daily processes is highlighted by a growing body of research that has recently started to combine the experience sampling method with network analysis to model interactive emotion dynamics in daily-life (e.g., Daumiller et al., 2024; Hasmi et al., 2017). Following this line of research, this approach may enable the direct testing of theoretical assumptions regarding bidirectional links between EG and different ER strategies and ultimately a fine-grained investigation of how EG and ER co-occur in the moment and influence one another over time.

1.3. The Potential Role of Sleep as an Index of Allostatic Regulation

A possible explanation for the inconsistency of the results described above may lie in mechanisms that potentially moderate the within-person link between daily fluctuations in EG and ER. In this study, we advance the hypothesis that factors that reflect allostatic functioning are likely to shape both EG and use of ER strategies (Barrett, 2017a; Shaffer et al., 2022). Among these factors, research has shown that sleep plays a central role in maintaining allostatic functioning (Irwin, 2015; McEwen & Karatsoreos, 2022; ten Brink et al., 2022): Sleep is known to restore depleted metabolic and physiological resources (Feeney et al., 2025; Irwin, 2015), thereby optimizing predictive efficiency and the organism's capacity for adaptive responding (Lutz et al., 2018). When sleep is disrupted, the efficiency of allostatic regulation is compromised (Christensen et al., 2022). This reduced capacity for accurate prediction and resource allocation, in turn, may impact emotional functioning.

Consistent with this hypothesis, a substantial bulk of research has examined the link between sleep, positive and negative emotional experience, and ER providing evidence of significant associations between poor sleep and reduced positive affect, increased negative affect, and increased difficulties with emotion regulation (for reviews, see Goldstein & Walker, 2014; Fairholme & Manber, 2015; Palmer & Alfano, 2017). Although most existing research has been cross-sectional, diary and experience sampling studies have been also conducted (Bouwmans et al., 2017; Lenneis et al., 2024; Narmandakh et al., 2021; Parsons et al., 2022; Parsons & Young, 2022) showing that, at the within-person level, better-than-usual sleep at night is followed by less negative and more positive emotions the day after (whereas the reverse effect from daytime affect to sleep was generally weaker). There is also evidence that fluctuations in daily sleep quality are associated with the reporting of ER strategies (Parsons et al., 2022). To our knowledge, only one study so far has examined the potential relationship between EG and sleep, finding that dispositional negative EG buffers daily stress reactivity and thereby reduces the negative indirect effect of daily stress on nightly sleep quality (Lischetzke et al., 2021).

2. The Present Study

The main goal of present study is to examine the within-person relationships between moment-to-moment fluctuations in EG (both positive and negative) and the use of five ER strategies (i.e., expressive suppression, rumination, social sharing, cognitive reappraisal, and distraction) while accounting for the intensity of positive and negative emotions, both concurrently and prospectively over time (Objective 1). In addition, a secondary aim is to investigate whether and how such relationships differ according to an individual's sleep patterns (Objective 2). To answer this goal, data was collected in a 10-day experience sampling study. Momentary emotional variables were measured using an EMA protocol administered throughout the day, whereas sleep patterns were measured using an online morning diary.

Objective 1. We were primarily interested in the in-the-moment and lagged relationship between positive and negative EG and ER strategies while controlling for emotional intensity. To address this research objective, a Multilevel Network Psychometric model (MNP; Epskamp, 2020) was computed. In particular, a contemporaneous network model was estimated to capture concurrent undirected relationships within the same measurement occasion, whereas a temporal network model was used to model directed, predictive associations among variables across subsequent measurement occasions.

Since both theoretical and preliminary empirical work suggest a bidirectional relationship between ER and EG (Barrett et al., 2001; Kalokerinos et al., 2019; O'Toole et al., 2021; Sels et al., 2024), we expected that positive and negative EG would be positively associated with adaptive ER strategies (i.e., social sharing and reappraisal) and negatively associated with maladaptive ones (i.e., rumination and suppression) at both the concurrent and prospective level of analysis. No specific hypothesis was formulated regarding distraction, as this strategy can function as both adaptive and maladaptive depending on context (McRae, 2016; Wolgast & Lundh, 2017). This objective was intended to more precisely delineate the nature of the theorized association between EG and distinct ER strategies, particularly with respect to its concurrent and prospective occurrence, presumed (mal)adaptive characterization, and temporal directionality.

As a related research question, we investigated the overall functioning of EG to gain further insight into its conceptual status relative to ER within the broader processes of emotion generation and regulation (Gross & Barrett, 2011). First, as it has been suggested that EG may serve as an ER strategy (Kashdan et al., 2015; Thompson, Springstein, et al., 2021), we focused on the temporal stability of these constructs to more clearly delineate similarities and differences in their functioning. We hypothesized that if they operated analogously, positive and negative EG and the five ER strategies would exhibit comparable patterns of stability and inertia (reflected in autoregressive coefficients; see the Methods section for further detail) and, importantly, be distinct from those of emotional intensity. Second, by analyzing centrality indices (examining the most central variables within each network; see the Methods section for further detail), we investigated the overall connectivity of EG and thus its concurrent and prospective contributions to the broader architecture of emotional functioning. To the best of our knowledge, no prior work has directly addressed the role of EG in the temporal dynamics of overall emotional functioning; accordingly, we addressed this research question exploratively, and no specific hypothesis was formulated.

Objective 2. We extended our analysis to examine sleep as a potential moderator of the relationships among emotional variables. This second objective allowed us to provide a more nuanced understanding of the conditions under which EG is associated with ER strategies. We employed Multilevel Latent Profile Analysis (MLPA; Vermunt, 2011) to identify subgroups of participants characterized by distinct latent sleep profiles, defined by daily sleep quality and hygiene. This person-centered approach allowed us to capture unobserved heterogeneity in sleep patterns by identifying distinct configurations of sleep characteristics that may not be adequately represented by variable-centered analyses or aggregate indices. Compared to Latent Profile Analysis (LPA; Oberski, 2016), which has been used in previous cross-sectional research on sleep and emotions (e.g., Fisher et al., 2022), MPLA explicitly accounts for day-to-day variability over time. This approach allowed us to identify latent profiles reflecting stable between-person differences in sleep while controlling for naturally occurring within-person fluctuations throughout the 10-day data collection period. Subsequently, to examine whether prospective and contemporaneous network structures of emotional variables varied as a function of sleep patterns, the MNP analysis described above was estimated separately within each identified sleep profile.

We hypothesized that the associations between EG and ER would differ across sleep profiles. Specifically, since good sleep has been generally linked to greater use of adaptive ER strategies while impaired sleep has been associated with increased use of maladaptive strategies (Fairholme & Manber, 2015; Fisher et al., 2022; Palmer & Alfano, 2017; Parsons & Young, 2022; Parsons et al., 2022), we expected that EG would be significantly associated with social sharing and reappraisal among participants with a restorative sleep profile, while we expected to observe an association between EG, rumination and suppression among poor sleepers.

In addition, we assessed the temporal stability and overall strength of connectivity of positive and negative EG (relative to ER strategies and positive and negative emotional intensity) separately within each latent sleep profile. This last research question was designed to determine whether the general functioning of EG is contingent upon sleep-related differences.

3. Methods

3.1. Participants

Participants were recruited online through posted advertisements and word-of-mouth. Eligible participants were adults from the general Italian population, aged 18 years or older, with good proficiency in the Italian language. They had no history of psychiatric disorders (i.e., depression, anxiety disorders, bipolar disorder, post-traumatic stress disorder, eating disorders, obsessive–compulsive disorder, personality disorders) or sleep disorders (i.e., insomnia, obstructive sleep apnea, narcolepsy, restless legs syndrome, bruxism, sleepwalking and parasomnias, circadian rhythm sleep–wake disorders). They also confirmed that they were not taking benzodiazepines or other sedative–hypnotic medications (e.g., diazepam, lorazepam, zolpidem) and that they were not engaged in night shift work.

A total of 317 eligible individuals were initially enrolled in the study. Participants who completed fewer than 25 daily prompts (out of 70) and fewer than 5 morning sleep diaries (out of 10) were considered to have insufficient compliance and were therefore excluded from the analyses[7]. This resulted in a final sample of 255 participants. The sociodemographic characteristics of the sample are reported in Table 1. The sample size was determined based on recommendations from previous studies employing methodologies and analytical procedures analogous to those used in the present study. Additional details concerning sample size justification and statistical power are provided in the Supplemental Material.

The participants received a €10 Amazon gift card upon completion of at least 80% of the scheduled assessments. Additionally, they received an individualized report generated via the *Markdown* package in *R v.4.4.1* (Allaire et al., 2014), describing their own sleep patterns over the study period and reporting personalized recommendations for improving or maintaining healthy sleep.

[7] Following literature guidelines on EMA methodology (Conner & Lehman, 2012; Hektner, Schmidt, & Csikszentmihalyi, 2007), we applied a cut-off of fewer than 35% of completed EMA assessments (i.e., fewer than 25 completed prompts), below which participants' data were excluded from the analyses. Similarly, the exclusion criterion of completing fewer than half of the morning diaries was adopted based on research guidelines on daily diary studies (Bolger & Laurenceau, 2013; Csikszentmihalyi, 2013).

Table 1. Sample characteristics.

		Full Sample (n = 255)	Profile 1 (n = 74)	Profile 2 (n = 81)	Profile 3 (n = 100)
Age	Mean	27.6	23.5	33.0	26.4
	Standard Deviation	12.9	8.86	15.8	11.5
	Range	18–71	18–67	18–71	19–69
Gender	Female	75.3	21.5	23.5	30.3
	Male	24.7	7.6	7.6	9.6
	Non-binary	0.0	0.0	0.0	0.0
Education	Middle school	1.6	0.8	0.4	0.4
	Vocational high school (3 years)	1.2	0.0	0.8	0.4
	High school (5 years)	60.6	21.9	13.5	25.1
	Bachelor's degree	12.4	3.6	3.6	5.2
	Master's degree	19.5	2.0	10.8	6.8
	Advanced postgraduate education	4.8	0.8	2.0	2.0
Occupation	Studying	62.5	23.5	13.5	25.5
	Working	32.3	4.4	15.9	12.0
	Housewife / househusband	1.6	0.4	0.4	0.8
	Unemployed or looking for a job	1.2	0.0	0.4	0.8
	Retired	2.4	0.8	0.8	0.8
Civil Status	Unmarried	85.1	26.1	22.5	36.5
	Married	11.6	2.0	6.8	2.8
	Divorced	2.4	0.4	1.2	0.8
	Widow	0.8	0.0	0.8	0.0

Note: Columns *Profile 1*, *Profile 2*, and *Profile 3* show descriptive statistics for the subsamples identified by the multilevel latent profile analysis, with each profile representing a distinct pattern of sleep (Profile 1 = Poor and dysregulated sleepers; Profile 2 = Poor sleepers despite effort; Profile 3 = Good sleepers). Gender, Education, Occupation, and Civil Status are reported as percentages. Advanced postgraduate education includes professional specialization programs and doctoral studies.

3.2. Procedure

All study procedures were conducted online. Individuals who were interested in participating in the study contacted the research team directly (contact information was provided in posted advertisements). During this initial contact, eligibility was confirmed, detailed information about the participation procedures and timeline was provided, and participants received an informative letter with information about the goals and procedures of the study. It was also explained that participation would require the compilation of an initial baseline survey followed by a 10-day experience sampling method (ESM) protocol. Informed consent was obtained online from all participants before the initiation of the study protocol. The study was approved by the Ethics Committee of the Catholic University of Milan (Protocol Number: 103-23).

The baseline online survey was administered on Saturday. This survey included questions about socio-demographic information and trait-level measures of sleep, well-being, and emotional experience (these measures have not been included in the present study). After one week, the participants engaged in the ESM protocol. They were asked to complete an online morning diary assessing their sleep for 10 consecutive days. Notifications were sent daily at 6:00 a.m., and participants were instructed to complete the diary within 90 minutes from waking to minimize recall bias. During the same 10-day period, participants were also asked to complete the EMA to measure emotional variables. Seven semi-random prompts per day were delivered each day between 10:00 a.m. and 9:45 p.m. At each prompt, the participants answered questions regarding their momentary emotional experience and their use of five ER strategies. Additional information was collected regarding context (i.e., current activity and social interactions) and the perceived passage of time (these variables were not included in the present study).

At the end of the study protocol, participants received an individualized report on their own sleep and an Amazon gift card by email.

3.3. Measures

3.3.1. EMA Measures

Momentary Emotion Regulation. At each measurement occasion, the participants reported the extent to which they were currently using five ER strategies: Expressive suppression ("*I'm trying not to let my feelings show on the outside*"), rumination ("*I keep thinking about and reflecting on my feelings*"), social sharing ("*I'm sharing my feelings and talking about them with someone*"), distraction ("*I'm trying to distract myself to avoid my feelings*"), and reappraisal *("I'm trying to look at the situation from another perspective*"). These items were adapted from prior studies employing ESM to assess emotion regulation (e.g., Kalokerinos et al., 2019; O'Toole et al., 2021). Each item was rated on a continuous slider scale ranging from 0 ("not at all") to 100 ("very much").

Momentary Emotions. Fifteen emotion items were administered including nine negative (i.e., *anxious, worried, sad, disheartened, angry, frustrated, bored, fed up, stressed*) and six positive labels (i.e., *happy, amused, satisfied, confident, serene, calm*). These labels were chosen as they represent both low-arousal and high-arousal based on Circumplex Model of Affect (Russell, 1980). At each measurement occasion, the participants were asked to rate the extent to which they were experiencing each emotion on a continuous slider scale ranging from 0 ("*not at all*") to 100 ("*very much*"). In addition to the predefined emotion labels, an alternative response option was available ("*None of these labels represent my current emotional state*"). When this option was selected, participants were invited to provide one or more freely generated emotion term(s) that best described their current affective experience, which they subsequently rated using the same 0–100 slider scale.

Momentary Emotional Granularity. To compute momentary positive and negative EG indices, data concerning emotion ratings were initially preprocessed. Since instances of null variance resulting from uniform zero emotion ratings within a single measurement occasion pose conceptual ambiguity in their interpretation, we examined participants' responses to the open-ended emotion option to solve this ambiguity. If no alternative label was provided (122 observations, 28 participants), uniform zero ratings were interpreted as low-quality data and were thus entered as missing.

After this preliminary step, positive and negative momentary EG indices were calculated following the procedure described by Erbas et al. (2022), which was implemented via the *emodiff* package in *R v.4.4.1*. Emotion ratings were first person-mean centered so that each score reflected deviations from the individual's own average level for that emotion. Then, for each measurement occasion, we computed the mean of the centered emotion scores, multiplied by the total number of emotions, and the resulting value was squared to form the numerator of the equation. The denominator was obtained by calculating the variance of each centered emotion score and summing these variances. The ratio of the numerator to the denominator was then multiplied by -1, such that higher scores indicated greater momentary EG. We observed numerators or denominators equal to zero for four participants (all assigned to sleep Profile 3) when computing negative EG and for five participants (three assigned to Profile 2, one to Profile 1, and one to Profile 3) when computing positive EG. To avoid misinterpretation, we treated all such cases as missing values.

3.3.2. Morning Diary Measures

The items included in the morning diary were adapted from the Consensus Sleep Diary (Carney et al., 2012) and from prior research (Åkerstedt et al., 2012; Lischetzke et al., 2021).

The following domains related to nightly sleep were covered:

Perceived Sleep Quality: "*How well did you sleep last night*?" and "*How disturbed did your sleep feel*?"; second item is reverse-coded.

Feeling Rested Upon Awaking: "*This morning, how rested did you feel when you woke up for the day*?"

Sleep Interruptions: "*How many times did you wake up during the night*?"

Sleep Onset Difficulty: "*How much difficulty did you have falling asleep*?".

Perceived Sleep Duration "*How many hours do you feel like you slept*? *Please, answer based on your subjective perception, not on the actual number of hours spent sleeping*".

Actual Sleep Duration: assessed as the time interval elapsed between the reported wake-up and asleep time.

Asleep Time: "*At what* time did you fall asleep?"

Wake-up Time: "*At what time did you wake up*?".

Discrepancy Between Actual and Desired Asleep Time: assessed as the difference between the participant's desired asleep time ("*Regardless of external factors – e.g., personal commitments, difficulty falling asleep, etc., at what time would you have liked to fall asleep last night*?") and actual asleep time.

Discrepancy Between Actual and Desired Wake-up Time: assessed as the difference between the participant's desired wake-up time ("*Regardless of external factors – e.g., personal commitments, difficulty waking-up, etc., what time would you have liked to wake up this morning*?") and actual wake-up time.

Sleep Hygiene: measured via four items: "*Last night, before going to bed, to what extent: Did you make use of stimulating substances (e.g., coffee, tea, energy drinks, cola beverages*)?" (reverse-coded); "*Did you make use of substances that promote sleep (e.g., sleeping herbal pills, herbal teas)*?"; "*Did you feel weighed down by your dinner*?" (reverse-coded); "*Did you use your bed for activities other than sleeping or sexual activity (e.g., using your phone, watching TV, eating, working or studying*)?" (reverse-coded).

Items related to perceived sleep quality, feeling rested upon awaking, sleep onset difficulty, and sleep hygiene were rated on a 5-point Likert scale (1 = "not at all" to 5 = "very much").

3.4. Statistical Analysis

Multilevel Network Psychometric models (MNP; Epskamp, 2020; Epskamp, Waldorp, et al., 2018) were estimated on the full sample to analyze a) within-person prospective effects across subsequent time points and b) contemporaneous undirected relationships among the emotional variables measured in the EMA protocol (i.e., positive and negative EG; ER strategies; positive and negative emotional intensity). This analysis allowed us to investigate the first objective of the present study.

As a second step, a Multilevel Latent Profile Analysis (MLPA; Vermunt, 2011) was conducted on data from the morning diaries to cluster participants into different latent sleep profiles. Subsequently, MNP models were estimated for each identified sleep profile, both at the prospective and contemporaneous level. This second bulk of analyses was designed to investigate the second objective of the study.

Data and codes are available at https://osf.io/sa9y7/overview.

3.4.1. Multilevel Network Psychometric Analysis of Daily Emotional Dynamics

A MNP analysis was conducted using Multi Level Vector-Auto Regressive models (mlVAR; Bringmann et al., 2013, 2018). These models apply vector autoregressive modeling (Brandt & Williams, 2007) to multilevel time-series data, thereby capturing both autoregressive effects (i.e., how each variable is predicted by its own past values) and cross-lagged effects (i.e., how variables predict each other over time within individuals).

Since the mlVAR models rely on the assumption of mean stationarity of data (Epskamp, Waldorp, et al., 2018), we first assessed the presence of temporal trends across the EMA period for each emotional variable. Individual multilevel models were estimated using *lme4* and *lmerTest* packages in *R v.4.4.1* (Bates et al., 2015; Kuznetsova et al., 2017), with each variable regressed on a time index. Most emotional variables showed significant changes over time, indicating sensitivity to repeated measurement (for further details, see Table S1 in the Supplemental Material). To account for such temporal trends, the residuals of these multilevel models were retained for further analysis (Curran & Bauer, 2011).

After this preliminary step, we estimated multilevel network models using the *mlVAR* in *R v.4.4.1* (Epskamp, Waldorp, et al., 2018) and relying on the *two-step frequentist method* developed by Epskamp, Waldorp, et al. (2018). Two types of network models were estimated (Epskamp, van Borkulo, et al., 2018; Epskamp, Waldorp, et al., 2018): A temporal and a contemporaneous network. The *temporal network* examines associations quantified via lagged regression coefficients (i.e., a given variable at time t is regressed onto a lagged t–1 variable). In more detail, two types of lagged relationships were estimated: *Autoregressive effects* (i.e., a variable is regressed on itself at the prior measurement occasion, capturing the stability or inertia of the process over time) and *cross-lagged effects* (i.e., a variable is regressed on all other variables at the previous time point, allowing for the examination of predictive relationships between variables across time). The c*ontemporaneous network* consists of a Gaussian Graphical Model (GGM; Epskamp, Borsboom, et al., 2018; Lauritzen, 1996), which captures the pattern of undirected relationships between variables within the same measurement occasion after accounting for temporal effects. Edges in this network are estimated from the residuals of the multilevel model that estimate the temporal effects and represent partial correlations that capture within-person relationships between variables.

To estimate the network models, we set the *dayvar* argument (indicating assessment day) to make sure that the first measurement of a day was not regressed on the last measurement of the previous day, and the *beepvar* argument (indicating measurement occasion per day) to cause non-consecutive beeps to be treated as missing. Pairwise deletion was performed to handle missing data. With respect to edge significance, thresholding for both the temporal and contemporaneous networks was represented by p values. Since the contemporaneous network is a function of two parameters that are standardized and averaged (i.e., a regression parameter for the regression model of Node A and a regression parameter for the regression model of Node B), two p-values are obtained for each edge; we retained edges for which at least one of the two p-values was significant, following the “or” rule (Barber & Drton, 2015).

To determine whether temporal effects should be modeled with correlated or uncorrelated random effects[8], we compared model specifications using information criteria, including the AIC and BIC. Based on results from information criteria for model comparison, temporal effects were modeled using uncorrelated random effects (i.e., orthogonal estimation; additional information is reported in Tables S2–S5 in the Supplemental Material).

We plotted the network graphs using the *qgraph* package in *R v.4.4.1* (Epskamp et al., 2017). In the graphical visualization, stronger associations are represented as thicker edges. Non-significant edges were removed from the plotted network for ease of interpretation.

Centrality indices were computed to describe the network structural properties and to identify the patterns of relationships maintained by each node within the networks (Opsahl et al., 2010). In more detail, we considered *strength* indices, computing in-strength and out-strength indices for temporal networks. In-strength reflects the sum of the absolute values of all edges directed toward a node, whereas out-strength reflects the sum of the absolute values of all edges extending from a node to others. For contemporaneous networks, a single strength index was estimated, indicating the absolute sum of edge weights connected to a given node. Centrality indices provide complementary information on the relative influence and connectivity of each emotional variable within the networks.

We first estimated temporal and contemporaneous mlVAR models on the full sample to examine within-person relationships between moment-to-moment fluctuations in EG and the use of five ER strategies, while accounting for emotional intensity (*Objective 1*). Subsequently, to investigate these relationships while accounting for the moderating role of sleep (*Objective 2*), separate temporal and contemporaneous mlVAR models were estimated for each sleep profile identified via MLPA (see Section 3.4.2). Each network comprised nine nodes, representing positive and negative EG, the five ER strategies, and the intensity of positive and negative emotions.

3.4.2. Multilevel Latent Profile Analysis: Identification of Sleep Profiles

An MLPA was conducted using *Mplus v.7.3* (Muthén & Muthén, 2017) to identify between-person latent profiles of sleep characteristics (Level 2) while accounting for within-person, day-to-day variability in the observed indicators (Level 1). We used this approach to identify subgroups of participants exhibiting similar patterns of nightly sleep and sleep-related behaviors on the basis of their responses to the indicators (Bauer, 2022) included in the morning diary (see section 1.3.1). All these indicators were samplewise standardized (Mäkikangas et al., 2018) to ensure comparability across variables.

The MLPA was conducted via full information maximum likelihood (FIML) estimation, which is recommended because it is robust to the nesting of observations within higher-level units (Mäkikangas et al.,

[8] For the estimation of the temporal network, orthogonal estimation (which assumes uncorrelated random effects) can be preferable when the number of variables is >8. As our model included nine variables (placing it at the threshold), we conducted a check to determine whether temporal effects should be modeled with correlated or uncorrelated random effects.

2018). Random starting value sets of 500 were used to avoid local maxima, thereby reducing the risk of obtaining solutions that may appear optimal but do not represent the true best fit (Masyn, 2013). On the basis of these 500 initial sets, the 100 best-fitting models were further iterated to locate the likelihood maxima, increasing the probability of obtaining a stable and global solution[9]. Variances at both Level 1 and Level 2 were freely estimated, as they are considered a modeled source of heterogeneity that contributes to the formation of the latent profiles. In contrast, covariances between the indicators were not freely estimated, which is consistent with the assumption of local independence (Nylund-Gibson & Choi, 2018). Mean values were allowed to differ between the latent profiles only at Level 2 (i.e., between participants), as we did not aim to identify latent profiles of sleep patterns at the measurement occasion level (i.e., within participants, Level 1).

To determine the optimal number of latent profiles at Level 2, we estimated and compared a series of *k*-class models, starting with a one-class solution and sequentially increasing the number of classes until the model could no longer be properly identified. Model selection was based on both statistical criteria and theoretical interpretability of the profiles (Nylund et al., 2007). The best model solution showed lower values of information criteria, including the Akaike Information Criterion (AIC) (Bozdogan, 1987), the Bayesian Information Criterion (BIC) (Schwarz, 2007), and the Sample-size Adjusted BIC (SABIC) (Sclove, 1987). In addition to these fit indices, the Vuong-Lo-Mendell-Rubin likelihood ratio test (VLMR-LRT) (Vermunt, 2024) and the Lo-Mendell-Rubin adjusted likelihood ratio test (LMR-LRT) (Lo et al., 2001) were conducted to evaluate whether a model with k classes provided a significantly better fit than a model with $k-1$ classes. For both the VLMR-LRT and the LMR-LRT, 400 random starting value sets were used, of which the 80 best-fitting were further iterated.

To assess the precision and stability of individual classifications within profiles, we examined classification diagnostics, including entropy and class proportions (CP or π). Concerning entropy, values greater than 0.70 commonly indicate a well-defined model solution (Fonseca & Cardoso, 2007). With respect to CP, a more parsimonious solution was preferred if adding an extra class in a k-class model yielded only a minor variation compared to a class already identified in the $k-1$-class model (Hadiwijaya et al., 2015). Finally, the substantive interpretability of the profiles was evaluated in the context of relevant theoretical frameworks (Nylund et al., 2007).

[9] If the log-likelihood had not been replicated across several starting value sets or if convergence problems had occurred, the number of starting value sets would have been increased.

4. Results

Descriptive statistics and correlations were computed. Descriptive statistics of EMA measures and the morning diary are presented in Table S6 in the Supplemental Material.

4.1. Objective 1: Multilevel Psychometric Network Analysis on the Full Sample

Because the contemporaneous network models were estimated from the residuals of the temporal models, the results are presented first for the temporal network and subsequently for the contemporaneous network.

4.1.1. Temporal Network Model on the Full Sample

The temporal network structures are displayed in Figure 1. Fixed effects of the temporal network model are reported in Table S7 in the Supplemental Material. Centrality indices are illustrated in Figure 2 and summarized in Table S8 in the Supplemental Material.

First, the temporal network exhibited 25 significant direct associations between nodes out of 72 possible direct associations, indicating a moderate level of connectivity.

Second, when examining the reciprocal associations between EG and ER (while accounting for emotional intensity), neither negative EG at *t–1* nor positive EG at *t–1* significantly predicted any ER strategy at the subsequent time point. In contrast, when considering the inverse direction of effects, negative EG at *t* was predicted by suppression at *t–1* (β = -0.05, *SE* = 0.02, *p* = .006), while positive EG at *t* was predicted by rumination at *t–1* (β = -0.03, *SE* = 0.02, *p* = .020). Thus, when participants reported a greater-than-usual tendency to suppress their emotions, they subsequently showed a reduced ability to differentiate among negative emotional states. On the other hand, higher momentary use of rumination to regulate one's emotions in a certain moment decreased the granularity in discriminating against positive emotional states at the next occasion. Notably, none of the remaining ER strategies exhibited significant lagged associations with EG.

Third, with respect to the stability of the emotional variables over time, the intensity of positive (β = 0.40, *SE* = 0.02, *p* = .000) and negative emotions (β = 0.39, *SE* = 0.02, *p* = .000) emerged as the two variables with the strongest autoregressive effects, indicating high temporal stability. By contrast, EG (both positive and negative) and ER strategies showed comparably lower autoregressive effects. Negative EG showed the lowest autoregressive effect (β = 0.14, *SE* = 0.02, *p* = .000), followed by social sharing, distraction, rumination and reappraisal (β = 0.17, *SE* = 0.02, *p* = .000), and by positive EG (β = 0.20, *SE* = 0.03, *p* = .000) and suppression (β = 0.21, *SE* = 0.02, *p* = .000).

Lastly, concerning predictive influence (i.e., strength centrality indices), both positive EG at *t–1* (out-strength = 0.035) and negative EG at *t–1* (out-strength = 0.086) exerted a very low overall impact over time.

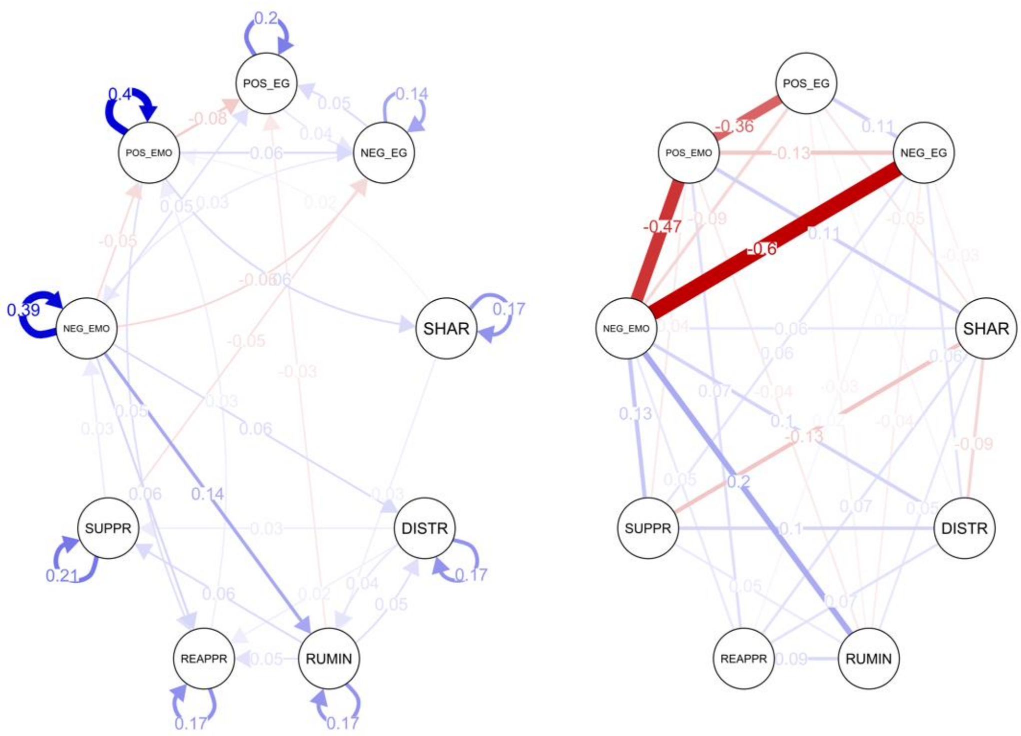

Figure 1. Temporal and contemporaneous network models for Profile 1 (i.e., Poor and dysregulated sleepers), Profile 2 (i.e., Poor sleepers despite effort), and Profile 3 (i.e., Good sleepers).

Note: POS_EG = Positive Emotional Granularity; NEG_EG = Negative Emotional Granularity; SHAR = Social sharing; DISTR = Distraction; RUMIN = Rumination; REAPPR = Reappraisal; SUPPR = Suppression; NEG_ EMO = Negative Emotions; POS_ EMO = Positive Emotions. Networks are depicted using the circular layout to facilitate the visual comparison of models. In the temporal network, blue lines indicate positive associations; red lines indicate negative associations; straight arrows indicate directed effects between two consecutive measurement occasions within a day; and circular arrows indicate autoregressive effects. In the contemporaneous network, blue undirected edges indicate positive partial correlations between two variables within the same measurement occasion, while red undirected edges indicate negative partial correlations between two variables within the same measurement occasion.

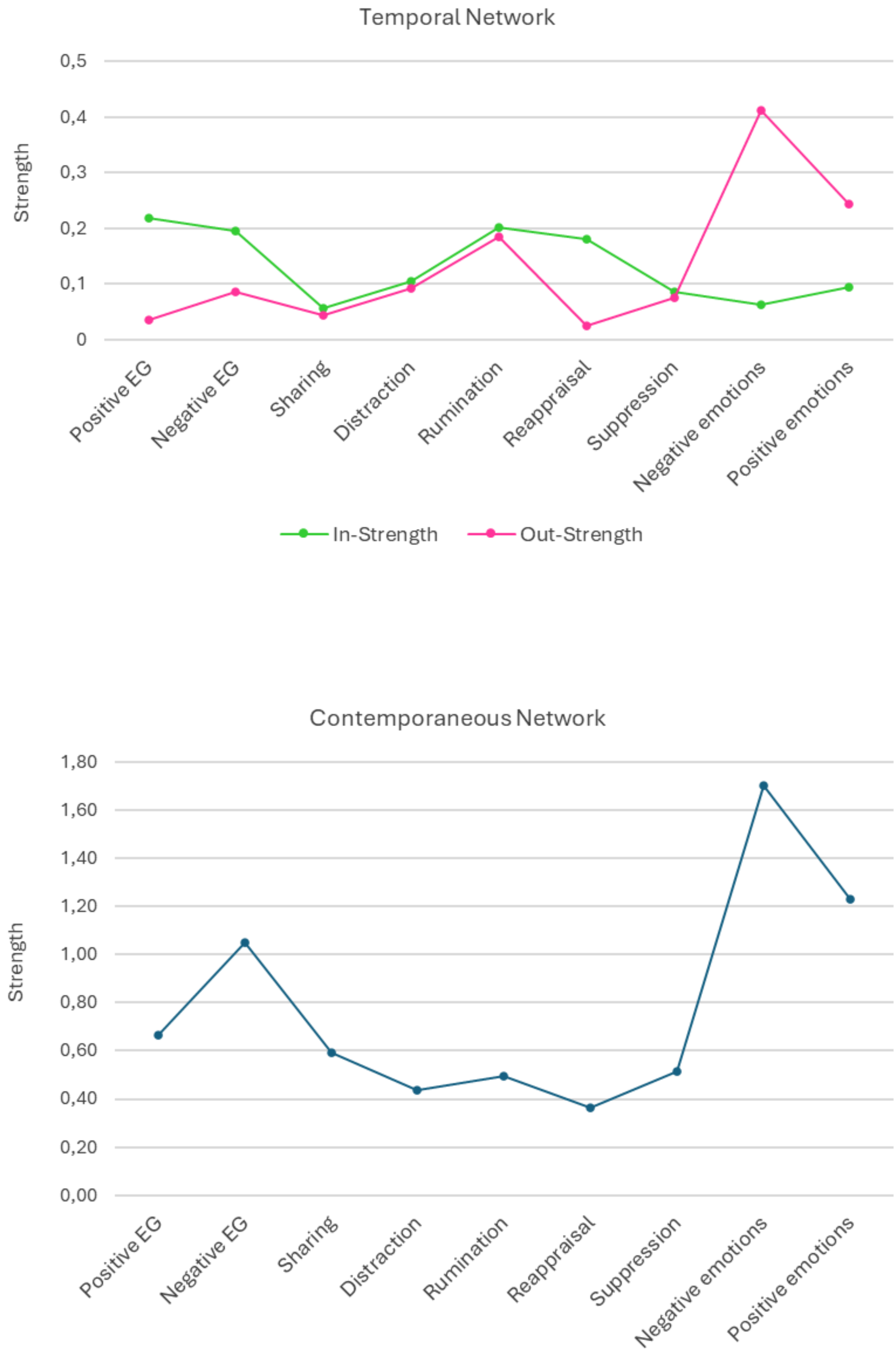

Figure 2. Centrality indices of temporal (out-strength, in-strength) and contemporaneous (strength) network models for Profile 1 (i.e., Poor and dysregulated sleepers), Profile 2 (i.e., Poor sleepers despite effort), and Profile 3 (i.e., Good sleepers).

Note: EG = Emotional Granularity.

Nonetheless, they were among the most impacted variables (positive EG in-strength = 0.218; negative EG in-strength = 0.196). Overall, these results suggest that the momentary ability to differentiate among positive emotions does not seem to be a driver of change in emotional functioning, while it emerges as a target of fluctuations in other emotional components over time.

This same pattern did not extend to ER strategies, with the only exception of reappraisal, which displayed a similarly asymmetric pattern characterized by very low out-strength (0.026) and comparatively high in-strength (0.181). In contrast, suppression (out-strength = 0.076; in-strength = 0.086), social sharing (out-strength = 0.043; in-strength = 0.057), distraction (out-strength = 0.093; in-strength = 0.104), and rumination (out-strength = 0.185; in-strength = 0.202) exhibited moderate levels of overall predictive influence over time.

Notably, the intensity of negative emotions was the variable exerting the strongest influence over time (out-strength = 0.412), followed by intensity of positive emotions (out-strength = 0.224). This result indicates that fluctuations in negative and positive emotionality represented the primary source of variation in the temporal dynamics of emotional functioning.

4.1.2. Contemporaneous Network Model on the Full Sample

The contemporaneous network structure is displayed in Figure 1. Post-hoc estimates of the contemporaneous network model are reported in Table S9 in the Supplemental Material. Centrality indices are illustrated in Figure 2 and summarized in Table S8 in the Supplemental Material.

Compared to the temporal network, the contemporaneous network structure exhibited a higher degree of connectivity, with 31 significant undirected connections out of 36 possible significant correlations.

When looking at the relationship between EG (positive and negative) and ER strategies, negative EG was significantly correlated with all ER strategies examined. In particular, it showed an inverse relationship with social sharing (r_{partial} = -0.03) and rumination (r_{partial} = -0.04) and a positive relationship with reappraisal (r_{partial} = 0.02), suppression (r_{partial} = 0.06) and distraction (r_{partial} = 0.06). In contrast, positive EG exhibited a more selective pattern of undirected associations. It was negatively correlated with social sharing (r_{partial} = -0.05) and rumination (r_{partial} = -0.03) and positively correlated with distraction (r_{partial} = 0.02). No significant associations emerged between positive EG and either reappraisal or suppression. Overall, these findings indicate that higher-than-usual ability to precisely differentiate among positive and negative states in a certain moment is related to the concurrent greater use of distraction and reduced reliance on social sharing and rumination. In addition, when participants were more granular than usual in differentiating among negative emotions, they were also more likely to regulate these emotions through reappraisal and suppression.

Finally, when examining node strength within the contemporaneous network, the highest absolute strength values (i.e., the nodes with the strongest overall connections to other nodes) were observed for negative emotional intensity (strength = 1.701) and positive emotional intensity (strength = 1.235), followed by negative EG (strength = 1.051). In contrast, positive EG (strength = 0.667) exhibited strength values comparable to those of the emotion regulation strategies, including social sharing (strength = 0.591), suppression (strength = 0.513), rumination (strength = 0.469), distraction (strength = 0.439) and reappraisal (strength = 0.366).

4.2. Objective 2: Multilevel Psychometric Network Analysis Across Distinct Sleep Profiles

4.2.1. Identification of Sleep Profiles

The MLPA results led to the identification of three distinct between-person sleep profiles (see Figure 3). Detail information about model selection and model solutions is provided in the Supplemental Material.

The first profile (n = 74) was labeled *Poor and dysregulated sleepers* (Profile 1). The participants in this group reported poor sleep and maladaptive sleep-related behaviors. They indicated low perceived sleep quality, not feeling rested upon awakening, and greater difficulty falling asleep. Nevertheless, once asleep, they generally maintained the continuity of sleep. They also exhibited a discrepancy between perceived and actual sleep duration, typically underestimating the number of hours they slept. Compared to the other groups, their asleep times and wake-up times were delayed, with a substantial mismatch between desired and actual schedules. Despite these delayed rhythms, they expressed a wish to fall asleep and wake up earlier. This profile was further characterized by poor sleep hygiene. In summary, this group comprises individuals with poor sleep, marked by delayed and misaligned sleep–wake patterns and maladaptive sleep practices.

The second profile (n = 81) was labeled *Poor sleepers despite effort* (Profile 2) and included participants who reported poor sleep outcomes despite adopting healthy sleep behaviors. On the one hand, these participants reported low sleep quality and feeling unrested upon awakening. On the other hand, they also reported good sleep hygiene practices and relatively early asleep times and wake-up times. Although they did not experience significant difficulties falling asleep, their sleep was characterized by frequent nocturnal awakenings. A notable discrepancy between perceived duration and actual duration emerged, with participants frequently underestimating the amount of sleep obtained. This pattern suggests that despite healthy sleep behaviors, participants' sleep is perceived as fragmented and unsatisfying.

The third profile (n = 100) was labeled *Good sleepers* (Profile 3). In this group, participants reported good sleep quality, restful awakenings, no significant sleep interruptions, and no difficulty initiating sleep. They also exhibited good sleep hygiene. Compared with actual hours, their perceived sleep duration was slightly overestimated, and consistent with this perception, they expressed a wish to sleep less by falling asleep later and waking up earlier. They typically maintained somewhat earlier wake-up times and later asleep times but without major discrepancies. Overall, this profile shows healthy habits regarding nocturnal sleep and restorative sleep patterns.

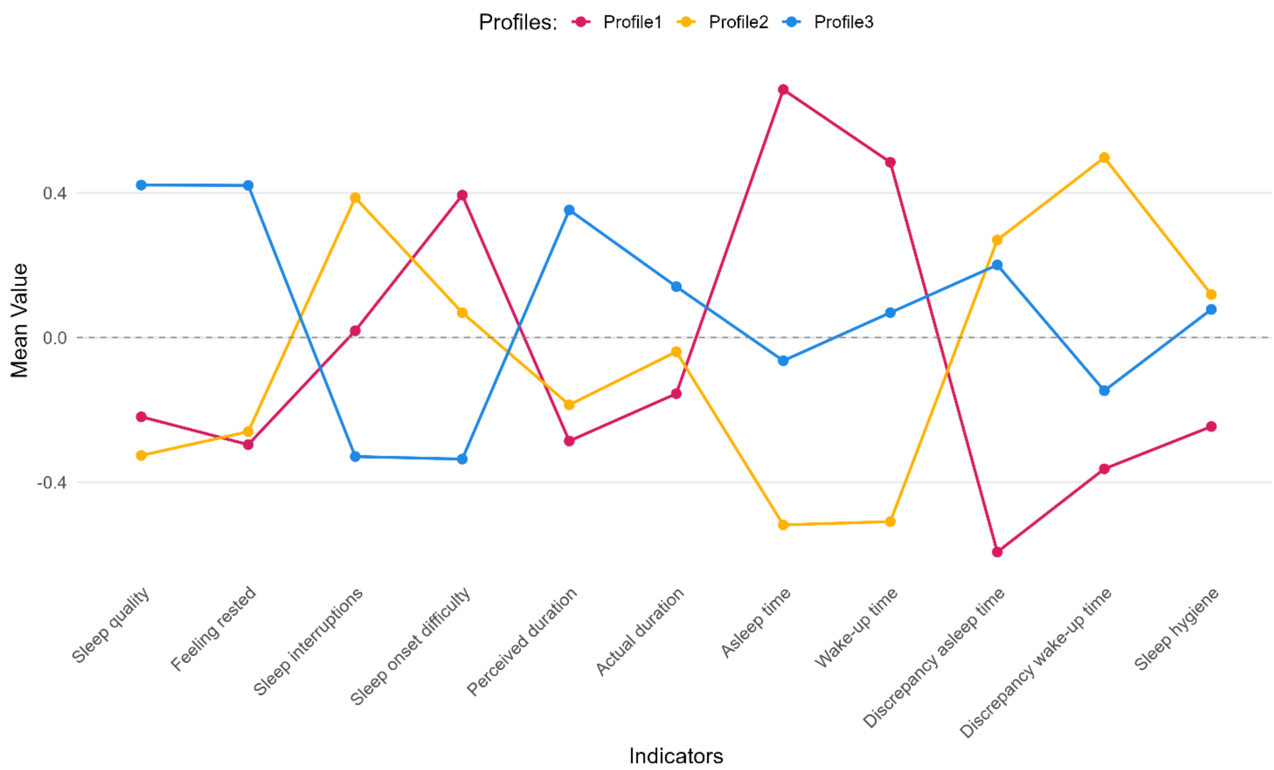

Figure 3. Latent sleep profiles from the 3-class model at the person level (Level 2).
Note: Profile 1 (n = 74) = Poor and dysregulated sleepers; Profile 2 (n = 81) = Poor sleepers despite effort; Profile 3 (n = 100) = Good sleepers. Bars represent the standard deviations of each of the eleven profile indicators relative to the overall sample mean. All values have been standardized (M = 0, SD = 1) to facilitate interpretation.

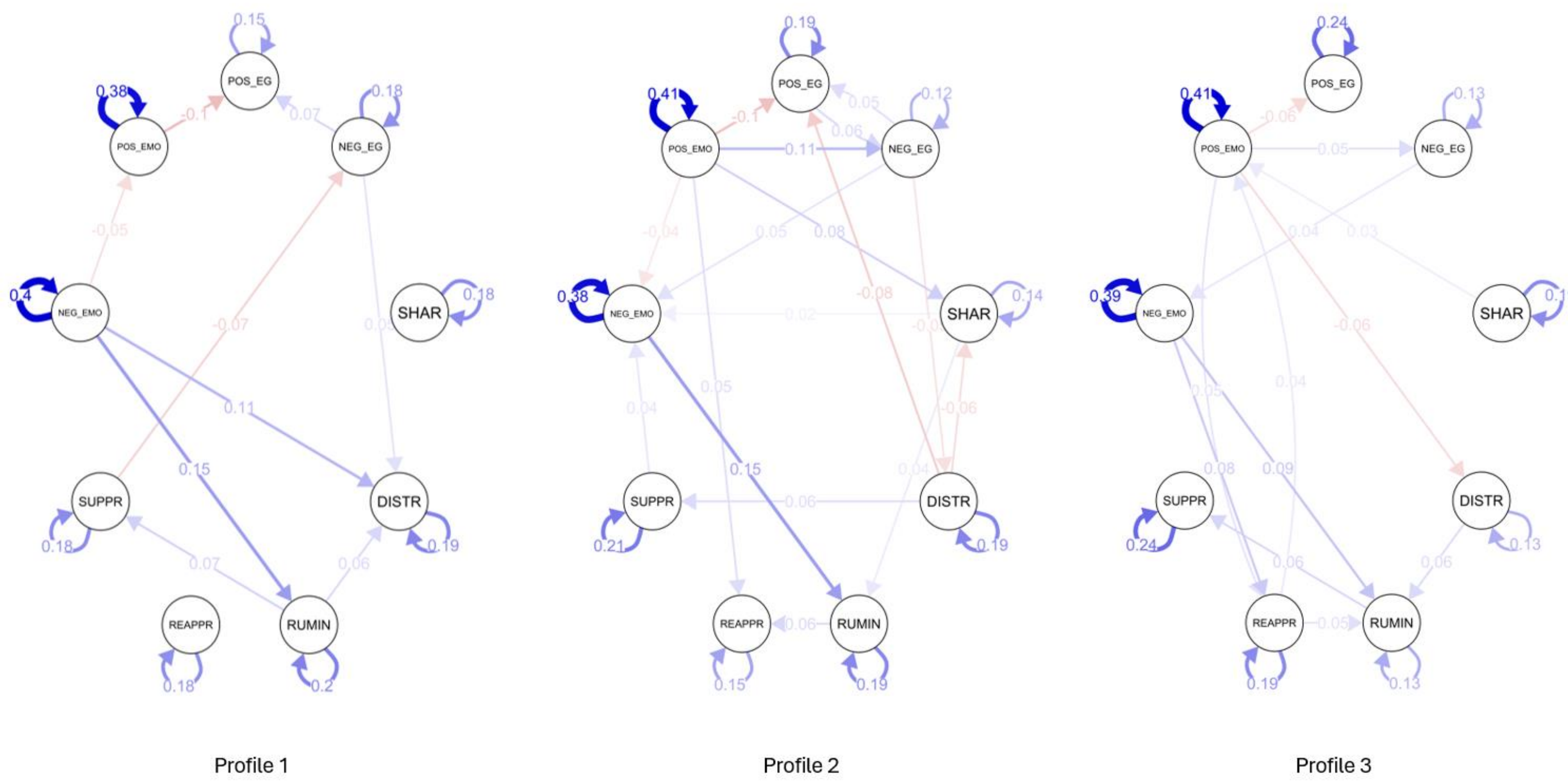

Figure 4. Temporal network models for Profile 1 (i.e., Poor and dysregulated sleepers), Profile 2 (i.e., Poor sleepers despite effort), and Profile 3 (i.e., Good sleepers).

Note: POS_EG = Positive Emotional Granularity; NEG_EG = Negative Emotional Granularity; SHAR = Social sharing; DISTR = Distraction; RUMIN = Rumination; REAPPR = Reappraisal; SUPPR = Suppression; NEG_ EMO = Negative Emotions; POS_ EMO = Positive Emotions. Networks are depicted using the circular layout to facilitate the visual comparison of models. Blue lines indicate positive associations; red lines indicate negative associations. Straight arrows indicate directed effects between two consecutive measurement occasions within a day. Circular arrows indicate autoregressive effects.

Figure 5. Centrality indices (out-strength, in-strength) of temporal network models for Profile 1 (i.e., Poor and dysregulated sleepers), Profile 2 (i.e., Poor sleepers despite effort), and Profile 3 (i.e., Good sleepers).
Note: EG = Emotional Granularity.

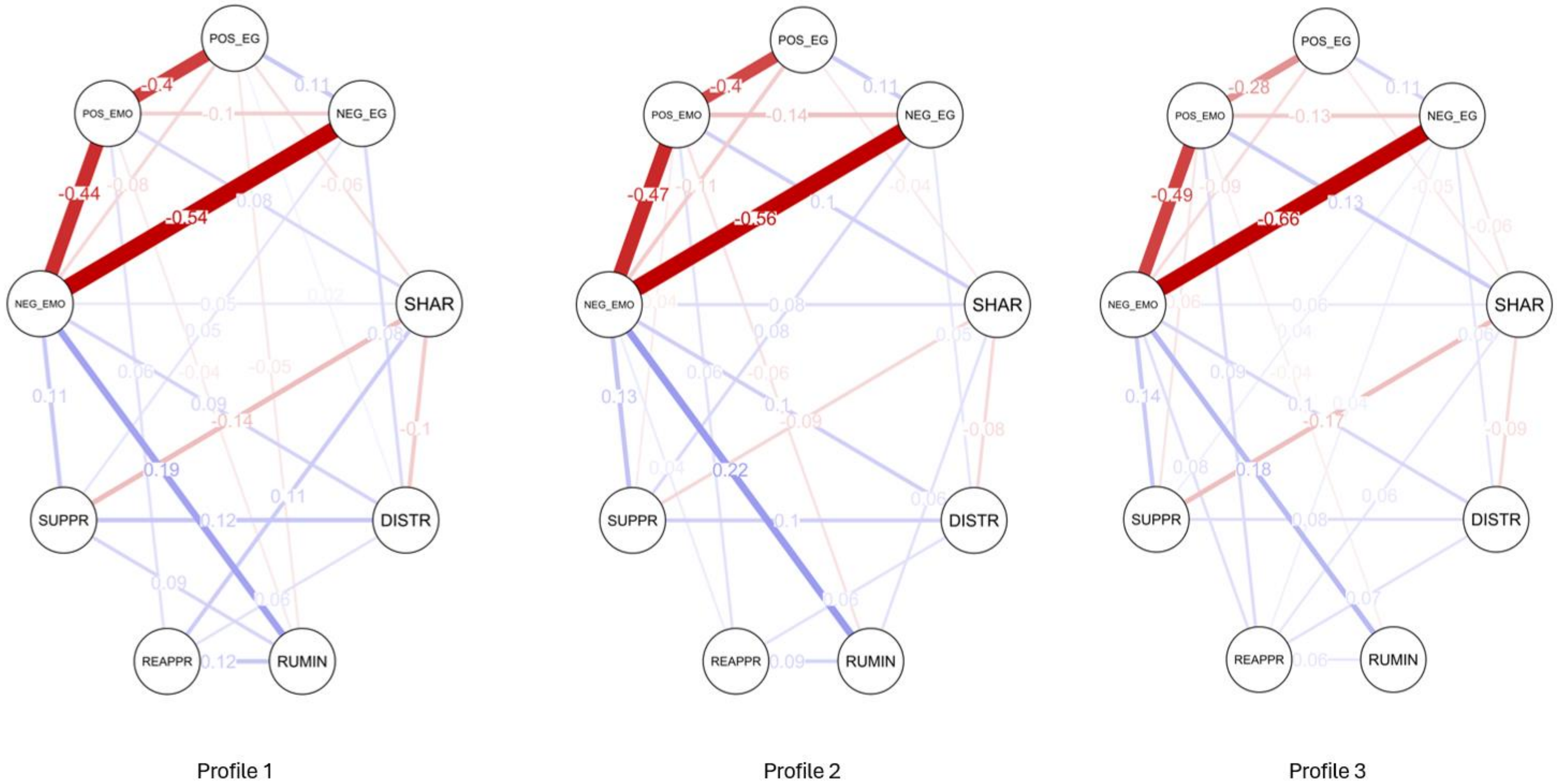

Figure 6. Contemporaneous network models for Profile 1 (i.e., Poor and dysregulated sleepers), Profile 2 (i.e., Poor sleepers despite effort), and Profile 3 (i.e., Good sleepers).

Note: POS_EG = Positive Emotional Granularity; NEG_EG = Negative Emotional Granularity; SHAR = Social sharing; DISTR = Distraction; RUMIN = Rumination; REAPPR = Reappraisal; SUPPR = Suppression; NEG_ EMO = Negative Emotions; POS_ EMO = Positive Emotions. Networks are depicted using the circular layout to facilitate the visual comparison of models. Blue undirected edges indicate positive partial correlations between two variables within the same measurement occasion. Red undirected edges indicate negative partial correlations between two variables within the same measurement occasion.

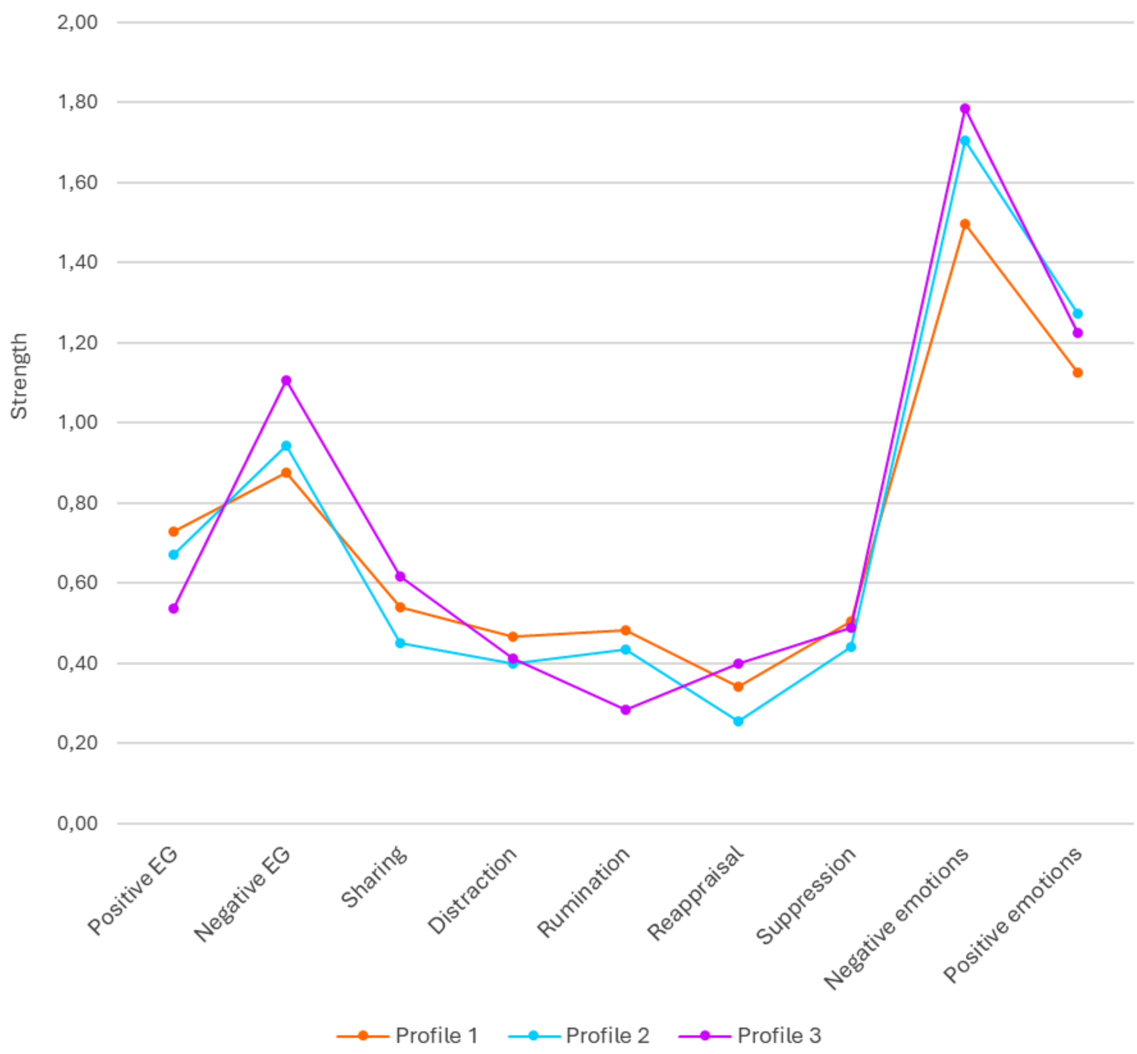

Figure 7. Centrality indices (strength) of contemporaneous network models for Profile 1 (i.e., Poor and dysregulated sleepers), Profile 2 (i.e., Poor sleepers despite effort), and Profile 3 (i.e., Good sleepers).
Note: EG = Emotional Granularity.

4.2.2. Temporal Network Models Across Distinct Sleep Profiles

The temporal network structures for each profile are displayed in Figure 4. Fixed effects of temporal network models are reported in Tables S11–S13 in the Supplemental Material. Centrality indices are illustrated in Figure 5 and summarized in Table S14 in the Supplemental Material. The results revealed substantial differences in the overall structure of temporal networks across the three sleep profiles, indicating sleep-dependent patterns in the prospective association among emotional variables.

First, temporal networks exhibited different levels of connectivity depending on sleep profile. In more detail, compared with the other profiles, profile 1 (*poor and dysregulated sleepers*) displayed a sparse pattern of associations, with only 9 significant direct associations between nodes. Notably, two ER strategies (social sharing and reappraisal) did not show significant predictive associations with any other variable, indicating that their fluctuations over time were independent of the changes in the network components at the previous measurement occasion. In contrast, when considering profile 2 (*poor sleepers despite effort*) and 3 (*good sleepers*), temporal networks were characterized by elevated or moderate connectivity over time, including 17 and 12 significant associations between nodes respectively.

Second, when looking at the reciprocal associations between EG and ER (while accounting for emotional intensity), the results revealed substantial differences across the three sleep profiles. When considering profile 1, we found that negative EG at *t–1* predicted distraction at time *t* (β = 0.05, *SE* = 0.02, *p* = .004), while negative EG at *t* was predicted by suppression at *t–1* (β = -0.07, *SE* = 0.03, *p* = .014). Thus, when the participants were more granular than usual in the differentiation of their negative emotions, they reported an increased tendency to rely on avoidant ER in the subsequent measurement occasion. On the other hand, a lower use of suppression to regulate one's emotions in a certain moment increased the granularity in discriminating negative emotional states at the next occasion. Notably, positive EG did not exhibit any significant lagged association with ER.

When considering profile 2 (*poor sleepers despite effort*), negative EG showed a significant lagged effect on distraction (β = -0.05, *SE* = 0.01, *p* = .000), but this effect was negative, indicating that, in this group, greater than usual differentiation of negative states was associated with a reduced tendency to move attention away from emotional experience in the subsequent measurement occasion. Also, distraction at *t–1* (β = -0.08, *SE* = 0.03, *p* = .015) predicted positive EG, meaning that lower reliance on distraction at a given moment was associated with a greater ability to differentiate among positive states at the subsequent time point.

Finally, with respect to profile 3 (*good sleepers*), neither positive nor negative EG displayed any significant associations with ER strategies.

Third, despite minor differences, similarities emerged across profiles with respect to the stability of positive and negative EG and the other emotional variables (i.e., the five ER strategies, positive and negative emotional intensity) over time. Across all sleep profiles, the intensity of positive and negative emotions emerged as the two variables with the strongest autoregressive effects, indicating high temporal stability. By contrast, EG (both positive and negative) and ER strategies showed comparably lower autoregressive effects, despite some profile-specific differences in their autoregressive coefficients. In sleep profile 1 (*poor and dysregulated sleepers* and 2 (*poor sleepers despite effort*), EG and ER displayed comparable autoregressive effects, with either positive EG (profile 1: $\beta = 0.15$, $SE = 0.03$, $p = .000$) or negative EG (profile 2: $\beta = 0.12$, $SE = 0.03$, $p = .000$) showing the lowest autoregressive coefficient. In profile 3 (*good sleepers*), negative EG ($\beta = 0.13$, $SE = 0.03$, $p = .000$), distraction ($\beta = 0.13$, $SE = 0.03$, $p = .000$) and rumination ($\beta = 0.13$, $SE = 0.03$, $p = .000$) showed the lowest, whereas positive EG ($\beta = 0.24$, $SE = 0.03$, $p = .000$) and suppression ($\beta = 0.24$, $SE = 0.02$, $p = .000$) the strongest autoregressive effects.

Lastly, we observed different patterns of predictive influence (i.e., strength centrality indices). Focusing on EG within the temporal network structure, positive EG at *t–1* exerted a very low overall influence over time in all the networks (profile 1 out-strength = 0.000, profile 2 out-strength = 0.062, profile 3 out-strength = 0.041). Nonetheless, it emerged as a strongly impacted variable in profile 1 (in-strength = 0.171) and profile 2 (in-strength = 0.230), but not in profile 3 (in-strength = 0.058) networks. Negative EG exerted a strong overall influence in profile 2 network (out-strength = 0.147), while its influence was lower in profile 1 (out-strength = 0.113) and 3 networks (out-strength = 0.041). Finally, negative EG was strongly overall impacted by other variables in profile 2 network (in-strength = 0.174), whereas it was impacted to a low extent in profile 1 (in-strength = 0.070) and profile 3 networks (in-strength = 0.052). Overall, these results suggest that, across all sleep profiles, the momentary ability to differentiate among positive emotions does not seem to be a driver of change. Nonetheless, in poor sleepers (profiles 1 and 2), it emerges as a target of fluctuations in other emotional components over time. Conversely, the momentary ability to differentiate among negative emotions emerged as a moderate driver of change in poor sleepers (profiles 1 and 2) and as a target of change in sleep profile 2.

Notably, in profile 1, the intensity of negative emotions was the variable exerting the strongest overall impact over time (out-strength = 0.322), meaning that fluctuations in negative emotionality represented the primary source of variation in the temporal dynamics of emotional functioning in this group. In contrast, the intensity of positive emotions emerged as the most influential predictor within the network of profile 2 (out-strength = 0.381), resulting as the primary driver of change in emotional dynamics in this group. The intensity of positive emotions was also the strongest lag-1 predictor of other variables in profile 3 (out-strength = 0.216), followed by the intensity of negative emotions (out-strength = 0.178).

Finally, examination of ER strategies revealed generally low levels of both in-strength and out-strength across profiles, with only a few notable exceptions. In profile 1, rumination exhibited high levels of both in-strength (0.155) and out-strength (0.133), indicating that it tends to operate both as reactive component of emotional functioning and as primary sources of change. In contrast, in profiles 2 and 3, it consistently showed high in-strength (profile 2 in-strength = 0.190, profile 3 in-strength = 0.202) coupled with low out-strength (profile 2 out-strength = 0.062, profile 3 out-strength = 0.065), indicating that it primarily functioned as a target rather than a driver of temporal influences. A similar pattern was observed for reappraisal in profiles 2 (in-strength = 0.116, out-strength = 0.000) and 3 (in-strength = 0.130, out-strength = 0.087), social sharing in profile 2 (in-strength = 0.132, out-strength = 0.059), and distraction in profile 1 (in-strength = 0.222, out-strength = 0.000). In contrast, distraction in profile 2 exhibited low in-strength but relatively high out-strength (in-strength = 0.049, out-strength = 0.190), suggesting a more active role in shaping subsequent emotional dynamics within this subgroup.

4.2.3. Contemporaneous Network Models Across Distinct Sleep Profiles

The contemporaneous network structures for each profile are displayed in Figure 6. Post-hoc estimates of contemporaneous network models are reported in Tables S15–S17 in the Supplemental Material. Centrality indices are illustrated in Figure 7 and summarized in Table S14 in the Supplemental Material.

Compared to temporal networks, contemporaneous network structures exhibited minimal variation across sleep profiles, indicating that the in-the-moment interplay between emotional components operated similarly regardless of the characteristics of participants' sleep. In more detail, the three sleep profiles showed largely similar patterns of relationships among emotional variables and, consequently, a comparable degree of connectivity: 25 undirected connections were significant when considering profile 1 *(poor and dysregulated sleepers)*, 24 and 26 connections were significant in profile 2 *(poor sleepers despite effort*) and profile 3 (*good sleepers)* respectively.

Likewise, when looking at the relationship between EG (positive and negative) and ER strategies, the results revealed a certain degree of similarity across the three sleep profiles. In all the groups, negative EG exhibited a positive link with suppression (r_{partial} = 0.05 in profile 1; r_{partial} = 0.08 in profile 2; r_{partial} = 0.04 in profile 3) and distraction (r_{partial} = 0.08 in profile 1; r_{partial} = 0.05 in profile 2; r_{partial} = 0.06 in profile 3). Thus, regardless of sleep patterns, when participants were more granular than usual in differentiating among negative emotions, they were also more likely to regulate these emotions through suppression and distraction. Additionally, in all the sleep profiles, we observed a negative correlation between positive EG and social sharing (r_{partial} = -0.06 in profile 1; r_{partial} = -0.04 in profile 2; r_{partial} = -0.05 in profile 3), indicating that a decreased ability to precisely differentiate among positive states in a certain moment is related to the concurrent tendency to share these emotions with others.

Besides these similarities, we also observed two profile-specific relationships. The first association concerns profile 1: Positive EG was related to distraction (r_{partial} = 0.02) and rumination (r_{partial} = -0.05), indicating that when participants were able to precisely differentiate among positive emotions, they were more likely to rely on distraction and less likely to brood. The second association was observed in profile 3 network: Negative EG was positively related to reappraisal (r_{partial} = 0.04) and negatively related to social sharing (r_{partial} = -0.06). Thus, a greater ability to differentiate among negative emotional states was related to a higher tendency to reframe such negative experiences and a lower tendency to share them with others.

Lastly, the overall strength of each node within contemporaneous networks was comparable across profiles. Negative EG exhibited higher strength values (profile 1 strength = 0.877, profile 2 strength = 0.942, profile 3 strength = 1.105) compared to positive EG (profile 1 strength = 0.730, profile 2 strength = 0.671, profile 3 strength = 0.535). The intensity of negative emotions was the node with the highest absolute strength (i.e., the node with the strongest overall connections to other nodes; profile 1 strength = 1.497, profile 2 strength = 1.706, profile 3 strength = 1.784), followed by the intensity of positive emotions (profile 1 strength = 1.125, profile 2 strength = 1.273, profile 3 strength = 1.225). In contrast, two ER strategies, that is reappraisal in poor sleepers (profile 1 strength = 0.341, profile 2 strength = 0.255) and rumination in good sleepers (profile 3 strength = 0.283) emerged as the variables with the lowest strength.

5. Discussion

This study had two primary objectives. The first was to examine the within-person association between positive and negative EG and ER strategies (i.e., suppression, rumination, social sharing, distraction, and cognitive reappraisal) while controlling for positive and negative emotional intensity. Specifically, these relationships were investigated both in terms of reciprocal lagged influences over time and undirected associations in the same time window. In addition, we sought to characterize the general functioning of EG relative to ER strategies and emotional intensity within the broader emotional network, as reflected by centrality indices and autoregressive coefficients.

The second objective was to determine whether and how the relationship between EG and ER varies across distinct latent sleep profiles, conceptualizing sleep as an index of allostatic regulation that may moderate this association both prospectively and concurrently. In this context, we also examined the temporal stability and overall connectivity of positive and negative EG, relative to ER strategies and emotional intensity, within each sleep profile to evaluate potential sleep-dependent differences in EG functioning.

5.1. Objective 1: Network Modeling on the Full sample

5.1.1. Prospective Associations Between Emotional Granularity and Regulatory Strategies

The temporal network estimated across the full sample indicated that a momentarily higher-than-usual ability to differentiate one's emotions did not exert any temporal effect on subsequent ER. This finding is noteworthy given theoretical accounts positing that higher EG facilitates the selection and effective use of ER strategies, particularly by promoting adaptive regulation and reducing maladaptive regulation (Kashdan et al., 2015; Thompson, Springstein, et al., 2021). Our findings suggest that this mechanism may not hold over extended temporal windows: While higher EG may influence ER at the concurrent level, this effect does not appear to propagate over time.

In contrast, the reverse process seems to emerge, with ER exerting a lagged influence on EG. Consistent with our hypothesis, we observed inverse lagged associations involving two putatively maladaptive ER strategies, namely, suppression and rumination. Specifically, greater-than-usual momentary use of rumination was associated with subsequent decreased ability in distinguishing positive emotional states. This finding aligns with emerging evidence showing that momentary increases in rumination can hinder the concurrent ability to generate nuanced instances of negative emotions (Sels et al., 2024). Our results extend this literature by demonstrating that this pattern also applies prospectively to positive EG. Rumination is characterized by repetitive thought (Nolen-Hoeksema et al., 2008) and sensitivity to contextual information (Watkins, 2008), which may promote dwelling on specific aspects of an event in a decontextualized manner. Such processing likely limits opportunities to map affective experiences onto distinct emotional concepts and labels. Furthermore, because rumination involves repeated rehearsal of emotional states, rendering them resistant to change (Watkins, 2008), and because positive emotional states typically exhibit weak categorical boundaries and blended labeling (Vlasenko et al., 2021), these features may help explain the observed lagged effect of rumination on reduced positive EG.

In addition, we found that momentary increases in emotional suppression were prospectively associated with a diminished ability to differentiate negative emotional states. To our knowledge, no previous study has examined the effects of suppression on either positive or negative EG, at either the state or dispositional level. Our findings provide preliminary evidence that the use of suppression may impair subsequent differentiation of negative emotions. Given that suppression is a cognitively demanding ER strategy (Cameron & Overall, 2018; Richards & Gross, 1999), its regulatory costs may persist over time, particularly in the context of negative affect, thereby undermining the capacity for fine-grained emotional differentiation.

Notably, the observed lagged effects of ER on EG were confined to maladaptive strategies. In line with recent speculations (O'Toole et al., 2021), maladaptive ER strategies may interfere with emotional awareness processes, ultimately impairing the ability to differentiate emotional experiences. In contrast, adaptive ER strategies may be employed to enhance emotional understanding and thus support higher EG. However, the supposed protective function of adaptive strategies does not appear sufficiently robust to persist over time and yield enduring beneficial effects in EG. By comparison, maladaptive strategies seem to exert a more pronounced and persistent influence, propagating over time and leading to sustained reductions in EG. This highlights an asymmetric temporal influence of ER on EG. Maladaptive ER strategies appear to have enduring detrimental effects on EG, whereas adaptive strategies may confer more transient, moment-specific benefits.

5.1.2. Concurrent Relationships Between Emotional Granularity and Regulatory Strategies

In the contemporaneous network, positive and negative EG exhibited partly overlapping undirected relationships with ER strategies. Contrary to our hypothesis, both positive and negative EG were negatively correlated with social sharing. Despite not being fully consistent, the results from previous studies suggested a significant inverse association between differentiating negative states (both at the dispositional and momentary level) and sharing these negative states with others (Kalokerinos et al., 2019; Sels et al., 2024).

Our findings corroborate and extend this literature, suggesting that this path of relationship may hold true for the differentiation of both negative and positive emotions. Sharing one's emotions with others allows individuals to process these experiences and gain clarity about how they feel (Stroebe et al., 2001). It is plausible that when people are able to generate nuanced and differentiated emotional experiences, they may feel less need to share these experiences with others. Conversely, engaging in social sharing may in some contexts hinder effective emotion differentiation. Sharers often seek, and listeners provide, empathetic support, which may increase closeness but not necessarily promote emotional understanding (Nils & Rimè, 2012; Pauw et al., 2018; Pauw et al., 2019).

Consistent with our prediction, positive and negative EG were further negatively correlated with rumination. To date, investigations of this ER strategy have primarily examined negative EG, with findings pointing to a reciprocal negative influence between the these two variables (Kalokerinos et al., 2019; Sels et al., 2024). Our results add to previous literature suggesting that when individuals are more likely to regulate their emotions through rumination, they are also less granular than usual in differentiating among these emotions. It is possible that reduced clarity regarding one's emotional states fosters a tendency to ruminate on how an individual feels in an effort to gain understanding (O'Toole et al., 2021; Sels et al., 2024). Conversely, because rumination is characterized by repetitive, self-focused thinking (Treynor et al 2003; Watkins, 2004), persistently brooding may interfere with the ability to differentiate and make sense of one's emotional experiences.

Finally, both positive and negative EG were positively correlated with distraction. Previous studies have examined negative EG predicting distraction and generally yielded non-significant effects, both at the dispositional and the daily level (Kalokerinos et al., 2019; O'Toole et al., 2021). Literature reports that distraction can function as both adaptive and maladaptive depending on context (McRae, 2016; Wolgast & Lundh, 2017), and our study focused on the *momentary* level, which is particularly sensitive to contextual demands. This may explain our results reporting a significant association between this ER strategy and EG. When individuals actively differentiate and construct nuanced emotional experiences, they may simultaneously engage in distraction to manage momentary emotional intensity, shifting attention away from emotions that are difficult to process or overwhelming (Shafir et al., 2015). However, given the correlational nature of these results and the lack of prior empirical evidence on this association, causal conclusions cannot be drawn, and the mechanisms underlying this relationship remain speculative.

In addition to these common patterns of associations across positive and negative EG, we also found two ER strategies related to negative EG only, namely, reappraisal and suppression. The existing literature has reported inconsistent and mostly non-significant results concerning the associations between the differentiation of negative emotions and these two regulatory strategies (Kalokerinos et al., 2019; O'Toole et al., 2021). This prior research has typically examined these associations in separate models, either at the dispositional or daily level, and has predominantly assumed a unidirectional effect of negative EG on ER. Our findings suggest that when individuals differentiate their negative emotions more than usual, they are more prone to suppress these emotions and attempt to reappraise the current negative experience. Differentiating emotional states requires contextual appraisal and evaluation of situational cues (Springstein et al., 2024) Given that suppression is context-dependent and linked to social responding (Butler et al., 2003; English et al., 2012; McRae et al., 2011), heightened awareness of one's negative states may facilitate their inhibition in socially or contextually relevant situations. Similarly, heightened negative EG may support reappraisal by allowing individuals to recognize and distinguish specific emotional states before attempting to reinterpret the situation. Reappraisal itself, by reformulating the meaning of a situation (Gross & John, 2003), may further support refined differentiation of emotions. However, due to the correlational nature of these findings, the directionality of these associations remains unclear. It is possible that heightened negative EG drives the concurrent use of these strategies, or alternatively, that engaging in suppression and reappraisal influences the differentiation of negative emotions.

5.1.3. Overall Functioning of Emotional Granularity

The temporal and contemporaneous networks allowed us to gain information about the overall functioning of EG. First, when examining how EG unfolds over time in the temporal network, it showed similar patterns with ER strategies. Indeed, positive and negative EG and ER strategies consistently had weaker autoregressive effects than positive and negative emotional intensity. As such, both the ability to differentiate emotions and the use of ER strategies showed high sensitivity to fluctuations compared with the relative inertia exhibited by emotional intensity. This pattern supports the speculation that EG may resemble ER in its functioning (Kashdan et al., 2015; Thompson, Springstein, et al., 2021). Furthermore, these results add information about EG conceptualization, corroborating evidence suggesting that it can act both as a dispositional and state-level characteristic (Thompson, Springstein, et al., 2021) and exhibit context-dependent fluctuations over time (Erbas et al., 2018; Schmitt et al., 2024; Springstein et al., 2023). The heightened temporal variability of EG thus aligns with the view that differentiating emotions constitutes a situated regulatory process, operating at the interface between emotion generation and regulation, rather than a downstream outcome of these processes (Barrett et al., 2014; Gross & Barrett, 2011).

Second, examination of centrality indices in the temporal network highlighted a notable pattern of reciprocal prospective influences between EG and other emotional variables. Both positive and negative EG showed high sensitivity to lagged influence from other emotional components and both exerted limited predictive effects over time. This suggests that EG may function primarily as a passive outcome and target of broader emotional fluctuations, rather than as a primary driver of emotional dynamics across time. Notably, this pattern was more pronounced for positive than negative EG. Negative emotions are more relevant for personal strivings and goal pursuits compared to positive emotions (Barrett et al., 2001; Erbas et al., 2014), which in turn exhibit greater fluidity and conceptual overlapping (Vlasenko et al., 2021). As such, the more pronounced passivity observed for positive EG compared to negative EG may reflect qualitative differences in the structure and intrinsic nature of positive versus negative emotional experiences. Along this line, negative emotional intensity emerged as the strongest driver of fluctuations in overall emotional functioning, whereas positive emotional intensity, despite playing a relevant role in shaping temporal dynamics, exerted a comparatively weaker influence. This valence-specific symmetry may help explain the subtle differences observed in the overall predictive influence of positive versus negative EG.

Lastly, these patterns were further clarified by the examination of the overall strength of concurrent associations between EG and other emotional variables within the contemporaneous network. At the momentary level, both positive and negative EG exhibited moderate overall connectivity with the remaining nodes. However, again, negative EG demonstrated greater prominence than positive EG, emerging as the third most central emotional variable in the network following negative and positive emotional intensity. The intensity of emotional states, particularly negative emotions, typically signals the need to mobilize regulatory resources to support allostatic regulation (Barrett et al., 2001). Accordingly, the ability to construct nuanced representations of negative emotional states may constitute a central component of momentary emotional functioning, acting as a key hub linking emotional intensity (especially negative intensity) to other regulatory processes. Emerging evidence indicates that higher dispositional negative EG supports more effective regulation of negative emotions (Kalokerinos et al., 2019). Our findings are consistent with this literature and further suggest that a similar pattern may characterize momentary within-person fluctuations in emotional functioning.

In contrast, positive EG within the contemporaneous network exhibited a pattern of overall strength of connectivity more closely aligned with specific ER strategies. Momentary positive emotions are thought to possess a unique capacity to broaden cognitive repertoires and to foster enduring personal resources that can be mobilized in future adverse situations requiring regulatory effort (Fredrickson, 1998, 2001, 2004). This "broaden-and-build" mechanism may support a reduced propensity to invest in the fine-grained differentiation of positive emotional states, given their lower regulatory urgency, while preserving cognitive resources for future negative events (Barrett et al., 2001). Furthermore, such a "broaden-and-build" mechanism may primarily facilitate the differentiation of negative emotional states by allocating cognitive resources toward processing affectively salient information. Conversely, elevated negative emotionality may constrain the ability to leverage positive affect for the processing and differentiation of positive emotional experiences.

Overall, these findings suggest a dual nature of EG, reflecting both general mechanisms shared with ER strategies and valence-dependent characteristics that shape its role within emotional networks. On the one hand, both positive and negative EG exhibited comparable levels of temporal stability and fluctuated over time in a way similar to ER strategies. Moreover, EG (particularly positive EG) and ER showed a comparable overall strength of concurrent associations within the contemporaneous network. Therefore, consistent with constructionist accounts of emotion generation and regulation (Barrett et al., 2014; Gross & Barrett, 2011), EG ultimately appears to reflect an active process of affective meaning-making that varies over time in response to internal and external demands. At the same time, it retains valence-specific properties, suggesting distinct functional mechanisms as a function of emotional valence. Negative EG appears to serve as a key hub for overall emotional functioning, both at the momentary level and prospectively over time. It may reflect an increased engagement in interpreting and categorizing bodily sensations due to their salience in front of a negative event (Barrett et al., 2001; Erbas et al., 2014), thereby serving as a pivotal regulatory process embedded within broader emotional functioning (Gross & Barrett, 2011). In contrast, positive EG appears to play a less prominent role and reveals analogous associative patterns with some ER strategies (particularly at the momentary level), likely reflecting the intrinsic characteristics of positive emotional states (Vlasenko et al., 2021).

5.2. Objective 2: Network Modeling Across Distinct Sleep Profiles

We identified three subgroups of sleepers, each characterized by distinct latent patterns of sleep quality and sleep-related behaviors. The first group of participants, *poor and dysregulated sleepers* (profile 1), exhibited below average levels of sleep quality indicators (e.g., poor sleep quality, unrestful awakenings, difficulties initiating sleep) and maladaptive sleep behaviors (e.g., delayed asleep times and wake-up times, poor sleep hygiene, short sleep duration). The participants grouped in the second sleep profile were named *poor sleepers despite effort* (profile 2), as they reported disrupted sleep (e.g., poor sleep quality, unrestful awakenings, sleep interruptions) despite healthy sleep behaviors (e.g., good sleep hygiene). Finally, we identified a subgroup of *good sleepers* (profile 3), who presented above average levels of good sleep indicators (e.g., good sleep quality, restful awakenings) and low levels of problematic sleep (e.g., no significant sleep interruptions, no difficulty initiating sleep).

When examining emotional network of each group, temporal network analyses revealed distinct patterns of prospective emotional functioning across latent sleep profiles. Overall, this variability possibly reflects distinct degrees of sleep-related allostatic efficiency associated with daily emotional functioning over time (Irwin, 2015; McEwen & Karatsoreos, 2022; ten Brink et al., 2022). In contrast, the contemporaneous network structures revealed broadly similar configurations and minimal variability in terms of connectivity across the three sleep profiles. Collectively, these results suggest that sleep patterns primarily modulate the prospective integration of emotional components rather than their momentary covariation. Although sleep may influence the unfolding of emotional dynamics over time (Goldstein & Walker, 2014), the interplay of emotional variables at any given moment appears to be relatively independent of sleep patterns.

5.2.1. Profile-Specific Prospective Associations Between Emotional Granularity and Regulatory Strategies

An examination of the lagged effects within the temporal network revealed that the three sleep profiles differed in terms of the bidirectional temporal influences among positive and negative EG and ER strategies. Contrary to our prediction, no temporal effects emerged in good sleepers (profile 3); thus, these two components of emotional functioning appear to operate relatively independently over time when sleep is restorative. By contrast, poor sleepers exhibited significant but distinct temporal associations.

Specifically, in poor and dysregulated sleepers (profile 1), prior use of suppression reduced negative EG, while in poor sleepers despite effort (profile 2), distraction undermined subsequent positive EG. These results contribute to previous evidence highlighting the role of poor sleep in diminishing the effectiveness of ER (Kirwan et al., 2019; OLeary et al., 2017; Sullivan et al., 2023; Wang et al., 2023). Consistent with our hypothesis, under conditions of impaired sleep specific ER strategies may exert a maladaptive function, ultimately impairing the differentiation of emotional states. However, the manifestation of these maladaptive effects (including the type of regulatory strategy involved and the valence of EG affected) appears to be contingent upon the specific pattern of non-restorative sleep.

When looking at the opposite direction (i.e., whether EG impacts ER) in these same sleep profiles, only negative EG predicted subsequent regulatory processes, particularly the use of distraction. This lagged association was positive for poor and dysregulated sleepers (profile 1) but negative for poor sleepers despite effort (profile 2); this opposite direction of effects across the two profiles may derive from the dual nature of distraction, which can serve both adaptive and maladaptive regulatory functions (McRae, 2016; Wolgast & Lundh, 2017). Prior research has linked poor sleep with greater reliance on avoidant ER strategies (Boon et al., 2023; Zhang et al., 2019); our findings extend this evidence by emphasizing the lagged effect of negative EG on subsequent distraction and underscoring the importance of distinguishing among different forms of impaired sleep conditions.

By leveraging a temporal network approach, this study attempted to clarify the directionality (i.e., EG predicting ER, and vice versa) and functional nature (i.e., adaptive vs. maladaptive) of the relationship between EG and ER over time. Although the ability to create nuanced instances of emotions has been theoretically proposed to support adaptive ER (Kashdan et al., 2015; Thompson, Springstein, et al., 2021), our results did not provide evidence of a beneficial prospective impact of positive EG on ER; similarly, only marginal evidence emerged for negative EG, and under poor sleep conditions only. Conversely, maladaptive ER appeared to exert prospective impairing effects on both positive and negative EG, yet this occurred exclusively among individuals with poor sleep. Overall, our findings indicate that the temporal unfolding of the EG–ER relationship becomes observable primarily in the presence of sleep-related allostatic burden, possibly due to its impact on the ability to sustain adaptive emotional functioning. Accordingly, they underscore the importance of accounting for modulators of allostatic regulation as downstream mechanisms in the relationship between EG and ER when evaluating their temporal directionality and reciprocal (mal)adaptive function.

5.2.2. Profile-Specific Concurrent Relationships Between Emotional Granularity and Regulatory Strategies

At the momentary level, the relationship between EG and the five ER strategies exhibited both profile-specific patterns and associations that were consistent across profiles. Across all groups, and in line with the results of the network model estimated on the full sample, positive EG was negatively related to social sharing, whereas negative EG was positively related to both suppression and distraction. These convergent findings indicate that the links between EG and these ER strategies extend beyond profile-specific differences in sleep-related allostatic functioning.

In poor and dysregulated sleepers (profile 1), positive EG was further negatively correlated with rumination and positively correlated with distraction. To date, these two ER strategies have primarily been studied in relation to negative EG, yielding mixed and inconsistent findings. Rumination has occasionally been found to influence negative EG, and vice versa (Kalokerinos et al., 2019; Sels et al., 2024); by contrast, the association between negative EG and distraction has been examined primarily in the direction of negative EG predicting distraction and generally yielded non-significant effects (Kalokerinos et al., 2019; O'Toole et al., 2021). The present findings advance this evidence by revealing that the within-person relationships between these ER strategies and positive EG appear to be partially modulated by sleep patterns. Consistent with our hypothesis, the sleep-related allostatic burden arising from poor sleep and unhealthy sleep behaviors may contribute to the emergence of a significant relationship between the selection of putatively maladaptive ER strategies and the differentiation of positive states.

In good sleepers (profile 3), a greater than usual momentary ability to precisely differentiate among negative emotions was additionally linked to putatively adaptive strategies, including an inverse relationship with social sharing and a positive correlation with cognitive reappraisal. Prior evidence has indicated that negative EG may reduce the likelihood of engaging in social sharing, whereas the reverse effect (i.e., social sharing undermining negative EG) has occasionally but not consistently been observed (Kalokerinos et al., 2019; Sels et al., 2024). Similarly, in some studies, cognitive reappraisal has been found to decrease negative EG over time, although this effect does not always emerge (Kalokerinos et al., 2019; O'Toole et al., 2021). Our findings add to this literature by suggesting that these inconsistencies may reflect unmeasured heterogeneity in sleep-related allostatic regulation and that such relationships emerge primarily under conditions of restorative sleep. In the presence of sufficient allostatic resources provided by adequate sleep, individuals may preferentially engage in internal processing of negative states, supported by enhanced differentiation, rather than seeking social disclosure. At the same time, adequate sleep may facilitate both fine-grained identification and cognitive reframing of negative emotional experiences.

Overall, although preliminary and correlational in nature, the present pattern of findings suggests that sleep-related allostatic functioning partly moderates the momentary association between EG and ER, yet our hypotheses were only partially supported. On the one hand, some EG–ER links that yielded mixed and inconsistent evidence in previous studies emerged here to be sleep-dependent (potentially accounting for the heterogeneity of past results). On the other hand, the in-the-moment relationship between EG and ER does not appear to be necessarily confined to an adaptive versus maladaptive function of the two constructs. Importantly, emotion regulation theorists have highlighted that ER strategies are not inherently adaptive or maladaptive but rather acquire their function through contextual contingencies (Aldao et al., 2015). This view aligns with the TCE (the theoretical framework in which EG is embedded), which underscores the role of context in the construction of nuanced instances of emotions (Barrett, 2017a). Accordingly, the variability observed in the present associations may reflect that the concurrent relationship between EG and ER is not determined by their presumed adaptiveness per se but rather emerges as a function of both allostatic functioning and situational demands.

5.2.3. Profile-Specific Overall Functioning of Emotional Granularity

Consistent with results from network models estimated on the full sample, both positive and negative EG and ER strategies showed higher sensibility to fluctuations compared to positive and negative emotional intensity across sleep profiles. This consistent pattern corroborates the hypothesis that EG and ER may partially overlap in their functioning and downstream mechanisms (Kashdan et al., 2015; Thompson, Springstein, et al., 2021).

Moving toward an examination of the overall pattern of reciprocal temporal influences between EG and the other emotional variables, some profile-specific differences emerged as noteworthy. Among poor sleepers (profiles 1 and 2), positive EG primarily functioned as a downstream target of broader fluctuations in emotional intensity and regulatory strategies, rather than as an active driver of emotional change. In contrast, within these same individuals, negative EG emerged as a key driver of emotional dynamics over time, thereby representing a central mechanism through which emotional dynamics propagate across the day. In this context, sleep-related allostatic burden may deploy the engagement with positive experiences and constrain the focus on negative emotional states (Parsons et al., 2022; Parsons & Young, 2022; Thompson et al., 2022). As a result, positive EG may unfold as more reactive to ongoing emotional dynamics rather than a proactive component of modulation and integration of emotional functioning over time. Conversely, negative EG may capture increased efforts to interpret and categorize aversive bodily sensations associated with heightened allostatic load, thereby playing a pivotal role in regulating broader emotional shifts (Gross & Barrett, 2011).

In contrast to poor sleepers, in individuals with restorative sleep (profile 3), both positive and negative EG showed minimal sensitivity to prospective influence from other emotional variables and exerted equally limited predictive effects: In the context of adequate sleep, EG appears to operate independently, as an autonomous component of emotional functioning over time. Collectively, these findings suggest that the prospective role of EG in shaping emotional dynamics is not unconditional; rather, it is sleep-dependent and presumably reflects different characterizations of allostatic processes. As such, it should be understood within the broader framework of allostatic regulation and in relation to the multidimensional structure of emotional functioning, rather than being inferred from isolated, univariate associations.

Importantly, both positive and negative EG exhibited an overall pattern of predictive influence that closely resembled that of specific ER strategies, although these similarities were explicitly sleep profile–dependent rather than uniform across subgroups of sleepers. In contrast, emotional intensity exerted a central role in driving fluctuations and change in emotional functioning over time, in a valence-specific manner that varied as a function of sleep profile. This overall pattern aligns with the assumption that EG may serve as an ER strategy embedded within the ongoing process of emotion generation (Gross & Barrett, 2011; Kashdan et al., 2015; Thompson, Springstein, et al., 2021). However, because the construction of emotional experience is fundamentally oriented toward allostatic regulation and is intrinsically grounded in internal bodily signals (Barrett, 2017a; Barrett et al., 2025), the specific role of EG and of individual ER strategies within the emotional network appears to depend critically on allostatic regulatory demands.

Finally, when focusing on the momentary level, positive and negative EG both exhibited moderate overall strength of concurrent relationships with other emotional variables across the three sleep profiles. However, negative EG showed slightly higher values compared to positive EG. In contrast, positive EG showed an overall level of strength of connectivity aligned with that of ER strategies. This pattern of findings is consistent with results from the contemporaneous network estimated in the full sample and corroborates the idea that positive and negative EG exert valence-specific functions in the emotional functioning in light of the distinct nature of positive and negative emotional experiences (Barrett et al., 2001; Erbas et al., 2014; Vlasenko et al., 2021).

Taken together, the present findings suggest that the general functioning of EG is only partially contingent upon sleep-related allostatic regulation. On the one hand, the prospective role of EG appears to shift as a function of sleep, alternately emerging as a downstream target or an active driver of emotional change over time. Moreover, the overall pattern of predictive influence exerted by EG converges with that of specific ER strategies in a sleep profile–dependent manner. On the other hand, EG consistently emerged as a highly dynamic construct, characterized by substantial variability across the day regardless of sleep profile. Moreover, at the momentary level, EG maintained a largely comparable pattern of overall connectivity with other emotional variables across subgroups of sleepers, albeit with clear valence-specific distinctions. Overall, these findings support the conclusion that, while the downstream processes and functional implications of EG are shaped by sleep-related allostatic load, EG also preserves core functional properties that transcend individual differences in allostatic regulation. More broadly, EG appears to unfold at the intersection of context-sensitive allostatic demands and specific functional mechanisms intrinsic to emotional processing that transcend individual differences in allostatic burden.

5.3. Limitations and Future Directions

Some limitations of the present study warrant consideration. First, the reliance on subjective sleep measures without complementary objective assessments (e.g., actigraphy, polysomnography) limits the physiological precision of our sleep profiles. Additionally, the absence of direct biomarkers of allostatic load (e.g., cortisol, heart rate variability, and inflammatory markers) restricts our ability to fully capture the neurobiological mechanisms underlying sleep-related allostatic regulation. Future research could benefit from the integration of multimodal measures that account for objective sleep patterns and physiological indicators of allostatic regulation. Such an approach would increase the validity of sleep profiling and clarify how specific sleep characteristics interact with allostatic mechanisms to shape emotional functioning.

Second, we applied MLPA to identify distinct sleep profiles at the between-person level and to evaluate whether individuals characterized by distinct sleep patterns have similar within-person daily emotional functioning. Compared with LPA, which is conducted on cross-sectional data, MPLA is particularly valuable because it allows for the separation of between- and within-person variance and helps avoid retrospective bias. While this between-person approach was informative, we could have also conducted a within-person MLPA, in which each day (rather than each person) would be assigned to a distinct profile. This approach would have allowed us to examine and compare within-person daily emotional dynamics across distinct within-person, day-specific sleep profiles. However, this type of research question cannot be addressed via the combination of the MLPA and multilevel network models. Building on the present findings, future studies could adopt intensive longitudinal designs that incorporate within-person sleep profiling alongside statistical approaches suitable for modeling daily fluctuations in emotional dynamics at the within-person level.

Finally, although MNP analysis via mlVAR models allows the estimation of between-person network structures, the profiles' sample size was too small to conduct this analysis. This prevented us from explicitly testing the concurrent and prospective interplay between EG and ER strategies at the dispositional level. Investigating whether the sleep-dependent associations observed at the within-person level also hold at the between-person level remains an important direction for future research.

Despite these limitations, the present study provides novel insights into how state-level EG intertwines with ER strategies, also accounting for emotional intensity, in a way that is partially dependent on sleep patterns. Furthermore, to our knowledge, this is the first study to investigate the relationship between state-level positive EG and ER, as well as the first to examine the interplay between multiple components of the emotional process (namely EG, ER, and emotion intensity) within a single multivariate model, accounting for both prospective and concurrent temporal relationships.

6. Conclusion

This study pursued two primary objectives. First, it aimed to clarify the within-person relationships between positive and negative EG and five ER strategies, while also accounting for emotional intensity. By combining temporal and contemporaneous network analyses, we captured both lagged reciprocal influences and co-occurrent undirected connections among these emotional variables. Second, the study sought to determine whether these relationships vary across distinct latent sleep profiles, conceptualized as indices of sleep-related allostatic regulation.

Our findings indicate that prospective and in-the-moment emotional functioning differed markedly, with the latter not showing particular sensitivity to sleep. At the prospective level, lagged EG did not exert any influence on subsequent ER. In contrast, the reverse directionality was observed (i.e., ER negatively influencing positive and negative EG), although confined to maladaptive ER strategies. Interestingly, when considering the moderating role of sleep, this association was significant only among poor sleepers. At the momentary level, multiple correlations emerged between positive and negative EG and ER strategies, suggesting that their relationships span emotional valence rather than being restricted to positive or negative domains, and encompass both adaptive and maladaptive strategies. Notably, the observed associations varied only partially as a function of sleep.

Network analysis provided further insights about the overall functioning of EG. First, similarly to ER strategies, both positive and negative EG showed high variability across the day, regardless of sleep patterns. Second, in poor sleepers, positive EG emerged as a primary target of fluctuations from other emotional variables, while negative EG was an important driver of changes in overall emotional functioning over time. In contrast, in good sleepers, neither positive nor negative EG played a prominent role in the overall prospective emotional functioning. Third, both positive and negative EG showed patterns of overall predictive influence closely mirroring those of individual ER strategies, though these parallels were dependent on participants' sleep profiles. Finally, at the momentary level, negative EG consistently acted as a central hub of emotional functioning, while positive EG showed overall connectivity strength closely aligned with specific ER strategies, independent of sleep.

Taken together, these results suggest that the relationship between EG and ER is conditional and closely dependent on the temporal window examined. Sleep, as a modulator of allostatic regulation, appears to play an important role in determining when and how EG and ER support or undermine one another. Importantly, EG and ER seem to share downstream processes affecting broader emotional functioning, while retaining core individual properties; these processes are both shaped by sleep-related allostatic load and extend beyond individual differences in sleep patterns. Overall, these findings call for a reconsideration of EG as a uniformly adaptive construct and point to a conceptualization of EG as a form of ER embedded within the ongoing process of emotion generation and regulation. They also underscore the importance of integrating modulators of allostatic regulation, such as sleep, into models of emotional functioning.

Emotional Granularity and Emotion Regulation: Network Modeling of Within-Person Concurrent and Prospective Emotional Dynamics Across Distinct Latent Sleep Profiles

Chapter 2 Supplemental Material

List of Content:

4. Figures

1. Method

1.1. Sample Size Justification

For the MLPA and multilevel network models, there are no closed-form available for estimating statistical power. Consequently, we relied on published recommendations to guide our assessment of sample adequacy.

Sample size planning for MLPA was based on practical guidelines and simulation evidence (Bauer, 2022; Masyn, 2013). In the MLPA, stable estimation critically depends on the number of Level 2 units (persons), the average number of Level 1 observations (days per person), and the number of indicators (Nylund-Gibson & Choi, 2018; Tein et al., 2013). Our analysis included 255 participants (Level 2) and 5–10 measurement occasions (Level 1) across 11 sleep indicators. The average number of daily observations per participant (*M* = 9.66 days per participant, *SD* = 0.83; total of 2,463 observations) is above the threshold of 5–7 observations required to reliably estimate within-person variability (Yang et al., 2022), ensuring that the between-person profiles are accurately estimated by accounting for day-to-day fluctuations (Bauer, 2022). The sample size of 255 participants exceeds the recommended minimum of 200 participants for latent profile analysis with more than 10 indicators (Nylund et al., 2007; Tein et al., 2013). It also provides more than 50 cases per expected profile (assuming up to 5 profiles), which reduces the risk of spurious solutions (Tein et al., 2013). Furthermore, the ratio of participants to indicators (approximately 23:1) is well above the conservative recommendation of 10:1 for mixture models (Masyn, 2013). Simulation studies for similar MLPA designs indicate that this sample size provides greater than 90% power to detect between-person latent profile separation with an expected entropy above 0.80 (Dalmaijer, 2023; Dalmaijer et al., 2022; Peugh & Fan, 2015). Taken together, these considerations support the adequacy of our planned sample for identifying and characterizing multilevel latent profiles of sleep between participants.

With respect to multilevel network models, both the number of participants and the average number of measurement occasions per participant were considered, as they influence the precision and stability of within-person relationships. Empirical examples (Epskamp, Waldorp, et al., 2018) suggest that stable networks with 6–17 nodes can be reliably estimated with approximately 25–60 participants, each providing at least 50–35 repeated measurements. Additional guidance from previous studies suggested that in multilevel network models with 4–10 nodes, estimated on approximately 30 participants with 56–70 time points, the statistical power can reach at least 95.5–99.8% (J. Curtiss et al., 2019; J. E. Curtiss et al., 2022). This evidence indicates that even relatively small samples with sufficient repeated measurements can yield robust estimates of temporal and contemporaneous network models. Accordingly, our analysis included 9 nodes for 255 participants assigned to three subsamples (Sample 1 = 74; Sample 2 = 81; Sample 3 = 100) on the basis of the MLPA (see Results section). The participants completed, on average, 59.26 assessments (*SD* = 10.21) out of 70 possible measurement occasions, yielding a total of 15,111 EMA observations. The average completion rates across subsamples were as follows: Sample 1, *M* = 57.87 (*SD* = 10.58); Sample 2, *M* = 61.21 (*SD* = 9.93);

and Sample 3, $M = 58.71$ ($SD = 10.02$). This level of completion meets established recommendations to provide sufficient power to detect moderate network connections and ensure convergence of the multilevel network models.

2. Results

2.1. Multilevel Latent Profile Analysis: Identification of Sleep Profiles

The MLPA results led to the identification of three distinct between-person sleep profiles. The iterative estimation process of the *k*-profile model was stopped at the 4-class solution, as this model included a between-person profile representing less than 5% of the sample and was therefore deemed unfit.

As shown in Table S10 in the Supplemental Material, information criteria (i.e., AIC, BIC, SABIC) progressively decreased with the increasing of the number of classes, remaining relatively stable between the three- and four-class models (see also Figure S1 in the Supplemental Material). The 4-class model was nonetheless excluded because the change in fit was marginal compared to the 3-class solution and the results of the VLMR-LRT and LMR-LRT indicated that the inclusion of a fourth class did not significantly improve model fit. Finally, the 4-class solution produced highly unbalanced profile sizes and a lower entropy than the 3-class solution.

When comparing the 2- and 3-class solutions, information criteria improved substantially from the 2- to the 3-class solution, but the results of the VLMR-LRT and LMR-LRT suggested that the addition of a third class to the 2-class model did not add significant information. Therefore, based on theoretical considerations (Nylund et al., 2007), the 3-class model was preferred, as it provided a finer and more robust differentiation of three qualitatively distinct and well-separated profiles. This solution also displayed good entropy and a more balanced distribution across the three classes. For completeness, the 2-class solution is presented in Figure S2 in the Supplemental Material.

3. Tables

3.1. Table S1: Individual Multilevel Models of Temporal Trends Across the Course of the EMA for Each Emotional Variable

Table S1. Individual multilevel models of temporal trends across the course of the EMA for each emotional variable.

Emotional Variable	Est. (*SE*)	95% *CI*	*t*	*p*
Positive Emotional Granularity	**0.03 (0.00)**	**[0.03, 0.04]**	**18.23**	**<.001**
Negative Emotional Granularity	**0.02 (0.00)**	**[0.02, 0.03]**	**10.77**	**<.001**
Positive Emotions	**-0.13 (0.01)**	**[-0.14, -0.11]**	**-19.86**	**<.001**
Negative Emotions	**-0.06 (0.01)**	**[-0.06, -0.05]**	**-12.06**	**<.001**
Social Sharing	**-0.05(0.01)**	**[-0.07, -0.04]**	**-5.88**	**<.001**
Distraction	**-0.06(0.01)**	**[-0.07, -0.04]**	**-6.40**	**<.001**
Reappraisal	**-0.04(0.01)**	**[-0.05, -0.02]**	**-4.81**	**<.001**
Rumination	**-0.03(0.01)**	**[-0.04, -0.01]**	**-2.81**	**0.005**
Expressive Suppression	-0.01(0.01)	[-0.03, 0.01]	-0.59	0.558

Note: Boldface indicates significant effects. CI = confidence interval. CIs were estimated using 2,500 bootstrap resamples.

3.2. Table S2. Network Model Comparison Results for the Entire Sample

Table S2. Network model comparison results for the entire sample.

	Orthogonal Estimation		Correlated Estimation		Fixed Estimation		Best Information Criterion	
Variable	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC
Positive EG	28,500.84	28,712.65	28,484.44	29,024.90	29,036.11	29,182.18	correlated	orthogonal
Negative EG	29,301.68	29,513.49	29,312.03	29,852.50	29,688.11	29,834.18	orthogonal	orthogonal
Social Sharing	28,243.08	28,454.89	28,267.10	28,807.56	28,448.78	28,594.85	orthogonal	orthogonal
Distraction	23,162.96	23,374.76	23,169.67	23,710.13	23,570.33	23,716.40	orthogonal	orthogonal
Rumination	23,446.41	23,658.21	23,475.72	24,016.18	23,833.77	23,979.84	orthogonal	orthogonal
Reappraisal	23,301.33	23,513.13	23,293.69	23,834.16	23,694.70	23,840.77	correlated	orthogonal
Suppression	23,460.58	23,672.38	23,507.14	24,047.60	23,714.70	23,860.77	orthogonal	orthogonal
Negative Emotions	18,183.35	18,395.15	18,187.48	18,727.94	18,588.82	18,734.89	orthogonal	orthogonal
Positive Emotions	21,171.74	21,383.54	21,207.16	21,747.62	21,409.75	21,555.82	orthogonal	orthogonal

Note: Orthogonal estimation assumes uncorrelated random effects. Correlated estimation correlates random effects. Fixed estimation assumes no random effects. AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; EG = Emotional Granularity.

3.3. Tables S3–S5: Network Model Comparison Results for Profile 1, Profile 2, and Profile 3

Table S3. Model comparison results for Profile 1 (i.e., Poor and dysregulated sleepers).

	Orthogonal Estimation		Correlated Estimation		Fixed Estimation		Best Information Criterion	
Variable	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC
Positive EG	8,073.095	8,248.230	8,098.050	8,544.948	8,222.449	8,343.232	orthogonal	orthogonal
Negative EG	7,920.821	8,095.957	7,935.740	8,382.638	7,992.788	8,113.571	orthogonal	orthogonal
Social Sharing	8,256.874	8,432.009	8,310.305	8,757.203	8,269.777	8,390.560	orthogonal	fixed
Distraction	6,614.025	6,789.160	6,644.568	7,091.466	6,727.322	6,848.105	orthogonal	orthogonal
Rumination	6,632.498	6,807.634	6,674.091	7,120.989	6,747.975	6,868.759	orthogonal	orthogonal
Reappraisal	6,914.933	7,090.068	6,939.749	7,386.647	7,046.314	7,167.097	orthogonal	orthogonal
Suppression	6,822.347	6,997.483	6,893.358	7,340.256	6,900.898	7,021.681	orthogonal	orthogonal
Negative Emotions	5,043.620	5,218.755	5,068.737	5,515.634	5,113.077	5,233.861	orthogonal	orthogonal
Positive Emotions	5,249.312	5,424.448	5,280.550	5,727.448	5,315.588	5,436.371	orthogonal	orthogonal

Note: Orthogonal estimation assumes uncorrelated random effects. Correlated estimation correlates random effects. Fixed estimation assumes no random effects. AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; EG = Emotional Granularity.

Table S4. Model comparison results for Profile 2 (i.e., Poor sleepers despite effort).

	Orthogonal Estimation		Correlated Estimation		Fixed Estimation		Best Information Criterion	
Variable	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC
Positive EG	9,761.064	9,941.229	9,816.751	10,276.481	9,855.744	9,979.996	orthogonal	orthogonal
Negative EG	10,192.160	10,372.320	10,249.540	10,709.270	10,318.490	10,442.740	orthogonal	orthogonal
Social Sharing	9,063.431	9,243.595	9,098.940	9,558.671	9,144.803	9,269.054	orthogonal	orthogonal
Distraction	6,989.068	7,169.232	7,046.238	7,505.968	7,072.492	7,196.744	orthogonal	orthogonal
Rumination	7,279.788	7,459.953	7,335.721	7,795.451	7,330.272	7,454.523	orthogonal	fixed
Reappraisal	7,095.252	7,275.417	7,143.918	7,603.648	7,234.759	7,359.010	orthogonal	orthogonal
Suppression	7,229.024	7,409.189	7,279.004	7,738.734	7,310.413	7,434.665	orthogonal	orthogonal
Negative Emotions	5,208.517	5,388.682	5,249.347	5,709.077	5,336.936	5,461.188	orthogonal	orthogonal
Positive Emotions	7,188.043	7,368.208	7,228.628	7,688.358	7,237.505	7,361.756	orthogonal	fixed

Note: Orthogonal estimation assumes uncorrelated random effects. Correlated estimation correlates random effects. Fixed estimation assumes no random effects. AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; EG = Emotional Granularity.

Table S5. Model comparison results for Profile 3 (i.e., Good sleepers).

	Orthogonal Estimation		Correlated Estimation		Fixed Estimation		Best Information Criterion	
Variable	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC
Positive EG	10,669.360	10,853.240	10,689.080	11,158.270	10,953.970	11,080.780	orthogonal	orthogonal
Negative EG	11,230.530	11,414.400	11,267.040	11,736.240	11,419.820	11,546.630	orthogonal	orthogonal
Social Sharing	10,924.000	11,107.870	10,979.700	11,448.890	10,997.550	11,124.360	orthogonal	orthogonal
Distraction	9,818.831	10,002.700	9,844.368	10,313.560	9,991.940	10,118.750	orthogonal	orthogonal
Rumination	9,655.049	9,838.922	9,688.523	10,157.720	9,818.750	9,945.559	orthogonal	orthogonal
Reappraisal	9,250.991	9,434.865	9,261.343	9,730.537	9,349.178	9,475.987	orthogonal	orthogonal
Suppression	9,686.280	9,870.153	9,741.367	10,210.560	9,737.661	9,864.470	orthogonal	fixed
Negative Emotions	8,434.617	8,618.490	8,467.445	8,936.638	8,610.638	8,737.448	orthogonal	orthogonal
Positive Emotions	8,811.506	8,995.379	8,860.953	9,330.147	8,897.666	9,024.475	orthogonal	orthogonal

Note: Orthogonal estimation assumes uncorrelated random effects. Correlated estimation correlates random effects. Fixed estimation assumes no random effects. AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; EG = Emotional Granularity.

3.4. Table S6: Descriptive Statistics of EMA Measures (Emotional Experience) and Morning Diary Measures (Sleep Characteristics)

Table S6. Descriptive statistics of EMA measures (emotional experience) and morning diary measures (sleep characteristics).

	Full Sample (n = 255)			Profile 1 (n = 74)			Profile 2 (n = 81)			Profile 3 (n = 100)		
	M	SD_{within}	$SD_{between}$	*M*	SD_{within}	$SD_{between}$	*M*	SD_{within}	$SD_{between}$	*M*	SD_{within}	$SD_{between}$
Emotional Experience												
Negative EG	-2.85	5.58	1.14	-2.93	5.68	1.19	-2.78	5.29	1.07	-2.84	5.74	1.17
Positive EG	-2.69	4.03	0.77	-2.60	4.14	0.79	-2.69	4.12	0.66	-2.76	3.89	0.84
Negative emotions	14.73	10.01	15.32	17.37	11.09	17.06	16.81	9.75	17.28	11.08	9.42	11.11
Positive emotions	28.58	15.23	17.09	26.32	13.90	19.56	26.91	14.30	15.83	31.60	16.96	15.78
Expressive suppression	25.14	21.88	23.48	13.80	20.57	10.87	14.18	17.90	15.06	15.25	21.74	12.90
Rumination	22.85	20.20	21.18	27.53	22.18	23.80	27.49	19.30	26.33	19.17	20.02	18.62
Social sharing	14.49	20.18	13.06	25.83	21.98	22.28	24.10	19.10	22.78	19.62	19.78	18.64
Distraction	24.24	20.42	23.08	16.52	17.11	17.04	15.46	14.95	20.34	15.97	17.66	18.16
Reappraisal	15.97	16.64	18.51	30.60	24.31	26.02	27.65	20.96	24.82	19.06	20.82	18.78
Sleep												
Perceived sleep quality	3.30	0.77	0.47	3.30	0.77	0.47	3.17	0.81	0.43	3.88	0.75	0.39
Feeling rested upon waking	2.60	0.85	0.52	2.60	0.85	0.52	2.63	0.80	0.48	3.33	0.83	0.47
Wake-up time	8.80	1.33	0.75	8.50	1.33	0.75	07.16	1.00	1.03	8.08	1.05	0.80
Falling asleep time	25.44	1.19	0.73	1.26	1.19	0.73	23.44	0.87	0.64	0.22	0.99	0.71
Actual–desired wake-up time discrepancy	-0.08	1.04	0.90	-0.08	1.04	0.90	1.03	0.88	0.77	0.18	0.87	0.63
Actual–desired asleep time discrepancy	-1.72	1.01	0.76	-1.72	1.01	0.76	-0.72	0.76	0.53	-0.80	0.80	0.50
Actual sleep duration	7.37	1.38	0.77	7.37	1.38	0.77	7.53	1.09	0.81	7.78	1.07	0.64
Perceived sleep duration	5.75	1.82	1.09	5.75	1.82	1.09	5.96	1.51	1.12	7.02	1.35	0.92
Sleep interruptions	1.21	1.05	0.93	1.21	1.05	0.93	1.67	1.12	0.89	0.74	0.91	0.45
Sleep onset difficulty	2.26	0.88	0.75	2.26	0.88	0.75	1.93	0.72	0.66	1.50	0.60	0.39
Sleep hygiene	3.48	0.39	0.33	3.48	0.39	0.33	3.65	0.37	0.38	3.63	0.37	0.32

Note: EG = Emotional Granularity. Descriptive statistics for the wake-up and sleep onset times are presented in 24-hour time notation. With respect to the discrepancy between the actual and desired wake-up times, higher values indicate a preference to wake up later, whereas lower values indicate a preference to wake up earlier. With respect to the discrepancy between actual and desired asleep time, higher values indicate a preference to fall asleep later, whereas lower values indicate a preference to fall asleep earlier. Actual and desired sleep duration refers to the total number of hours, whereas sleep interruptions refer to the count of nocturnal awakenings. Profile 1 = Poor and dysregulated sleepers; Profile 2 = Poor sleepers despite effort; Profile 3 = Good sleepers. *M* = Mean; *SD* = Standard Deviation.

3.5. Table S7: Fixed Effects for the Temporal Network Model of the Entire Sample

Table S7. Fixed effects for the temporal network model of the entire sample.

From	To	Fixed Effect	*SE*	*p*
Positive EG	**Positive EG**	**0.20**	**0.02**	**0.000**
Positive EG	**Negative EG**	**0.04**	**0.02**	**0.034**
Positive EG	Social sharing	-0.01	0.01	0.212
Positive EG	Distraction	-0.01	0.01	0.151
Positive EG	Rumination	-0.01	0.01	0.422
Positive EG	Reappraisal	0.00	0.01	0.625
Positive EG	Suppression	-0.01	0.01	0.407
Positive EG	Negative emotions	-0.01	0.01	0.309
Positive EG	Positive emotions	-0.01	0.01	0.407
Negative EG	**Positive EG**	**0.05**	**0.01**	**0.000**
Negative EG	**Negative EG**	**0.14**	**0.02**	**0.000**
Negative EG	Social sharing	-0.00	0.01	0.930
Negative EG	Distraction	-0.01	0.01	0.450
Negative EG	Rumination	0.01	0.01	0.467
Negative EG	Reappraisal	0.01	0.01	0.617
Negative EG	Suppression	0.00	0.01	0.988
Negative EG	**Negative emotions**	**0.03**	**0.01**	**0.001**
Negative EG	Positive emotions	-0.02	0.01	0.050
Social sharing	Positive EG	-0.01	0.01	0.206
Social sharing	Negative EG	-0.02	0.01	0.102
Social sharing	**Social sharing**	**0.17**	**0.02**	**0.000**
Social sharing	Distraction	0.01	0.01	0.287
Social sharing	**Rumination**	**0.03**	**0.01**	**0.007**
Social sharing	Reappraisal	0.01	0.01	0.399
Social sharing	Suppression	-0.01	0.01	0.282
Social sharing	Negative emotions	0.01	0.01	0.323
Social sharing	**Positive emotions**	**0.02**	**0.01**	**0.043**
Distraction	Positive EG	-0.03	0.02	0.099
Distraction	Negative EG	-0.02	0.02	0.285
Distraction	Social sharing	-0.02	0.01	0.284
Distraction	**Distraction**	**0.17**	**0.02**	**0.000**
Distraction	**Rumination**	**0.04**	**0.01**	**0.001**
Distraction	**Reappraisal**	**0.02**	**0.01**	**0.039**
Distraction	**Suppression**	**0.03**	**0.01**	**0.010**
Distraction	Negative emotions	0.02	0.01	0.056
Distraction	Positive emotions	0.00	0.01	0.837
Rumination	**Positive EG**	**-0.03**	**0.02**	**0.020**
Rumination	Negative EG	-0.01	0.02	0.446
Rumination	Social sharing	0.01	0.02	0.336
Rumination	**Distraction**	**0.05**	**0.02**	**0.001**
Rumination	**Rumination**	**0.17**	**0.02**	**0.000**
Rumination	**Reappraisal**	**0.05**	**0.01**	**0.001**

From	To	Fixed Effect	*SE*	*p*
Rumination	**Suppression**	**0.06**	**0.01**	**0.000**
Rumination	Negative emotions	0.01	0.01	0.205
Rumination	Positive emotions	0.00	0.01	0.697
Reappraisal	Positive EG	0.00	0.02	0.762
Reappraisal	Negative EG	0.01	0.01	0.710
Reappraisal	Social sharing	0.00	0.01	0.985
Reappraisal	Distraction	0.02	0.01	0.191
Reappraisal	Rumination	0.02	0.01	0.124
Reappraisal	**Reappraisal**	**0.17**	**0.02**	**0.000**
Reappraisal	Suppression	0.00	0.01	0.751
Reappraisal	Negative emotions	0.01	0.01	0.409
Reappraisal	**Positive emotions**	**0.03**	**0.01**	**0.006**
Suppression	Positive EG	-0.00	0.01	0.753
Suppression	**Negative EG**	**-0.05**	**0.02**	**0.006**
Suppression	Social sharing	0.00	0.01	0.897
Suppression	Distraction	0.02	0.01	0.096
Suppression	Rumination	0.00	0.01	0.763
Suppression	Reappraisal	0.01	0.01	0.278
Suppression	**Suppression**	**0.21**	**0.02**	**0.000**
Suppression	**Negative emotions**	**0.03**	**0.01**	**0.001**
Suppression	Positive emotions	0.01	0.01	0.208
Negative emotions	**Positive EG**	**0.05**	**0.02**	**0.032**
Negative emotions	**Negative EG**	**-0.06**	**0.02**	**0.013**
Negative emotions	Social sharing	0.04	0.02	0.079
Negative emotions	**Distraction**	**0.06**	**0.02**	**0.003**
Negative emotions	**Rumination**	**0.14**	**0.02**	**0.000**
Negative emotions	**Reappraisal**	**0.06**	**0.02**	**0.001**
Negative emotions	Suppression	0.01	0.02	0.455
Negative emotions	**Negative emotions**	**0.39**	**0.02**	**0.000**
Negative emotions	**Positive emotions**	**-0.05**	**0.02**	**0.001**
Positive emotions	**Positive EG**	**-0.08**	**0.02**	**0.000**
Positive emotions	**Negative EG**	**0.06**	**0.02**	**0.001**
Positive emotions	**Social sharing**	**0.06**	**0.02**	**0.001**
Positive emotions	Distraction	-0.02	0.01	0.117
Positive emotions	Rumination	0.00	0.01	0.933
Positive emotions	**Reappraisal**	**0.05**	**0.01**	**0.000**
Positive emotions	Suppression	-0.03	0.01	0.068
Positive emotions	Negative emotions	-0.02	0.01	0.056
Positive emotions	**Positive emotions**	**0.40**	**0.02**	**0.000**

Note: SE = Standard Error; EG = Emotional Granularity. Boldface indicates significant effects.

3.6. Table S8: Centrality Indices for Temporal and Contemporaneous Network Models of the Entire Sample

Table S8. Centrality indices for temporal and contemporaneous network models of the entire sample.

	Temporal		Contemporaneous
	In-Strength	Out-Strength	Strength
Positive EG	0.218	0.035	0.667
Negative EG	0.196	0.086	1.051
Sharing	0.057	0.043	0.591
Distraction	0.104	0.093	0.439
Rumination	0.202	0.185	0.496
Reappraisal	0.181	0.026	0.366
Suppression	0.086	0.076	0.513
Negative emotions	0.062	0.412	1.701
Positive emotions	0.095	0.244	1.235

Note: EG = Emotional Granularity.

3.7. Table S9: Post Hoc Estimates for the Contemporaneous Network Model of the Entire Sample

Table S9. Post-hoc estimates for the contemporaneous network model of the entire sample.

Node 1	Node 2	*p* from Node 1 to Node 2	*p* from Node 2 to Node 1	$r_{partial}$	*r*
Negative EG	**Positive EG**	**0.000**	**0.000**	**0.11**	**0.15**
Social sharing	**Positive EG**	**0.000**	**0.000**	**-0.05**	**-0.12**
Social sharing	**Negative EG**	**0.020**	**0.002**	**-0.03**	**-0.09**
Distraction	**Positive EG**	**0.005**	**0.102**	**0.02**	**0.04**
Distraction	**Negative EG**	**0.000**	**0.000**	**0.06**	**-0.01**
Distraction	**Social sharing**	**0.000**	**0.000**	**-0.09**	**-0.10**
Rumination	**Positive EG**	**0.002**	**0.002**	**-0.03**	**-0.03**
Rumination	**Negative EG**	**0.014**	**0.473**	**-0.04**	**-0.26**
Rumination	**Social sharing**	**0.001**	**0.001**	**0.05**	**0.06**
Rumination	Distraction	0.732	0.385	0.01	0.06
Reappraisal	Positive EG	0.841	0.142	0.01	-0.02
Reappraisal	**Negative EG**	**0.011**	**0.040**	**0.02**	**-0.03**
Reappraisal	**Social sharing**	**0.000**	**0.000**	**0.06**	**0.07**
Reappraisal	**Distraction**	**0.000**	**0.000**	**0.07**	**0.07**
Reappraisal	**Rumination**	**0.000**	**0.000**	**0.09**	**0.11**
Suppression	Positive EG	0.396	0.955	-0.00	0.04
Suppression	**Negative EG**	**0.000**	**0.000**	**0.06**	**-0.06**
Suppression	**Social sharing**	**0.000**	**0.000**	**-0.13**	**-0.14**
Suppression	**Distraction**	**0.000**	**0.000**	**0.10**	**0.14**
Suppression	**Rumination**	**0.006**	**0.003**	**0.05**	**0.11**
Suppression	Reappraisal	0.101	0.132	-0.09	-0.01
Negative emotions	**Positive EG**	**0.000**	**0.000**	**-0.60**	**-0.64**
Negative emotions	**Negative EG**	**0.000**	**0.000**	**0.06**	**0.04**
Negative emotions	**Social sharing**	**0.000**	**0.000**	**0.10**	**0.12**
Negative emotions	**Distraction**	**0.000**	**0.000**	**0.20**	**0.36**
Negative emotions	**Rumination**	**0.000**	**0.000**	**0.05**	**0.06**
Negative emotions	**Reappraisal**	**0.000**	**0.000**	**0.13**	**0.20**
Negative emotions	**Suppression**	**0.000**	**0.000**	**-0.36**	**-0.33**
Positive emotions	**Positive EG**	**0.000**	**0.000**	**-0.13**	**0.19**
Positive emotions	**Negative EG**	**0.000**	**0.000**	**0.11**	**0.12**
Positive emotions	**Social sharing**	**0.000**	**0.000**	**0.01**	**-0.08**
Positive emotions	Distraction	0.422	0.150	-0.04	-0.20
Positive emotions	**Rumination**	**0.000**	**0.000**	**0.07**	**0.04**
Positive emotions	**Reappraisal**	**0.000**	**0.000**	**-0.04**	**-0.17**
Positive emotions	**Suppression**	**0.000**	**0.000**	**-0.47**	**-0.50**
Positive emotions	**Negative emotions**	**0.000**	**0.000**	**-0.473**	**-0.503**

Note: EG = Emotional Granularity. Boldface indicates significance relationships for at least one of the two parameters (i.e., path from Node 1 to Node 2; path from Node to 2 Node 1).

3.8. Table S10: Fit Indices and Classification Diagnostics in the Multilevel Latent Profile Analysis

Table S10. Fit indices and classification diagnostics in the multilevel latent profile analysis.

Model	LL	*df*	AIC	BIC	SABIC	VLMR-LRT		LMR-LRT		Entropy	Class (N)	CP or π
						Value	*p*	Value	*p*			
1–class	-38381.04	22	76806.09	76933.94	76864.04	–	–	–	–	–	255	1.000
2–class	-37585.26	34	75238.52	75436.11	75328.09	-38381.04	0.014	1574.77	0.015	0.951	92, 163	0.361, 0.639
3–class	**-37089.01**	**46**	**74270.03**	**74537.36**	**74391.21**	**-37585.26**	**0.225**	**982.01**	**0.230**	**0.940**	**74, 81, 100**	**0.290, 0.318, 0.392**
4–class	-36835.50	58	73787.01	74124.08	73939.80	-37089.03	0.634	501.67	0.635	0.943	84, 12, 87, 72	0.329, 0.047, 0.341, 0.282

Note: LL = model log likelihood; *df* = degrees of freedom; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; SABIC = Sample-size Adjusted Bayesian Information Criterion; VLMR-LRT = Vuong-Lo-Mendell-Rubin likelihood ratio test; LMR-LRT = Lo-Mendell-Rubin adjusted likelihood ratio test; CP or π = corresponding class proportion. Boldface indicates the selected model.

3.9. Table S11–S13: Fixed Effects for the Temporal Network Model of Profile 1, Profile 2, and Profile 3

Table S11. Fixed effects for the temporal network model of Profile 1 (i.e., Poor and dysregulated sleepers).

From	To	Fixed Effect	*SE*	*p*
Positive EG	**Positive EG**	**0.15**	**0.03**	**0.000**
Positive EG	Negative EG	-0.00	0.02	0.975
Positive EG	Social sharing	0.01	0.02	0.689
Positive EG	Distraction	-0.01	0.01	0.366
Positive EG	Rumination	0.01	0.02	0.627
Positive EG	Reappraisal	0.02	0.01	0.237
Positive EG	Suppression	-0.00	0.01	0.947
Positive EG	Negative emotions	0.01	0.01	0.230
Positive EG	Positive emotions	-0.01	0.02	0.575
Negative EG	**Positive EG**	**0.07**	**0.03**	**0.010**
Negative EG	**Negative EG**	**0.17**	**0.03**	**0.000**
Negative EG	Social sharing	-0.02	0.02	0.370
Negative EG	**Distraction**	**0.05**	**0.02**	**0.004**
Negative EG	Rumination	-0.01	0.02	0.681
Negative EG	Reappraisal	0.02	0.02	0.254
Negative EG	Suppression	0.00	0.02	0.814
Negative EG	Negative emotions	0.01	0.02	0.558
Negative EG	Positive emotions	-0.02	0.01	0.196
Social sharing	Positive EG	-0.02	0.02	0.355
Social sharing	Negative EG	-0.01	0.02	0.485
Social sharing	**Social sharing**	**0.18**	**0.03**	**0.000**
Social sharing	Distraction	0.03	0.02	0.161
Social sharing	Rumination	0.03	0.02	0.101
Social sharing	Reappraisal	0.03	0.02	0.150
Social sharing	Suppression	-0.02	0.02	0.259
Social sharing	Negative emotions	0.01	0.01	0.501
Social sharing	Positive emotions	0.00	0.01	0.854
Distraction	Positive EG	-0.01	0.04	0.739
Distraction	Negative EG	0.02	0.02	0.485
Distraction	Social sharing	0.00	0.03	0.852
Distraction	**Distraction**	**0.19**	**0.03**	**0.000**
Distraction	Rumination	0.04	0.02	0.076
Distraction	Reappraisal	0.02	0.02	0.499
Distraction	Suppression	0.02	0.02	0.399
Distraction	Negative emotions	0.01	0.02	0.748
Distraction	Positive emotions	0.00	0.02	0.999
Rumination	Positive EG	-0.02	0.03	0.426
Rumination	Negative EG	0.03	0.02	0.267
Rumination	Social sharing	-0.03	0.02	0.191
Rumination	**Distraction**	**0.06**	**0.03**	**0.029**
Rumination	**Rumination**	**0.20**	**0.03**	**0.000**
Rumination	Reappraisal	0.05	0.03	0.079
Rumination	**Suppression**	**0.07**	**0.03**	**0.018**
Rumination	Negative emotions	-0.00	0.02	0.948
Rumination	Positive emotions	0.02	0.02	0.355
Reappraisal	Positive EG	-0.00	0.03	0.887

From	To	Fixed Effect	*SE*	*p*
Reappraisal	Negative EG	0.01	0.03	0.645
Reappraisal	Social sharing	-0.02	0.02	0.377
Reappraisal	Distraction	-0.01	0.02	0.713
Reappraisal	Rumination	-0.02	0.02	0.353
Reappraisal	**Reappraisal**	**0.18**	**0.03**	**0.000**
Reappraisal	Suppression	0.03	0.02	0.185
Reappraisal	Negative emotions	0.01	0.02	0.715
Reappraisal	Positive emotions	0.02	0.02	0.181
Suppression	Positive EG	-0.05	0.02	0.051
Suppression	**Negative EG**	**-0.07**	**0.03**	**0.014**
Suppression	Social sharing	-0.02	0.02	0.291
Suppression	Distraction	0.01	0.02	0.659
Suppression	Rumination	0.02	0.02	0.353
Suppression	Reappraisal	-0.02	0.03	0.467
Suppression	**Suppression**	**0.18**	**0.03**	**0.000**
Suppression	Negative emotions	0.03	0.02	0.107
Suppression	Positive emotions	-0.00	0.02	0.974
Negative emotions	Positive EG	0.03	0.04	0.472
Negative emotions	Negative EG	-0.07	0.04	0.085
Negative emotions	Social sharing	0.04	0.04	0.273
Negative emotions	**Distraction**	**0.12**	**0.04**	**0.003**
Negative emotions	**Rumination**	**0.15**	**0.04**	**0.000**
Negative emotions	Reappraisal	0.05	0.04	0.135
Negative emotions	Suppression	0.01	0.04	0.780
Negative emotions	**Negative emotions**	**0.40**	**0.03**	**0.000**
Negative emotions	**Positive emotions**	**-0.05**	**0.02**	**0.036**
Positive emotions	**Positive EG**	**-0.10**	**0.04**	**0.011**
Positive emotions	Negative EG	-0.01	0.03	0.781
Positive emotions	Social sharing	0.04	0.04	0.262
Positive emotions	Distraction	0.03	0.03	0.260
Positive emotions	Rumination	0.04	0.03	0.091
Positive emotions	Reappraisal	0.05	0.03	0.062
Positive emotions	Suppression	-0.05	0.03	0.104
Positive emotions	Negative emotions	0.01	0.02	0.793
Positive emotions	**Positive emotions**	**0.38**	**0.03**	**0.000**

Note: SE = Standard Error; EG = Emotional Granularity. Boldface indicates significant effects.

Table S12. Fixed effects for the temporal network model of Profile 2 (i.e., Poor sleepers despite effort).

From	To	Fixed Effect	*SE*	*p*
Positive EG	**Positive EG**	**0.19**	**0.03**	**0.000**
Positive EG	**Negative EG**	**0.06**	**0.03**	**0.031**
Positive EG	Social sharing	-0.01	0.02	0.457
Positive EG	Distraction	0.00	0.01	0.684
Positive EG	Rumination	-0.01	0.01	0.475
Positive EG	Reappraisal	-0.00	0.01	0.786
Positive EG	Suppression	-0.01	0.01	0.619
Positive EG	Negative emotions	-0.01	0.01	0.324
Positive EG	Positive emotions	-0.02	0.01	0.213
Negative EG	**Positive EG**	**0.05**	**0.02**	**0.024**
Negative EG	**Negative EG**	**0.12**	**0.03**	**0.000**
Negative EG	Social sharing	0.02	0.02	0.281
Negative EG	**Distraction**	**-0.05**	**0.01**	**0.000**
Negative EG	Rumination	0.00	0.01	0.978
Negative EG	Reappraisal	-0.02	0.02	0.186
Negative EG	Suppression	-0.01	0.01	0.391
Negative EG	**Negative emotions**	**0.05**	**0.01**	**0.001**
Negative EG	Positive emotions	-0.00	0.01	0.714
Social sharing	Positive EG	-0.00	0.02	0.913
Social sharing	Negative EG	-0.02	0.02	0.390
Social sharing	**Social sharing**	**0.14**	**0.03**	**0.000**
Social sharing	Distraction	0.00	0.01	0.838
Social sharing	**Rumination**	**0.04**	**0.01**	**0.008**
Social sharing	Reappraisal	-0.01	0.02	0.616
Social sharing	Suppression	0.00	0.01	0.829
Social sharing	**Negative emotions**	**0.02**	**0.01**	**0.039**
Social sharing	Positive emotions	0.01	0.01	0.454
Distraction	**Positive EG**	**-0.08**	**0.03**	**0.015**
Distraction	Negative EG	-0.04	0.03	0.123
Distraction	**Social sharing**	**-0.06**	**0.03**	**0.040**
Distraction	**Distraction**	**0.20**	**0.03**	**0.000**
Distraction	Rumination	0.01	0.02	0.480
Distraction	Reappraisal	0.03	0.02	0.136
Distraction	**Suppression**	**0.06**	**0.02**	**0.007**
Distraction	Negative emotions	0.02	0.02	0.167
Distraction	Positive emotions	0.01	0.02	0.524
Rumination	Positive EG	-0.03	0.02	0.182
Rumination	Negative EG	-0.02	0.03	0.618
Rumination	Social sharing	0.04	0.03	0.160
Rumination	Distraction	0.03	0.02	0.115
Rumination	**Rumination**	**0.19**	**0.02**	**0.000**
Rumination	**Reappraisal**	**0.06**	**0.02**	**0.012**
Rumination	Suppression	0.02	0.02	0.365
Rumination	Negative emotions	0.03	0.02	0.089
Rumination	Positive emotions	-0.02	0.02	0.236
Reappraisal	Positive EG	0.01	0.02	0.637
Reappraisal	Negative EG	-0.03	0.02	0.205
Reappraisal	Social sharing	0.02	0.03	0.494
Reappraisal	Distraction	0.01	0.02	0.421
Reappraisal	Rumination	0.04	0.02	0.095
Reappraisal	**Reappraisal**	**0.15**	**0.03**	**0.000**

From	To	Fixed Effect	*SE*	*p*
Reappraisal	Suppression	0.00	0.02	0.998
Reappraisal	Negative emotions	0.01	0.02	0.727
Reappraisal	Positive emotions	0.01	0.02	0.465
Suppression	Positive EG	0.02	0.02	0.438
Suppression	Negative EG	-0.05	0.04	0.242
Suppression	Social sharing	0.04	0.02	0.062
Suppression	Distraction	0.03	0.02	0.198
Suppression	Rumination	0.01	0.02	0.675
Suppression	Reappraisal	0.03	0.02	0.260
Suppression	**Suppression**	**0.21**	**0.02**	**0.000**
Suppression	**Negative emotions**	**0.04**	**0.02**	**0.008**
Suppression	Positive emotions	0.01	0.02	0.500
Negative emotions	Positive EG	0.05	0.04	0.314
Negative emotions	Negative EG	-0.08	0.04	0.072
Negative emotions	Social sharing	0.07	0.04	0.053
Negative emotions	Distraction	0.01	0.03	0.623
Negative emotions	**Rumination**	**0.15**	**0.04**	**0.000**
Negative emotions	Reappraisal	0.04	0.03	0.185
Negative emotions	Suppression	-0.01	0.03	0.853
Negative emotions	**Negative emotions**	**0.38**	**0.03**	**0.000**
Negative emotions	Positive emotions	-0.06	0.04	0.082
Positive emotions	**Positive EG**	**-0.10**	**0.04**	**0.004**
Positive emotions	**Negative EG**	**0.11**	**0.03**	**0.000**
Positive emotions	**Social sharing**	**0.07**	**0.03**	**0.006**
Positive emotions	Distraction	-0.02	0.02	0.394
Positive emotions	Rumination	-0.03	0.02	0.101
Positive emotions	**Reappraisal**	**0.05**	**0.02**	**0.006**
Positive emotions	Suppression	-0.04	0.02	0.108
Positive emotions	**Negative emotions**	**-0.04**	**0.02**	**0.028**
Positive emotions	**Positive emotions**	**0.41**	**0.02**	**0.000**

Note: SE = Standard Error; EG = Emotional Granularity. Boldface indicates significant effects.

Table S13. Fixed effects for the temporal network model of Profile 3 (i.e., Good sleepers).

From	To	Fixed Effect	*SE*	*p*
Positive EG	**Positive EG**	**0.24**	**0.03**	**0.000**
Positive EG	Negative EG	0.04	0.03	0.125
Positive EG	Social sharing	-0.02	0.02	0.245
Positive EG	Distraction	-0.02	0.01	0.167
Positive EG	Rumination	-0.02	0.01	0.200
Positive EG	Reappraisal	0.01	0.02	0.505
Positive EG	Suppression	-0.02	0.01	0.201
Positive EG	Negative emotions	-0.02	0.01	0.115
Positive EG	Positive emotions	-0.00	0.01	0.932
Negative EG	Positive EG	0.04	0.02	0.061
Negative EG	**Negative EG**	**0.13**	**0.03**	**0.000**
Negative EG	Social sharing	-0.00	0.02	0.914
Negative EG	Distraction	-0.01	0.02	0.384
Negative EG	Rumination	0.02	0.02	0.309
Negative EG	Reappraisal	0.02	0.02	0.350
Negative EG	Suppression	0.00	0.02	0.916
Negative EG	**Negative emotions**	**0.04**	**0.02**	**0.016**
Negative EG	Positive emotions	-0.02	0.01	0.166
Social sharing	Positive EG	-0.03	0.02	0.132
Social sharing	Negative EG	-0.02	0.02	0.215
Social sharing	**Social sharing**	**0.19**	**0.02**	**0.000**
Social sharing	Distraction	0.00	0.02	0.791
Social sharing	Rumination	0.02	0.02	0.338
Social sharing	Reappraisal	0.01	0.02	0.591
Social sharing	Suppression	-0.01	0.01	0.275
Social sharing	Negative emotions	-0.01	0.01	0.518
Social sharing	**Positive emotions**	**0.03**	**0.01**	**0.021**
Distraction	Positive EG	-0.00	0.02	0.829
Distraction	Negative EG	-0.03	0.02	0.217
Distraction	Social sharing	0.00	0.02	0.986
Distraction	**Distraction**	**0.13**	**0.03**	**0.000**
Distraction	**Rumination**	**0.06**	**0.02**	**0.001**
Distraction	Reappraisal	0.02	0.02	0.183
Distraction	Suppression	0.02	0.02	0.227
Distraction	Negative emotions	0.04	0.02	0.060
Distraction	Positive emotions	-0.00	0.02	0.833
Rumination	Positive EG	-0.04	0.02	0.076
Rumination	Negative EG	-0.04	0.03	0.184
Rumination	Social sharing	0.03	0.02	0.295
Rumination	Distraction	0.05	0.03	0.078
Rumination	**Rumination**	**0.13**	**0.03**	**0.000**
Rumination	Reappraisal	0.04	0.02	0.092
Rumination	**Suppression**	**0.06**	**0.02**	**0.001**
Rumination	Negative emotions	0.01	0.02	0.486
Rumination	Positive emotions	0.01	0.02	0.480
Reappraisal	Positive EG	0.01	0.02	0.749
Reappraisal	Negative EG	0.02	0.02	0.313
Reappraisal	Social sharing	0.00	0.02	0.848
Reappraisal	Distraction	0.04	0.02	0.083
Reappraisal	**Rumination**	**0.05**	**0.02**	**0.046**
Reappraisal	**Reappraisal**	**0.19**	**0.02**	**0.000**

From	To	Fixed Effect	*SE*	*p*
Reappraisal	Suppression	-0.01	0.02	0.515
Reappraisal	Negative emotions	0.01	0.02	0.526
Reappraisal	**Positive emotions**	**0.04**	**0.01**	**0.010**
Suppression	Positive EG	0.01	0.02	0.527
Suppression	Negative EG	-0.01	0.02	0.449
Suppression	Social sharing	-0.00	0.02	0.912
Suppression	Distraction	0.02	0.02	0.186
Suppression	Rumination	-0.01	0.02	0.604
Suppression	Reappraisal	0.03	0.02	0.081
Suppression	**Suppression**	**0.24**	**0.02**	**0.000**
Suppression	Negative emotions	0.02	0.02	0.120
Suppression	Positive emotions	0.02	0.01	0.142
Negative emotions	Positive EG	0.05	0.03	0.136
Negative emotions	Negative EG	-0.03	0.03	0.287
Negative emotions	Social sharing	-0.00	0.03	0.975
Negative emotions	Distraction	0.03	0.03	0.189
Negative emotions	**Rumination**	**0.10**	**0.03**	**0.000**
Negative emotions	**Reappraisal**	**0.08**	**0.03**	**0.005**
Negative emotions	Suppression	0.03	0.02	0.213
Negative emotions	**Negative emotions**	**0.39**	**0.03**	**0.000**
Negative emotions	Positive emotions	-0.04	0.02	0.088
Positive emotions	**Positive EG**	**-0.06**	**0.03**	**0.024**
Positive emotions	**Negative EG**	**0.05**	**0.02**	**0.040**
Positive emotions	Social sharing	0.04	0.03	0.111
Positive emotions	**Distraction**	**-0.06**	**0.02**	**0.008**
Positive emotions	Rumination	0.00	0.02	0.984
Positive emotions	**Reappraisal**	**0.05**	**0.02**	**0.016**
Positive emotions	Suppression	-0.01	0.02	0.733
Positive emotions	Negative emotions	-0.02	0.02	0.251
Positive emotions	**Positive emotions**	**0.41**	**0.02**	**0.000**

Note: SE = Standard Error; EG = Emotional Granularity. Boldface indicates significant effects.

3.10. Table S14: Centrality Indices for Temporal and Contemporaneous Network Models of Each Sleep Profile

Table S14. Centrality indices for temporal and contemporaneous network models of each sleep profile.

	Temporal		Contemporaneous
	In-Strength	Out-Strength	Strength
Profile 1 – Poor and dysregulated sleepers			
Positive EG	0.171	0.000	0.730
Negative EG	0.070	0.113	0.877
Sharing	0.000	0.000	0.540
Distraction	0.222	0.000	0.467
Rumination	0.155	0.133	0.482
Reappraisal	0.000	0.000	0.341
Suppression	0.072	0.070	0.506
Negative emotions	0.000	0.322	1.497
Positive emotions	0.053	0.104	1.125
Profile 2 – Poor sleepers despite effort			
Positive EG	0.230	0.062	0.671
Negative EG	0.174	0.147	0.942
Social sharing	0.132	0.059	0.450
Distraction	0.049	0.190	0.400
Rumination	0.190	0.062	0.433
Reappraisal	0.116	0.000	0.255
Suppression	0.056	0.041	0.440
Negative emotions	0.151	0.154	1.706
Positive emotions	0.000	0.381	1.273
Profile 3 – Good sleepers			
Positive EG	0.058	0.000	0.535
Negative EG	0.052	0.041	1.105
Social sharing	0.000	0.031	0.617
Distraction	0.060	0.058	0.413
Rumination	0.202	0.065	0.283
Reappraisal	0.130	0.087	0.398
Suppression	0.065	0.000	0.488
Negative emotions	0.041	0.178	1.784
Positive emotions	0.070	0.216	1.225

Note: EG = Emotional Granularity.

3.11. Table S15–S17: Post Hoc Estimates for the Contemporaneous Network Model of Profile 1, Profile 2, and Profile 3

Table S15. Post-hoc estimates for the contemporaneous network model of Profile 1 (i.e., Poor and dysregulated sleepers).

Node 1	Node 2	*p* from Node 1 to Node 2	*p* from Node 2 to Node 1	r_{partial}	*r*
Negative EG	**Positive EG**	**0.000**	**0.000**	**0.11**	**0.13**
Social sharing	**Positive EG**	**0.000**	**0.001**	**-0.06**	**-0.12**
Social sharing	Negative EG	0.742	0.626	-0.01	-0.05
Distraction	**Positive EG**	**0.038**	**0.560**	**0.02**	**0.06**
Distraction	**Negative EG**	**0.014**	**0.002**	**0.07**	**0.02**
Distraction	**Social sharing**	**0.000**	**0.000**	**-0.10**	**-0.12**
Rumination	**Positive EG**	**0.011**	**0.003**	**-0.05**	**-0.03**
Rumination	Negative EG	0.744	0.799	-0.01	-0.17
Rumination	Social sharing	0.080	0.105	0.05	0.05
Rumination	Distraction	0.277	0.253	0.04	0.08
Reappraisal	Positive EG	0.732	0.981	0.00	-0.03
Reappraisal	Negative EG	0.116	0.337	0.02	-0.01
Reappraisal	**Social sharing**	**0.000**	**0.000**	**0.11**	**0.11**
Reappraisal	**Distraction**	**0.033**	**0.040**	**0.06**	**0.06**
Reappraisal	**Rumination**	**0.000**	**0.000**	**0.12**	**0.14**
Suppression	Positive EG	0.838	0.961	0.00	0.05
Suppression	**Negative EG**	**0.175**	**0.010**	**0.05**	**-0.03**
Suppression	**Social sharing**	**0.000**	**0.000**	**-0.14**	**-0.15**
Suppression	**Distraction**	**0.000**	**0.000**	**0.12**	**0.16**
Suppression	**Rumination**	**0.006**	**0.012**	**0.08**	**0.14**
Suppression	Reappraisal	0.063	0.079	0.05	0.06
Negative emotions	**Positive EG**	**0.000**	**0.002**	**-0.08**	**0.03**
Negative emotions	**Negative EG**	**0.000**	**0.000**	**-0.54**	**-0.56**
Negative emotions	**Social sharing**	**0.028**	**0.050**	**0.05**	**0.01**
Negative emotions	**Distraction**	**0.000**	**0.001**	**0.09**	**0.11**
Negative emotions	**Rumination**	**0.000**	**0.000**	**0.19**	**0.31**
Negative emotions	Reappraisal	0.153	0.346	0.03	0.05
Negative emotions	**Suppression**	**0.000**	**0.000**	**0.11**	**0.17**
Positive emotions	**Positive EG**	**0.000**	**0.000**	**-0.40**	**-0.40**
Positive emotions	**Negative EG**	**0.000**	**0.000**	**-0.10**	**0.13**
Positive emotions	**Social sharing**	**0.005**	**0.003**	**0.08**	**0.12**
Positive emotions	Distraction	0.817	0.966	-0.00	-0.09
Positive emotions	**Rumination**	**0.039**	**0.045**	**-0.04**	**-0.15**
Positive emotions	**Reappraisal**	**0.007**	**0.004**	**0.06**	**0.04**
Positive emotions	Suppression	0.193	0.336	-0.02	-0.13
Positive emotions	**Negative emotions**	**0.000**	**0.000**	**-0.44**	**-0.46**

Note: EG = Emotional Granularity. Boldface indicates significance relationships for at least one of the two parameters (i.e., path from Node 1 to Node 2; path from Node to 2 Node 1).

Table S16. Post-hoc estimates for the contemporaneous network model of Profile 2 (i.e., Poor sleepers despite effort).

Node 1	Node 2	*p* from Node 1 to Node 2	*p* from Node 2 to Node 1	$r_{partial}$	*r*
Negative EG	**Positive EG**	**0.000**	**0.004**	**0.12**	**0.30**
Social sharing	**Positive EG**	**0.014**	**0.013**	**-0.04**	**0.14**
Social sharing	Negative EG	0.564	0.495	-0.01	0.15
Distraction	Positive EG	0.124	0.121	0.03	0.14
Distraction	**Negative EG**	**0.007**	**0.017**	**0.05**	**0.16**
Distraction	**Social sharing**	**0.000**	**0.001**	**-0.08**	**0.15**
Rumination	Positive EG	0.191	0.274	-0.02	0.22
Rumination	Negative EG	0.086	0.750	-0.03	0.23
Rumination	**Social sharing**	**0.016**	**0.034**	**0.06**	**0.18**
Rumination	Distraction	0.633	0.942	-0.01	0.19
Reappraisal	Positive EG	0.960	0.954	0.00	0.17
Reappraisal	Negative EG	0.961	0.546	0.00	0.14
Reappraisal	Social sharing	0.188	0.282	0.03	0.18
Reappraisal	**Distraction**	**0.108**	**0.021**	**0.06**	**0.19**
Reappraisal	**Rumination**	**0.000**	**0.000**	**0.09**	**0.15**
Suppression	Positive EG	0.902	0.793	0.00	0.19
Suppression	**Negative EG**	**0.020**	**0.002**	**0.08**	**0.26**
Suppression	**Social sharing**	**0.002**	**0.008**	**-0.08**	**0.19**
Suppression	**Distraction**	**0.000**	**0.000**	**0.10**	**0.17**
Suppression	Rumination	0.090	0.068	0.05	0.23
Suppression	Reappraisal	0.075	0.200	0.03	0.13
Negative emotions	**Positive EG**	**0.000**	**0.000**	**-0.11**	**0.33**
Negative emotions	**Negative EG**	**0.000**	**0.000**	**-0.56**	**0.35**
Negative emotions	**Social sharing**	**0.000**	**0.000**	**0.07**	**0.16**
Negative emotions	**Distraction**	**0.000**	**0.005**	**0.10**	**0.23**
Negative emotions	**Rumination**	**0.000**	**0.000**	**0.22**	**0.17**
Negative emotions	**Reappraisal**	**0.034**	**0.137**	**0.04**	**0.15**
Negative emotions	**Suppression**	**0.000**	**0.000**	**0.13**	**0.20**
Positive emotions	**Positive EG**	**0.000**	**0.000**	**-0.40**	**0.40**
Positive emotions	**Negative EG**	**0.000**	**0.000**	**-0.14**	**0.28**
Positive emotions	**Social sharing**	**0.000**	**0.000**	**0.10**	**0.14**
Positive emotions	Distraction	0.481	0.331	0.02	0.18
Positive emotions	**Rumination**	**0.004**	**0.001**	**-0.06**	**0.18**
Positive emotions	**Reappraisal**	**0.007**	**0.003**	**0.06**	**0.15**
Positive emotions	**Suppression**	**0.036**	**0.067**	**-0.04**	**0.18**
Positive emotions	**Negative emotions**	**0.000**	**0.000**	**-0.47**	**0.32**

Note: EG = Emotional Granularity. Boldface indicates significance relationships for at least one of the two parameters (i.e., path from Node 1 to Node 2; path from Node to 2 Node 1).

Table S17. Post-hoc estimates for the contemporaneous network model of Profile 3 (i.e., Good sleepers).

Node 1	Node 2	*p* from Node 1 to Node 2	*p* from Node 2 to Node 1	r_{partial}	r
Negative EG	**Positive EG**	**0.000**	**0.001**	**0.11**	**0.18**
Social sharing	**Positive EG**	**0.002**	**0.006**	**-0.05**	**-0.12**
Social sharing	**Negative EG**	**0.006**	**0.001**	**-0.06**	**-0.11**
Distraction	Positive EG	0.145	0.357	0.02	0.03
Distraction	**Negative EG**	**0.000**	**0.007**	**0.06**	**-0.02**
Distraction	**Social sharing**	**0.000**	**0.000**	**-0.09**	**-0.11**
Rumination	Positive EG	0.064	0.126	-0.02	-0.06
Rumination	Negative EG	0.125	0.380	-0.05	-0.30
Rumination	Social sharing	0.129	0.090	0.04	0.05
Rumination	Distraction	0.766	0.801	-0.00	0.04
Reappraisal	Positive EG	0.703	0.081	0.02	-0.02
Reappraisal	**Negative EG**	**0.003**	**0.037**	**0.04**	**-0.03**
Reappraisal	**Social sharing**	**0.021**	**0.029**	**0.06**	**0.07**
Reappraisal	**Distraction**	**0.017**	**0.009**	**0.07**	**0.07**
Reappraisal	**Rumination**	**0.021**	**0.016**	**0.06**	**0.08**
Suppression	Positive EG	0.200	0.582	-0.02	0.01
Suppression	**Negative EG**	**0.006**	**0.095**	**0.04**	**-0.12**
Suppression	**Social sharing**	**0.000**	**0.000**	**-0.16**	**-0.18**
Suppression	**Distraction**	**0.012**	**0.002**	**0.08**	**0.13**
Suppression	Rumination	0.758	0.351	0.01	0.10
Suppression	Reappraisal	0.708	0.764	-0.01	-0.00
Negative emotions	**Positive EG**	**0.000**	**0.008**	**-0.09**	**-0.08**
Negative emotions	**Negative EG**	**0.000**	**0.000**	**-0.66**	**-0.72**
Negative emotions	**Social sharing**	**0.000**	**0.001**	**0.06**	**0.04**
Negative emotions	**Distraction**	**0.000**	**0.000**	**0.10**	**0.11**
Negative emotions	**Rumination**	**0.000**	**0.000**	**0.18**	**0.38**
Negative emotions	**Reappraisal**	**0.000**	**0.000**	**0.08**	**0.06**
Negative emotions	**Suppression**	**0.000**	**0.000**	**0.14**	**0.24**
Positive emotions	**Positive EG**	**0.000**	**0.000**	**-0.28**	**-0.22**
Positive emotions	**Negative EG**	**0.000**	**0.000**	**-0.13**	**0.28**
Positive emotions	**Social sharing**	**0.000**	**0.000**	**0.13**	**0.13**
Positive emotions	Distraction	0.387	0.231	0.01	-0.08
Positive emotions	**Rumination**	**0.063**	**0.032**	**-0.04**	**-0.21**
Positive emotions	**Reappraisal**	**0.000**	**0.000**	**0.09**	**0.04**
Positive emotions	**Suppression**	**0.005**	**0.001**	**-0.06**	**-0.21**
Positive emotions	**Negative emotions**	**0.000**	**0.000**	**-0.49**	**-0.54**

Note: EG = Emotional Granularity. Boldface indicates significance relationships for at least one of the two parameters (i.e., path from Node 1 to Node 2; path from Node to 2 Node 1).

4. Figures

4.1. Figure S1: Model Fit Indices Across Latent Class Solutions

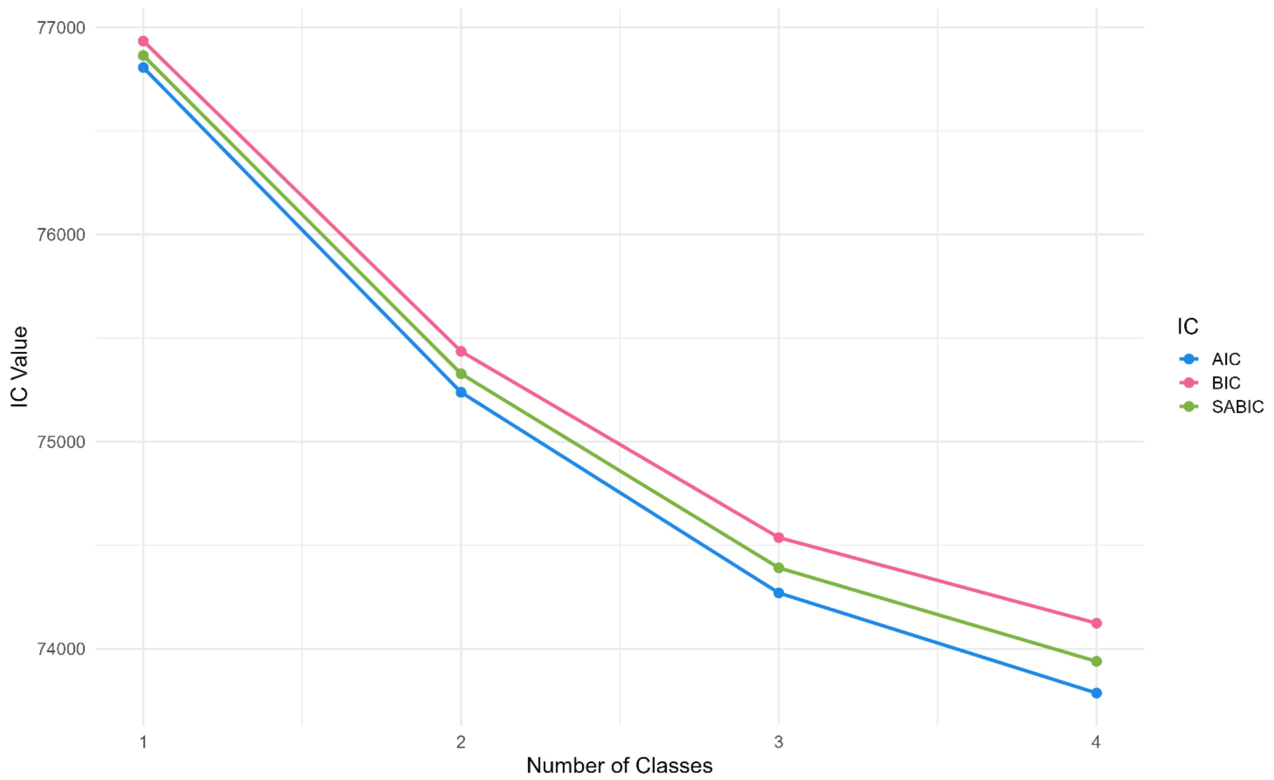

Figure S1. Model Fit Indices Across Latent Class Solutions.
Note: IC = Information Criterion; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; SABIC = Sample-size Adjusted Bayesian Information Criterion.

4.2. Figure S2: Latent Sleep Profiles from the 2-Class Model at the Person Level (Level 2)

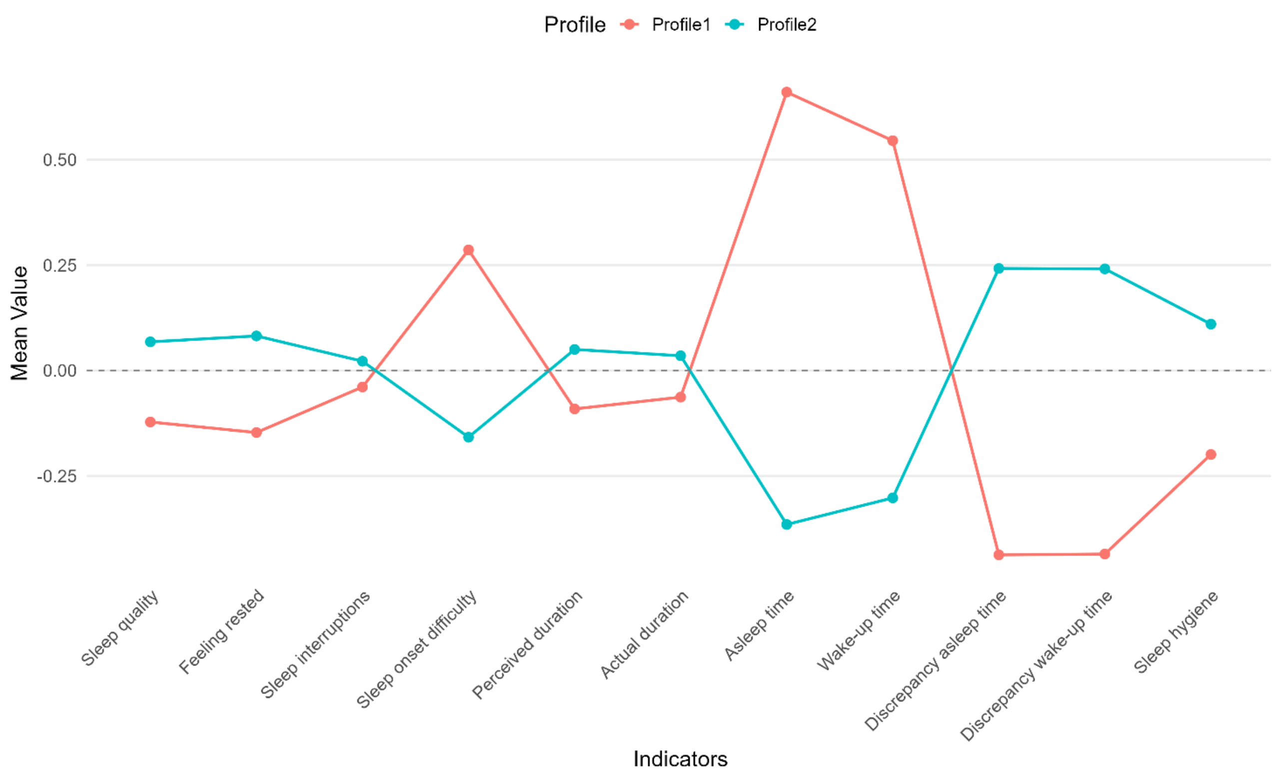

Figure S2. Latent sleep profiles from the 2-class model at the person level (Level 2).
Note: Profile 1 (n = 92) = Poor sleepers; Profile 2 (n = 163) = Good sleepers. Bars represent the standard deviations of each of the eleven profile indicators relative to the overall sample mean. All values have been standardized (M = 0, SD = 1) to facilitate interpretation.

Chapter 3

Pain or Emotion? The Role of Negative Emotional Granularity and Interoceptive Sensibility in Neuropathic and Nociplastic Chronic Pelvic Pain

Ilaria Telazzi[1], Eduardo Estrada Alonso[2], & Stefania Balzarotti[1,3]

[1]Università Cattolica del Sacro Cuore di Milano, Italy

[2] Universidad Autónoma de Madrid, Spain

[3]Communication Psychology Lab, Università Cattolica del Sacro Cuore di Milano, Italy

Abstract

Predictive coding models posit that both emotion and pain arise from interoceptive predictions. Emerging theories suggest that emotional granularity may act as a potential mechanism for neuropathic and nociplastic chronic pain, yet its role remains empirically unexplored. Using an event-contingent design, we investigated the within-person effect of negative granularity on pain and whether dispositional interoceptive sensibility (IAs) moderates this association.

Sixty-eight women with neuropathic and nociplastic chronic pelvic pain completed diary entries at each pain episode over one month. Integral, between- and within-category (anger, fear, sadness) granularity indices were computed. We fitted multilevel models to predict concurrent and subsequent pain intensity, controlling for self-reported unpleasantness, arousal, affect dominance and negative emotions.

A higher integral and between-category granularity predicted lower concurrent pain only for low-IAs participants. Within-category granularity showed no concurrent effect, whereas greater negative emotions, unpleasantness, and reduced dominance predicted more pain. Prospectively, greater fear-specific granularity in high-IAs participants and higher arousal predicted heightened subsequent pain.

We found that the effect of granularity on pain is conditional, varying by the type of granularity, time frame, and habitual interoceptive focus. These findings carry both theoretical and clinical implications, deepening our understanding of emotional granularity and informing future interventions for chronic pain management.

Keywords: emotional granularity, emotion differentiation, interoception, chronic pain, event-contingent design

1. Introduction

Emotional granularity, also known as emotion differentiation, reflects the ability to make subtle, fine-grained distinctions among emotional states (Barrett et al., 2001). It describes how individuals represent and describe their feelings in a given context. While some people can accurately and precisely articulate their current emotional states, others tend to report their experiences in more global or undifferentiated terms.

From a constructionist perspective (Barrett, 2017a), grounded in the idea of a Bayesian brain, emotions are not fixed biological reactions but situated constructions and emergent products of the brain's predictive regulation of the body. However, the brain's primary function is not to produce emotions but to regulate the *internal milieu* of the organism through a dynamic, anticipatory process known as allostasis. Through allostasis, the brain predicts and fulfills the body's physiological needs before they arise by managing energy resources such as glucose, oxygen, and hormonal activity (Kleckner et al., 2017).

This predictive regulation relies on interoception (Kleckner et al., 2017), the perception and integration of autonomic, hormonal, visceral and immunological homeostatic signals that collectively reflect the body's physiological state. Interoceptive sensations generate a foundational and ever-present state known as *core affect* (Lindquist et al., 2016), a neurophysiological state defined in two dimensions (Russell, 2003): Valence (pleasant–unpleasant) and arousal (activated–deactivated). Core affect forms the affective backdrop of all individuals' experiences.

To make sense of this core affect, the brain draws upon conceptual knowledge to interpret and categorize it within a specific context (Barrett et al., 2015). Depending on contextual cues, sensory information, past experiences, and the individual's conceptual repertoire, core affect may be categorized as a physical state (e.g., feeling hungry, painful) or an emotion (e.g., feeling angry, relieved) and can also include connotations of a motivational drive (e.g., feeling determinate, brave) or a cognitive evaluation (e.g., feeling safe, confused). This process, known as situated conceptualization (Barrett et al., 2014), is rooted in predictive coding: The brain continuously generates predictions on the basis of prior experience to anticipate and interpret sensory and interoceptive inputs. Mismatches between expected and actual inputs (prediction errors) update and refine the internal models of the brain and guide future responses.

Within this framework, emotional experiences are actively constructed through the categorization of core affective states. Whether core affect is interpreted as an emotion or something else depends on how the brain applies its conceptual knowledge in context (Lindquist, Satpute, et al., 2015). Therefore, constructing a granular emotional experience depends on the precision of the brain's predictive models, the efficiency of allostatic regulation, and the richness of the individual's conceptual repertoire. The ability to label and differentiate emotions with high granularity reflects a finely attuned integration of interoceptive signals and a well-developed conceptual system. Together, they allow for nuanced categorization of affective experiences in contextually appropriate and energy-efficient ways.

1.1. A Predictive Coding Perspective on Chronic Pain

According to the most recent definition by the International Association for the Study of Pain (IASP, 2012), pain is described as "An unpleasant sensory and emotional experience associated with, or resembling that associated with, actual or potential tissue damage". To further clarify this definition, the IASP specifies that *a)* pain is always a subjective experience affected by biological, psychological, and social factors; *b)* pain and nociception (defined as the neural process of encoding noxious sensory inputs) are distinct phenomena; *c)* pain cannot be inferred solely from activity in sensory neurons; and *d)* individuals learn the concept of pain through life experiences.

This multifaceted definition aligns closely with the Bayesian view of brain functioning applied to the experience of pain (Ongaro & Kaptchuk, 2018). When the brain receives nociceptive signals, it predicts and regulates pain experiences while simultaneously managing the body's energy resources in preparation for potential damage. However, prediction errors can occur: The brain may generate pain prediction in the absence of any actual or potential tissue damage (Roy et al., 2014). When these errors go uncorrected, the brain fails to update internal models and continues to allocate resources to address a threat that is not physically present (Poublan-Couzardot & Talmi, 2024).

Such persistent misallocations may underlie cases of chronic pain in the absence of damage to or threat of damage to nonneural body tissues. This is observed in neuropathic chronic pain, which is caused by a lesion or disease of the somatosensory nervous system, and in nociplastic chronic pain, which arises from altered nociception despite no clear evidence of peripheral tissue damage or somatosensory system injury (IASP, 2012). Patients may also present with a combination of both nociceptive and nociplastic pain. In these cases, individuals may have experienced intense nociceptive input in the past and continue to predict pain after tissue recovery by disregarding corrective prediction errors (Apkarian et al., 2013). It is also possible that the brain prioritizes and amplifies the salience of nociceptive inputs even when they are incredibly weak owing to their allostatic relevance, thus making aberrant predictions about internal bodily sensations (Moseley & Vlaeyen, 2015). In both scenarios, individuals may come to chronically experience pain as real and intense, despite the absence of an identifiable organic origin.

1.2. The Potential Role of Emotional Granularity in Chronic Pain

A growing body of evidence suggests that pain, like emotion, is a brain-based construction generated by a core predictive system. The brain networks involved in nociceptive processing overlap with those that support emotional experience (Woo et al., 2015). Recent evidence has even suggested that nociception may be conceptualized as a form of interoception (Craig, 2014; Damasio & Carvalho, 2013). Thus, the construction of emotional and pain experiences appears to rely on common, dynamically interacting neural systems with shared ascending and descending pathways (Chang et al., 2015; Wager et al., 2013, 2015).

This is particularly relevant in chronic pain conditions where no clear nonneural structural damage is found (Jungilligens et al., 2022; Poublan-Couzardot & Talmi, 2024). In such cases, pain and emotion may reflect different interpretations of similar bodily sensations. Chronic neuropathic and nociplastic pain may, in part, stem from difficulties in distinguishing and categorizing certain internal sensations as either painful or other affective states, such as emotions (Barrett, 2017b). This may be due to aberrant interoceptive predictions that fail to be corrected by updated internal models (Barrett, 2017b; Poublan-Couzardot & Talmi, 2024).

Individuals with low emotional granularity may be especially prone to this misclassification (Barrett, 2017b). Emotions (particularly negative emotions) are known to significantly alter pain perception (Bushnell et al., 2013; Wiech & Tracey, 2009). It is possible that low differentiators struggle to accurately distinguish the emotional component from the sensory experience of pain. It is even possible that they may misinterpret emotional distress and bodily discomfort as pain (Tracey, 2010). Over time, this misclassification may reinforce maladaptive interoceptive predictions, contributing to the persistence of pain (Poublan-Couzardot & Talmi, 2024).

Research supports this idea. Individual differences in constructs related to emotional granularity, such as alexithymia and emotional awareness, have also been linked to chronic pain. Specifically, individuals with chronic pain often report reduced emotional awareness (Lumley et al., 2021; Smith et al., 2020). Moreover, higher levels of emotional awareness are associated with lower levels of chronic pain (Zunhammer et al., 2015), suggesting that the ability to accurately identify and reflect on one’s emotional state may offer a protective function. By contrast, people with chronic pain often show higher levels of alexithymia, a trait characterized by difficulty identifying and describing emotions (Aaron et al., 2019). These findings support the notion that impairments in the conceptualization and differentiation of internal affective states may contribute to the miscategorization and persistence of chronic pain.

1.3. Interoception as a Shared Mechanism in Emotional Granularity and Chronic Pain

Interoception plays a foundational role in both emotional (Greenwood & Garfinkel, 2024) and pain experiences (Horsburgh et al., 2024). Being multidimensional in nature, interoception encompasses three distinct components: Interoceptive accuracy (IAc), which refers to the objective ability to detect bodily signals; interoceptive sensibility (IAs), which reflects self-reported attention and perceived sensitivity to internal sensations; and interoceptive awareness (IAw), which is defined as the meta-cognitive ability to accurately gauge bodily signals (Garfinkel et al., 2015). Given that both pain and emotion are constructed through the interpretation of internal bodily sensations, interoceptive ability is critical for accurately differentiating affective experiences.

Although theoretical models suggest that higher emotional granularity may reflect better differentiation of bodily sensations, only one study has so far directly tested this relationship. This study focused specifically on IAs and assessed granularity both in laboratory settings and in daily life via ecological measures (Ventura-Bort et al., 2021). The results revealed no significant association between IAs and granularity in laboratory-based assessments. By contrast, higher IAs was significantly related to greater granularity for negative emotions in ecological contexts. These findings suggest that the contribution of interoception to emotional granularity may be context sensitive, emerging most clearly when individuals engage in real-world affect categorization.

This evidence aligns with existing research on interoception and constructs closely related to granularity. For example, alexithymia has been associated with interoceptive impairments across multiple bodily domains and spans all three dimensions of interoception (Murphy et al., 2018). Moreover, individuals with high alexithymic traits have been shown to misattribute vague or poorly differentiated internal sensations to somatic causes rather than emotional ones (Scarpazza et al., 2015). This evidence supports the idea that difficulties in constructing nuanced emotional experiences may stem from imprecise or disrupted interoceptive predictions.

This pattern of findings has important implications for the understanding of chronic pain: Failures in interoceptive processing may contribute not only to emotional undifferentiation but also to the misclassification of affective states as pain. Interestingly, the relationship between interoception and chronic pain appears to vary depending on the interoceptive dimension assessed. Specifically, individuals with chronic pain tend to exhibit higher IAs but lower IAc, suggesting a mismatch between subjective interoceptive focus and objective performance. In other words, chronic pain sufferers appear to be more attuned to internal sensations while demonstrating a reduced ability to detect them accurately (Horsburgh et al., 2024).

2. The Present Study

In the present study, we investigated the relationship between negative emotional granularity, IAs, and chronic pain in a sample of women experiencing neuropathic and nociplastic chronic pelvic pain (CPP).

CPP is defined as persistent or recurrent pain perceived in the pelvic region, typically lasting for more than six months (American College of Obstetricians and Gynecologists, 2020). It is estimated to affect up to 27% of women worldwide. Notably, at least 30% of women with CPP present no identifiable organic pathology in pelvic tissues, underlying a condition of nociplastic or neuropathic CPP (Siqueira-Campos et al., 2022). This absence of identifiable tissue damage (and thus of objective clinical markers) is frequently associated with experiences of social invalidation and a sense of inadequacy. Many women report that their pain is neither recognized nor understood, describing it as profoundly limiting in its impact on daily functioning (Shallcross et al., 2018). Their narratives often reflect themes of helplessness, frustration, emotional exhaustion, and a perceived loss of control over both bodily states and interpersonal relationships (Niedenfuehr et al., 2023; Shallcross et al., 2018).

Given the substantial emotional burden associated with neuropathic and nociplastic CPP, our study focused specifically on negative emotional granularity (i.e., granularity in relation to negative emotions).

Furthermore, we distinguished among different components of negative granularity. In addition to examining integral granularity (i.e., granularity assessed across emotions belonging to distinct emotion clusters), we further differentiated into between-category and within-category granularity. Between-category granularity refers to the ability to distinguish emotions from different emotional clusters, whereas within-category granularity pertains to distinctions among emotions within the same cluster (Erbas et al., 2019). We focused on three core negative emotion clusters: Anger, fear, and sadness. These clusters were selected because of their prominence in the emotional experiences of women with CPP (Hawkey et al., 2022; Niedenfuehr et al., 2023; Shallcross et al., 2018). This allowed for a more fine-grained investigation of how different facets of emotional granularity relate to pain experiences in women with neuropathic and nociplastic CPP.

Using an ecological, event-contingent design, we examined the within-person effect of emotional granularity on momentary chronic pain intensity. Specifically, we investigated this relationship both concurrently (i.e., by assessing how momentary granularity relates to pain at the same time point) and prospectively (i.e., by examining whether granularity reported in a prior episode predicts subsequent momentary pain intensity). Both temporal perspectives are particularly relevant within the framework of the predictive processing model, which posits that chronic pain may result from persistent and aberrant interoceptive predictions. Given that interoception underpins both emotional and pain processing, we also examined whether dispositional IAs moderates the relationship between emotional granularity and pain intensity. We focused specifically on IAs, as prior research has linked heightened IAs both to emotional granularity (Ventura-Bort et al., 2021) and CPP (Scarpina et al., 2025; Spinoni et al., 2024).

We hypothesized that greater negative emotional granularity would be associated with lower pain intensity within individuals, particularly among women with lower levels of dispositional IAs. Our hypothesis was informed by prior findings linking granularity-related constructs, such as alexithymia and emotional awareness, to chronic pain. Specifically, alexithymia tends to be relatively high (Aaron et al., 2019), and emotional awareness is relatively low (Lumley et al., 2021; Smith et al., 2020) among individuals with chronic pain. Conversely, greater emotional awareness has been associated with lower pain intensity (Zunhammer et al., 2015). Furthermore, this hypothesis was based on evidence suggesting that high IAs is associated with greater alexithymia and lower granularity (Murphy et al., 2018; Ventura-Bort et al., 2021), as well as with more intense and persistent chronic pain (Horsburgh et al., 2024). Accordingly, among women with elevated IAs, it is possible that the potential protective effect of granularity is diminished or absent.

To isolate the specific contribution of emotional granularity, we applied a statistical model that allowed us to control for the valence, arousal, and dominance of the reported affective states, as well as the overall intensity of negative emotions. This approach ensured that any observed effects of granularity were not merely attributable to differences in general affective tone or emotional intensity. We specifically accounted for both affective dimensions and emotional intensity because affect reflects a generalized experiential state that may subsequently be categorized as either pain or emotion. Accordingly, in the immediate experience of pain, the boundaries between pain and emotion are often blurred (Craig, 2003), thereby justifying the inclusion of both affect and emotions as covariates to disentangle the unique contribution of EG from shared affective processes.

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 protocols described below received ethical approval by the Catholic University of Milan, protocol number 58-23. These methods were carried out according to the Declaration of Helsinki (2008).

3.1. Participants

The participants were women diagnosed with neuropathic and nociplastic CPP, with pelvic pain lasting at least six months and occurring on a minimum of three days per month. The exclusion criteria included 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.

The initial sample consisted of 84 participants. Two participants dropped out after the baseline assessment, and 14 participants reported fewer than three pain episodes during the month and were therefore excluded from the final analysis in accordance with the study criteria. This resulted in a final sample of 68 participants[10] (M = 27.98 years, SD = 6.69 years, age range 18–44 years).

The average number of pain episodes per month was 7.51 (SD = 5.32, range 3–42 episodes per month). With respect to pelvic pain diagnosis, 57.4% of the participants reported comorbidities involving multiple conditions, with vulvodynia being the most frequently reported diagnosis. A full description of the sample characteristics is presented in Table 1.

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[10] Sample size was determined with reference to recommendations by Maas and Hox (2005). They showed that multilevel models can yield accurate estimates with as few as three Level-1 observations per unit, as long as the number of Level-2 units is sufficiently large (typically 50 or more). The present study includes 68 participants, each with 3 or more observations (M = 7.51), thus meeting these conditions.

We further conducted a Monte Carlo simulation to assess the probability of detecting the cross-level interaction between within-person EG and between-person IAs on pain intensity. A total of 1,000 datasets were generated with characteristics matching the actual sample (68 participants, ≅ 7 observations per participant), assuming a within-person effect of EG on pain of -0.106, a direct effect of IAs of 0.247, a mean pain intercept of 3.662, random intercept variance of 0.684, and a residual variance of 1.211. Each simulated dataset was analyzed with a multilevel model analogous to the one applied to the real data. The cross-level interaction (EG × IAs) was considered statistically significant at $\alpha = 0.05$. The simulation yielded an estimated power of 0.575, indicating that, under the current sample size and number of observations, there is approximately a 58% probability of detecting the interaction effect if it truly exists. This suggests moderate statistical power, highlighting that non-significant findings should be interpreted with caution (Castillo et al., 2025).

Table 1. Sample Characteristics.

		Count	Percent
Education	Master's Degree	22	32.4
	High School	20	29.4
	Bachelor's Degree	13	19.1
	Advanced Postgraduate Education	10	14.7
	Middle School	1	1.5
Occupation	Working	34	50.0
	Studying	22	32.3
	Studying and Working	10	14.7
	Unemployed	1	1.5
Civil Status	Unmarried	56	82.3
	Married	8	11.8
	Divorced	3	4.4
No. Children	Zero	60	88.2
	One	5	7.3
	Two	2	2.9
Diagnosis	Vulvodynia	53	73.6
	Vulvar Vestibulitis/Vestibulodynia	37	51.4
	Pelvic Floor Hypertonia	33	45.8
	Pudendal Neuropathy	18	25.0
	Endometriosis	9	12.5
	Adenomyosis	7	9.7
	Clitoralgia/Clitorodynia	4	5.6
	Dyspareunia	4	5.6
	Interstitial Cystitis	2	2.8
	Dysmenorrhea	2	2.8
	Lichen	1	1.4
	Vaginismus	1	1.4
	Vulvostenia	1	1.4
Symptoms Onset	More than a Year	62	91.2
	Less than a Year	5	7.3
Pain Type	Spontaneous	43	63.2
	Provoked	24	35.3
Treatment	Both Pharmacological and Nonpharmacological	31	45.6
	Only Pharmacological	20	29.4
	Only Nonpharmacological	12	17.6
	None	4	5.9

Note: Advanced postgraduate education includes professional specialization programs and doctoral studies.
Spontaneous pain refers to pain that occurs without any apparent external stimulus or trigger. Provoked pain refers to pain that is elicited or intensified by a specific stimulus or activity, such as touch, pressure, movement, or temperature.
The percentages in the "Diagnosis" category exceeded 100% due to diagnostic comorbidities, as more than half of the participants (54.4%) reported having more than one diagnosis.
Pharmacological treatments included tricyclic antidepressants (e.g., amitriptyline/Laroxyl), SNRIs (e.g., duloxetine/Cymbalta), gabapentinoids (e.g., pregabalin/Lyrica, gabapentin), hormonal therapies (e.g., oral contraceptives, vaginal rings), benzodiazepines (e.g., diazepam, Ansiolin), muscle relaxants, topical preparations (e.g., creams with amitriptyline, gabapentin, testosterone, estrogens), and various adjuncts, such as nutraceuticals, probiotics, and anti-inflammatory agents. Local (vaginal) administration was frequently reported for some treatments, particularly benzodiazepines and compounded creams. Nonpharmacological treatments included pelvic floor rehabilitation (e.g., physiotherapy, manual therapy, biofeedback, TENS, radiofrequency, electroporation, dilators, and self-massage), psychological support (e.g., psychotherapy), nutritional interventions (e.g., functional nutrition plans, supplementation with magnesium, vitamin D, omega-6), topical nondrug treatments (e.g., CBD- or CBG-based creams and oils), and complementary therapies (e.g., acupuncture, ozone therapy). Pelvic physiotherapy was the most frequently reported intervention and was often conducted by specialized physiotherapists or midwives.

3.2. Materials

Pain intensity. Momentary pain intensity was assessed at each pain episode with a single item on a 7-point Likert-type scale ranging from 0 (*very mild*) to 6 (*very intense).* Previous experience sampling studies investigating pelvic pain used a single item to assess pain intensity (Pâquet et al., 2018; Rosen et al., 2015). Furthermore, recent research suggests that single items have good predictive and concurrent validity in intensive longitudinal designs (Song et al., 2023).

Negative emotions. 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, angry, frustrated, fed up, nervous, frightened, anxious, anguished, worried, sad, depressed, lonely, and demoralized*). These emotion labels were selected on the basis of two criteria. First, both low-arousal and high-arousal negative affect are represented in accordance with the Circumplex Model of Affect (Russell, 1980). Second, conceptual grouping into three core emotional clusters was performed: anger (*angry, frustrated, fed up, nervous*), fear (*frightened, anxious, anguished, worried*), and sadness (*sad, depressed, lonely, demoralized*). Two emotion items (*embarrassed* and *worn out*) did not clearly align with these clusters but were included on the basis of previous research highlighting their relevance in the context of CPP (Niedenfuehr et al., 2023; Toye et al., 2014).

Negative Emotional Granularity. We computed a momentary emotional granularity index reflecting the extent of emotion differentiation at each measurement occasion. To calculate this integral granularity index, we used the method proposed by Erbas, Kalokerinos, et al. (2022) and implemented the equation via the *emodiff* package in *R v.4.4.1*[11]. Following previous work, first we person-mean centered each of the fourteen emotion items described above. For each time point, we then calculated the mean of the centered emotion ratings, multiplied this mean by the number of emotion items, and squared the result, yielding the numerator of the equation. The denominator was obtained by summing the variances of each centered emotion item at that time point. The resulting ratio reflected an index of emotion nondifferentiation computed for each participant at each time point, with higher values indicating lower granularity (Erbas, Kalokerinos, et al., 2022). We were not able to calculate a granularity index for one participant due to insufficient variance among emotion ratings. To align the metric with conventional interpretations of

[11] Data preprocessing was performed before computing the momentary granularity index. When assessing emotional granularity, there may be observations where all emotion ratings are reported as zero. Such instances could be interpreted in two ways: As an indication of high emotional granularity (suggesting that emotions not captured by our predefined list may have been more relevant at those moments) or as low granularity (since all emotions were rated identically). To address this ambiguity, we provided participants with an additional option to freely label their current affective and emotional experiences alongside the predefined emotion ratings. In cases where no alternative emotional label was provided, we would have interpreted the uniform zero ratings as unreliable. In our data, there were eight observations where all emotion ratings were marked as “0”, and participants provided a free-form emotional label. Because participants were able to articulate their emotional experience in their own terms, we interpreted these cases as reflecting high emotional granularity.

emotional granularity, the ratio was reverse-coded so that higher values reflect greater momentary granularity.

In addition to the integral granularity index, we computed, for each person and time point, separate momentary indices of granularity within and between three core negative emotion clusters: Anger, fear, and sadness. Each within-category granularity index was computed via the same procedure described above, but considering the three specific subset of emotion items. To derive the between-category index, we first averaged the emotion ratings within each cluster and then applied the same calculation procedure to these cluster-level means.

Affect. The Self-Assessment Manikin (Bradley & Lang, 1994) was used to assess momentary affective states along the three core dimensions of the Circumplex Model of Affect (Russell, 1980): valence (ranging from unpleasant to pleasant), arousal (ranging from low to high activation), and dominance (ranging from feeling controlled to feeling in control). The participants rated each dimension via a single nonverbal pictorial item on a 9-point Likert scale, with higher scores indicating greater levels of the corresponding affective quality.

Interoceptive Sensibility. The *Awareness* section of the Porges Body Perception Questionnaire–Short Form (Cabrera et al., 2018; Cerritelli et al., 2021) was used to assess dispositional interoceptive sensibility. It consists of 26 items on bodily sensations. The participants rate how often they are aware of each other via a 5-point Likert scale (from 1 = *never* to 5 = *always*). In this study, reliability was good ($\omega = 0.905$; $\alpha = 0.902$).

3.3. 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 at regular time intervals of one month. Between the first and second assessments, participants were asked to complete a one-month experience sampling protocol using an event-contingent design. The present study focuses on data collected during the experience sampling period only. To ensure transparency, a comprehensive description of the full study procedure is provided in the Supplemental Materials.

First, the participants were invited to attend an initial session, during which the researches explained the objectives and structure of the study, confirmed eligibility, and informed consent was obtained. The participants then completed an online baseline questionnaire assessing sociodemographic information, medical history, interoceptive sensibility, and additional measures not analyzed in the present study.

During the initial session, the participants also received instructions to complete the one-month experience sampling protocol. In specifically, they were instructed to complete an online diary each time they experienced a pain episode. For each episode, they were asked to answer a rating of current pain intensity, standardized measures of their affective state, and a fixed set of fourteen emotion labels. The participants also provided an open-ended narrative describing the pain episode and ratings of self-generated affective adjectives, which however were not included in the present analyses. To control for potential confounding factors, we created two diary versions: In one version, affect and emotion measures were rated before providing the open-ended narrative while in the second version the participants were asked to provide the narrative before completing the emotion measures. The participants were randomly assigned to one of the two versions to counterbalance potential order effects.

Participation in the study was voluntary and without monetary compensation.

3.4. Transparency and Openness

Study materials, data, and analysis codes are available at https://osf.io/xsqgc/files/osfstorage. This study was preregistered on the Open Science Framework (OSF) before data collection[12] (https://osf.io/xsqgc/).

3.5. Data Analytic Plan

We investigated how emotional granularity relates to pain intensity both concurrently (using contemporaneous mixed effects models) and predictively (using prospective, i.e., time-lagged, mixed effects models). Moreover, we tested whether dispositional IAs moderates this association. All the analyses were conducted using the following indices of granularity: Integral, between-category, anger-related, fear-related, and sadness-related granularity. In all models, we controlled for the effect of time, as well as for the levels of affect valence, arousal, and dominance, and the intensity of negative emotions.

The analyses were conducted in *R v.4.4.1*. To fit linear mixed-effects models, we used *lme4* (Bates et al., 2015), and we calculated *p* values for the model coefficients via *lmerTest* (Kuznetsova et al., 2017). To prevent confounding within- and between-person effects, diary-level predictors were person-mean centered within participants, whereas IAs was grand-mean centered (Hamaker & Muthén, 2020). Furthermore, the predictors were standardized, allowing for direct comparability of coefficient estimates. Following recent

[12] We initially hypothesized that the association between emotional granularity and pain intensity would be stronger among individuals with neuropathic and nociplastic CPP compared to those with CPP due to tissue damage. However, this could not be tested, as our final sample included only participants with neuropathic and nociplastic CPP. This limitation was due to difficulties in recruiting participants with organic CPP who met the study's inclusion criteria and were available for intensive longitudinal data collection. Furthermore, the preregistration focused solely on prospective hypotheses. To capture potential moment-to-moment dynamics that may not be evident in prospective models alone, we added a non-preregistered objective to examine concurrent associations. Additionally, although IAs was mentioned in the preregistration as an exploratory variable, the specific moderation hypothesis was developed post hoc in light of new literature published after preregistration (Poublan-Couzardot & Talmi, 2024). Finally, preregistered hypotheses on changes in granularity and pain over time are not addressed here and will be examined in a separate manuscript.

recommendations (L. Wang et al., 2019), we adopted a clusterwise standardization approach for diary variables and global standardization for IAs.

Contemporaneous Mixed Effects Models. We began by exploring the within-person and between-person variability in both emotional granularity indices and pain intensity by calculating the intraclass correlation coefficient (ICC). Most of the variability in emotional granularity was observed within individuals over time rather than between individuals (between individuals ICC ≤ 0.001). By contrast, with respect to pain intensity, between-person variability accounted for a large portion of the total variance (ICC = 0.39). This preliminary step was necessary to specify the models in our subsequent analyses, which require between-person variability in the dependent variable and for which random slopes of the predictor depend on within-person variability.

To investigate the concurrent association between emotional granularity and pain intensity, we specified a two-level multilevel model with random intercepts[13], in which pain episodes (Level 1) were nested within participants (Level 2). Momentary pain intensity was modeled as a function of momentary emotional granularity. In addition, we included IAs as a Level 2 moderator of the within-person (Level 1) association between granularity and pain. The model was specified as follows:

Level 1 (pain episodes):

$$\text{Pain}_{\text{time } t,\text{ person } p} = \beta_{0p} + \beta_{1p} \cdot (\text{Granularity}_{tp}) + \beta_{2p} \cdot (\text{Granularity}_{tp} \cdot \text{IAs}_{p}) + \epsilon_{tp}$$

Level 2 (persons):

$$\beta_{0p} = \gamma_{00} + \gamma_{01} \cdot (\text{IAs}_{p}) + u_{0p}$$

We then estimated an additional model by adding momentary affect (valence, arousal, and dominance) and momentary negative emotions as additional predictors (covariates)[14]. The equation for this extended model is reported in the Supplemental Material.

This modeling procedure was repeated for each of the five indices of momentary emotional granularity (integral, between-category, anger-related, fear-related, and sadness-related granularity). Thus, two separate

[13] We did not include random slopes for emotional granularity in our model, since the ICC for all emotional granularity indices was extremely low (ICC ≤ 0.001). This suggests that almost all the variance in granularity occurred within individuals across time. Given this lack of meaningful between-person variation, including random slopes for emotional granularity would not substantially improve model fit and would introduce unnecessary complexity, contrary to the principle of parsimony guiding our modeling choices.

[14] Covariates were selected based on theoretical considerations rather than purely statistical criteria. Specifically, we included affective valence, arousal, dominance, and negative emotional intensity to account for variance associated with generalized affective experience. Affect is commonly conceptualized as a broad experiential state characterized by core dimensions (valence, arousal, dominance), while emotional intensity reflects the overall magnitude of the emotional experience. Because emotional granularity concerns the differentiation of emotional experiences rather than their general tone or strength, these variables were included to ensure that observed associations with EG were not driven by differences in overall affective valence or intensity. Importantly, the inclusion of these covariates is not intended to support strong causal claims, but rather to address conceptual overlap between EG and generalized affective processes (Wysocki, Lawson, & Rhemtulla, 2022).

models were estimated for each operationalization of granularity: (1) a baseline model testing the association between granularity and pain intensity, as well as its moderation by IAs; (2) a model adding covariates.

Finally, in all the models, a covariate indexing time within the experience sampling protocol was included to control for a potential confounding effect of time. This variable was defined as a continuous, standardized measure of the time elapsed at the moment of each entry relative to the start of the data collection period.

Prospective Mixed Effects Models. We specified a prospective two-level multilevel model with random intercepts, nesting pain episodes within participants. Pain at each pain episode (t) was predicted by emotional granularity at the previous pain episode (t-1) while simultaneously adjusting for the level of pain at the previous episode (t-1). We included IAs as moderator of the prospective effect of granularity on momentary pain. Since we used an event-contingent design, our observations were not equally spaced over time. To address this issue, we adjusted each within-person variable by multiplying it by a Delta Time (Δt) term, which represents the time interval between consecutive observations[15]. This approach allowed us to appropriately account for variability (both within the same participant and across participants) in the timing of assessments and control for potential time-related confounding factors. We specified the model as follows:

Level 1 (pain episodes):

$$\text{Pain}_{\text{time } t,\text{ person } p} = \beta_{0p} + [(\beta_{1p} + \beta_{2p} \cdot \Delta t_{tp}) \cdot \text{Granularity}_{t\text{-}1p}] + [(\beta_{3p} + \beta_{4p} \cdot \Delta t_{tp}) \cdot (\text{Granularity}_{t\text{-}1p} \cdot \text{IAs}_p)] + [(\beta_{5p} + \beta_{6p} \cdot \Delta t_{tp}) \cdot \text{Pain}_{t\text{-}1p}] + \epsilon_{tp}$$

Level 2 (persons):

$$\beta_{0p} = \gamma_{00} + \gamma_{01} \cdot (\text{IAs}_p) + u_{0p}$$

Following the same modeling logic applied in the contemporaneous analyses, we estimated an additional lagged model by adding lagged affect (i.e., the level of valence, arousal and dominance reported at the previous pain episode, t-1) and lagged negative emotions (i.e., the negative emotions reported at the previous pain episode, t-1) as covariates. The model equation for this extended model is presented in the Supplemental Material.

Once again, the models were independently estimated for each of the five indices of lagged emotional granularity (integral, between-category, anger-related, fear-related, and sadness-related granularity). For each index, we estimated two multilevel models to examine the predictive association with pain and the incremental contribution of the covariates.

[15] To compute Δt, we first scaled the time variable (which represents the date and time of each participant's entry) by converting the date and time of each participant's entry into a continuous scale spanning a 1-month period. This transformation resulted in a range from 0 to 30, with each decimal value representing a specific date and time within that period. We then calculated Δt by subtracting the scaled time of the previous measurement from the next measurement.

4. Results

The descriptive statistics and within- and between-person correlations are shown in Table 2.

To verify that the question order (i.e., the two diary versions) did not introduce systematic differences in the results, we conducted a set of linear mixed-effects models with random intercepts. No significant order effects were observed, indicating that the order in which questions were answered did not systematically bias self-reports. These results are reported in the Supplemental Material (Table S1).

With respect to the contemporaneous and prospective mixed effects models, the inclusion of time as an additional covariate did not significantly impact the parameter estimates or alter the overall pattern of the results. Thus, for clarity and ease of interpretation, the results reported below are based on models estimated without including this covariate. The full models, which include time into the study as a covariate, are provided in the Supplemental Material (Tables S8–S15).

4.1. Contemporaneous Mixed Effects Models

Momentary integral emotional granularity as a predictor of momentary pain intensity, with IAs as a moderator. As shown in Table 3, momentary integral emotional granularity was a significant predictor of momentary pain intensity. However, when covariates were included in the model, the effect of granularity was no longer significant.

The interaction between emotional granularity and IAs was significant, indicating that the relationship between momentary integral granularity and pain varied as a function of IAs. As depicted in Figure 1, simple slope analyses indicated that the relationship between granularity and pain was significant and negative at low (-1 *SD*: $B[SE]$ = -0.29[0.07], t = -3.88, $p < .001$) and average (*M*: $B[SE]$ = -0.11[0.05], t = -2.03, p = 0.04) IAs levels. By contrast, this association was not significant at high levels of IAs (+1 *SD*: $B[SE]$ = 0.07[0.07], t = 0.95, p = 0.34). When covariates were added into the model, the effect of granularity on pain remained statistically significant only at low levels of IAs (-1 *SD*: $B[SE]$ = -0.19[0.07], t = -2.88, $p < .001$; *M*: $B[SE]$ = -0.09[0.05], t = -1.83, p = 0.07; +1 *SD*: $B[SE]$ = 0.02[0.07], t = 0.29, p = 0.77).

When added into the model as covariates, momentary valence, dominance, and negative emotions were significant predictors of pain.

Table 2. Descriptives and within- and between-person correlations.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. EG (Integral)	–	0.96^{***}	0.68^{***}	0.65^{***}	0.72^{***}	$-0.09^{\dagger}$	-0.09^{*}	-0.07	-0.12^{**}	-0.06	-0.01	0.04	-0.02	$-0.08^{\dagger}$	–
2. EG (Between)	-0.11	–	0.71^{***}	0.72^{***}	0.73^{***}	-0.09^{*}	-0.09^{*}	-0.07	-0.11^{*}	-0.07	0.00	0.07	-0.02	-0.08	–
3. EG (Anger)	-0.04	-0.02	–	0.44^{***}	0.47^{***}	0.02	0.02	0.05	-0.02	0.02	-0.06	0.09^{*}	0.03	-0.03	–
4. EG (Fear)	$0.26^{\dagger}$	-0.33^{*}	-0.17	–	0.49^{***}	-0.06	-0.05	-0.07	-0.10^{*}	0.01	0.00	0.04	-0.02	-0.02	–
5. EG (Sadness)	0.00	-0.28^{*}	-0.12	0.24	–	-0.04	-0.04	-0.06	-0.04	-0.03	0.03	0.06	-0.01	-0.06	–
6. Negative Emotions	-0.06	-0.07	-0.09	0.19	0.04	–	0.98^{***}	0.81^{***}	0.81^{***}	0.84^{***}	-0.61^{***}	0.31^{***}	-0.48^{***}	0.46^{***}	–
7. Negative Emotions (Between)	0.11	0.02	0.16	-0.18	0.12	-0.14	–	0.82^{***}	0.83^{***}	0.85^{***}	-0.62^{***}	0.32^{***}	-0.48^{***}	0.44^{***}	–
8. Negative Emotions (Anger)	0.02	-0.04	-0.08	0.37^{**}	0.05	-0.15	-0.12	–	0.57^{***}	0.57^{***}	-0.56^{***}	0.39^{***}	-0.36^{***}	0.42^{***}	–
9. Negative Emotions (Fear)	0.11	$-0.24^{\dagger}$	-0.14	0.12	0.15	-0.09	0.06	0.05	–	0.61^{***}	-0.48^{***}	0.29^{***}	-0.39^{***}	0.37^{***}	–
10. Negative Emotions (Sadness)	-0.04	-0.09	0.04	-0.23	0.07	0.05	0.08	0.01	0.12	–	-0.55^{***}	0.16^{***}	-0.46^{***}	0.38^{***}	–
11. Valence	0.06	0.01	0.09	0.09	-0.18	-0.16	-0.02	0.10	0.22	0.02	–	-0.25^{***}	0.52^{***}	-0.40^{***}	–
12. Arousal	0.07	-0.04	0.15	0.08	0.07	0.23	0.00	0.05	-0.11	-0.11	-0.25^{*}	–	-0.20^{***}	0.19^{***}	–
13. Dominance	0.02	-0.05	-0.09	-0.24	-0.03	-0.08	0.00	-0.35^{**}	0.18	0.09	-0.12	0.16	–	-0.30^{***}	–
14. Pain	-0.13	0.04	0.05	0.00	-0.04	-0.10	-0.07	-0.05	-0.08	-0.07	-0.04	-0.08	$-0.24^{\dagger}$	–	–
15. IAs	-0.04	-0.16	0.03	-0.01	0.08	-0.18	0.16	0.03	-0.15	-0.15	-0.04	-0.14	-0.01	0.12	–
M	-4.22	-1.74	-1.97	-2.03	-1.91	3.18	3.27	3.84	2.91	3.07	3.67	5.00	3.63	3.66	2.81
SD_{Within}	5.41	2.27	2.36	2.36	2.55	0.76	0.80	0.97	0.89	0.93	1.27	1.48	1.45	1.04	–
$SD_{Between}$	2.29	0.44	0.61	0.56	0.60	1.24	1.27	1.31	1.40	1.36	1.12	1.24	1.23	0.98	0.68

Note: Within-person correlations are presented above the diagonal, between-person correlations are presented below the diagonal.

$^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$; $^{\dagger}.05 < p < .06$.

EG (Integral) = Integral Momentary Emotional Granularity. EG (Between) = Momentary Between-category Emotional Granularity. EG (Anger) = Momentary Anger-related Emotional Granularity. EG (Fear) = Momentary Fear-related Emotional Granularity. EG (Sadness) = Momentary Sadness-related Emotional Granularity. Negative Emotions (Between) = Mean of the cluster-specific average negative emotions ratings for anger, fear, and sadness. Negative Emotions (Anger) = Anger-related Emotions. Negative Emotions (Fear) = Fear-related Emotions. Negative Emotions (Sadness) = Sadness-related Emotions. IAs = Dispositional Interoceptive Sensibility.

Momentary between-category emotional granularity as a predictor of momentary pain intensity, with IAs as a moderator. As shown in Table 4, momentary between-category emotional granularity did not significantly predict momentary pain intensity, whereas the moderation effect of IAs was statistically significant. Simple slope analyses indicated that the relationship between granularity and pain was significant and negative at low levels of IAs (-1 *SD*: *B*[*SE*] = -0.27[0.07], $t = -3.66$, $p < .001$). By contrast, this association was not significant at average (*M*: *B*[*SE*] = -0.09[0.05], $t = -1.63$, $p = 0.10$) or high (+1 *SD*: *B*[*SE*] = 0.10[0.08], $t = 1.31$, $p = 0.19$) levels of IAs. When covariates were added into the model, the simple slope remained significant only at low levels of IAs (-1 *SD*: *B*[*SE*] = -0.17[0.07], $t = -2.54$, $p = .01$; *M*: *B*[*SE*] = -0.07[0.05], $t = -1.40$, $p = 0.16$; +1 *SD*: *B*[*SE*] = 0.04[0.07], $t = 0.57$, $p = 0.57$).

When included in the model, momentary valence, dominance, and negative emotions were also significant predictors of pain intensity.

Momentary anger-related, fear-related, and sadness-related emotional granularity as independent predictors of momentary pain intensity, with IAs as a moderator. As shown in Table 5, momentary within-category emotional granularity was not a significant predictor of momentary pain intensity for any of the three emotion clusters (i.e., anger, fear, and sadness). For all three clusters, the interaction between granularity and IAs was statistically significant in the baseline model but became nonsignificant when including covariates. Simple slope analyses are reported in the Supplemental Material (Table S2).

Both affect valence and cluster-related negative emotions significantly predicted pain levels in all three emotion clusters. By contrast, the effect of affect dominance was significant for the anger and fear clusters only.

4.2. Prospective Mixed Effects Models

Lagged integral emotional granularity as a predictor of momentary pain intensity, with IAs as a moderator. Previous integral emotional granularity did not significantly predict subsequent pain intensity, nor did its interaction with IAs. In addition, lagged pain intensity was not significantly associated with current pain.

When covariates were added to the model, only lagged arousal was positively associated with current pain intensity, *B*(*SE*) = 0.12(0.06), *CI*[0.01, 0.25], $t = 2.00$, $p = 0.046$. This effect indicates that greater levels of arousal as assessed in a pain episode predict greater pain intensity as assessed in the subsequent episode. Notably, the interaction effect between lagged arousal and Δt was not significant, suggesting that the effect of lagged arousal was not dependent on the time elapsed between pain episodes.

The models' results are reported in the Supplemental Material (Table S3).

Table 3. Multilevel concurrent models of momentary pain intensity predicted by momentary integral negative emotional granularity and its interaction with interoceptive sensibility (*Model a*) while controlling for momentary affective valence, arousal and dominance and momentary negative emotions (*Model b*).

	Model a				*Model b*			
	Est. (*SE*)	95% *CI*	*t*	*p*	Est. (*SE*)	95% *CI*	*t*	*p*
Intercept	**3.66 (0.12)**	**[3.44, 3.88]**	**31.51**	**<.001**	**3.65 (0.12)**	**[3.42, 3.87]**	**30.40**	**<.001**
Momentary EG (Integral)	**-0.11 (0.05)**	**[-0.21, -0.01]**	**-2.01**	**0.044**	-0.08 (0.05)	[-0.17, 0.01]	-1.74	0.083
IAs	0.25 (0.13)	[-0.01, 0.50]	1.93	0.058†	0.24 (0.13)	[-0.02, 0.49]	1.82	0.074
Momentary EG (Integral) × IAs	**0.18 (0.05)**	**[0.07, 0.28]**	**3.42**	**<.001**	**0.11 (0.05)**	**[0.01, 0.20]**	**2.25**	**0.025**
Momentary Valence					**-0.20 (0.06)**	**[-0.33, -0.08]**	**-3.14**	**0.002**
Momentary Arousal					0.03 (0.05)	[-0.07, 0.12]	0.62	0.535
Momentary Dominance					-0.11 (0.06)	[-0.23, 0.00]	-1.95	0.051†
Momentary Negative Emotions					**0.31 (0.06)**	**[0.18, 0.43]**	**4.79**	**<.001**

Note: Boldface indicates significant effects with $p < 0.05$. † indicates marginally significant effects. *CI* = confidence interval. CIs were estimated using 2,500 bootstrap resamples. Momentary EG (Integral) = Momentary Integral Emotional Granularity. IAs = Interoceptive Sensibility.

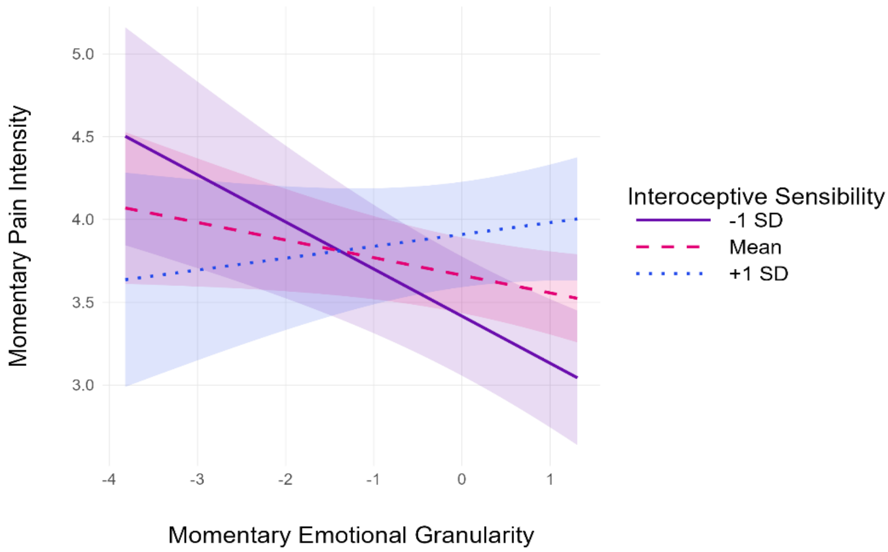

Figure 1. The contemporaneous association between emotional granularity and pain intensity, moderated by interoceptive sensibility (IAs).

Note. Lines indicate slopes for different levels of IAs; bands indicate a 95% confidence interval. The solid line represents the trajectory for an individual scoring one standard deviation below the mean score of IAs, the dashed line represents the trajectory at the mean score of IAs, and the dotted line represents the trajectory for one standard deviation above the mean score of IAs.

Table 4. Multilevel concurrent models of momentary pain intensity predicted by momentary between-category emotional granularity and its interaction with interoceptive sensibility (*Model a*) while controlling for momentary affective valence, arousal and dominance and momentary negative emotions (*Model b*).

	Model a				*Model b*			
	Est. (*SE*)	95% *CI*	*t*	*p*	Est. (*SE*)	95% *CI*	*t*	*p*
Intercept	**3.64 (0.12)**	**[3.40, 3.88]**	**30.25**	**<.001**	**3.63 (0.12)**	**[3.39, 3.87]**	**29.48**	**<.001**
Momentary EG (Between)	-0.09 (0.05)	[-0.19, 0.02]	-1.59	0.113	-0.06 (0.05)	[-0.16, 0.03]	-1.30	0.194
IAs	0.24 (0.13)	[-0.01, 0.50]	1.85	0.069	0.24 (0.13)	[-0.03, 0.48]	1.77	0.082
Momentary EG (Between) × IAs	**0.18 (0.05)**	**[0.08, 0.29]**	**3.53**	**<.001**	**0.11 (0.05)**	**[0.01, 0.21]**	**2.21**	**0.028**
Momentary Valence					**-0.18 (0.07)**	**[-0.32, -0.06]**	**-2.84**	**0.005**
Momentary Arousal					0.03 (0.05)	[-0.07, 0.14]	0.65	0.519
Momentary Dominance					**-0.12 (0.06)**	**[-0.23, -0.01]**	**-2.08**	**0.038**
Momentary Emotions (Between)					**0.30 (0.07)**	**[0.17, 0.43]**	**4.58**	**<.001**

Note: Boldface indicates significant effects. *CI* = confidence interval. CIs were estimated using 2,500 bootstrap resamples. Momentary EG (Between) = Momentary Between-category Emotional Granularity, computed using three negative emotion clusters: Anger, fear, and sadness. Momentary Emotions (Between) = Mean of the cluster-specific average momentary ratings for anger, fear, and sadness. IAs = Interoceptive Sensibility.

Table 5. Multilevel concurrent models of momentary pain intensity predicted by momentary anger-, fear-, and sadness-related emotional granularity and its interaction with interoceptive sensibility (*Model a*) while controlling for momentary affect valence, arousal and dominance and for momentary cluster-related emotions (*Model b*).

	Model a				*Model b*			
	Est. (*SE*)	95% *CI*	*t*	*p*	Est. (*SE*)	95% *CI*	*t*	*p*
Emotion Cluster: Anger								
Intercept	**3.72 (0.12)**	**[3.49, 3.96]**	**31.28**	**<.001**	**3.71 (0.12)**	**[3.47, 3.96]**	**29.83**	**<.001**
Momentary EG (Anger)	-0.03 (0.06)	[-0.14, 0.07]	-0.59	0.556	-0.06 (0.05)	[-0.16, 0.04]	-1.23	0.220
IAs	0.24 (0.13)	[-0.02, 0.48]	1.86	0.068	0.23 (0.13)	[-0.03, 0.50]	1.73	0.089
Momentary EG (Anger) × IAs	**0.15 (0.05)**	**[0.05, 0.26]**	**2.89**	**0.004**	0.05 (0.05)	[-0.04, 0.16]	1.09	0.276
Momentary Valence					**-0.20 (0.07)**	**[-0.33, -0.07]**	**-2.96**	**0.003**
Momentary Arousal					-0.00 (0.05)	[-0.11, 0.10]	-0.01	0.994
Momentary Dominance					**-0.16 (0.06)**	**[-0.27, -0.04]**	**-2.57**	**0.011**
Momentary Emotions (Anger)					**0.32 (0.07)**	**[0.19, 0.45]**	**4.81**	**<.001**
Emotion Cluster: Fear								
Intercept	**3.68 (0.12)**	**[3.44, 3.92]**	**30.18**	**<.001**	**3.67 (0.13)**	**[3.44, 3.91]**	**29.00**	**<.001**
Momentary EG (Fear)	-0.00 (0.06)	[-0.11, 0.11]	-0.08	0.938	0.01 (0.05)	[-0.09, 0.11]	0.22	0.828
IAs	0.25 (0.13)	[0.00, 0.51]	1.96	0.055†	0.25 (0.13)	[-0.02, 0.51]	1.85	0.070
Momentary EG (Fear) × IAs	**0.14 (0.05)**	**[0.04, 0.25]**	**2.71**	**0.007**	0.09 (0.05)	[-0.01, 0.19]	1.87	0.062
Momentary Valence					**-0.27 (0.06)**	**[-0.40, -0.15]**	**-4.34**	**<.001**
Momentary Arousal					0.09 (0.05)	[-0.01, 0.19]	1.74	0.083
Momentary Dominance					**-0.17 (0.06)**	**[-0.30, -0.05]**	**-2.83**	**0.005**
Momentary Emotions (Fear)					**0.15 (0.06)**	**[0.03, 0.27]**	**2.40**	**0.017**
Emotion Cluster: Sadness								
Intercept	**3.68 (0.12)**	**[3.44, 3.93]**	**29.64**	**<.001**	**3.66 (0.13)**	**[3.41, 3.91]**	**29.03**	**<.001**
Momentary EG (Sadness)	-0.07 (0.06)	[-0.18, 0.04]	-1.22	0.224	-0.05 (0.05)	[-0.15, 0.05]	-1.00	0.316
IAs	0.23 (0.13)	[-0.04, 0.48]	1.71	0.092	0.23 (0.14)	[-0.03, 0.51]	1.69	0.097
Momentary EG (Sadness) × IAs	**0.13 (0.05)**	**[0.02, 0.23]**	**2.35**	**0.019**	0.08 (0.05)	[-0.02, 0.17]	1.53	0.128
Momentary Valence					**-0.25 (0.07)**	**[-0.38, -0.12]**	**-3.84**	**<.001**
Momentary Arousal					0.07 (0.05)	[-0.03, 0.17]	1.29	0.200
Momentary Dominance					-0.11 (0.06)	[-0.23, 0.02]	-1.75	0.082
Momentary Emotions (Sadness)					**0.25 (0.06)**	**[0.13, 0.38]**	**3.94**	**<.001**

Note: Boldface indicates significant effects. † indicates marginally significant effects. *CI* = confidence interval. CIs were estimated using 2,500 bootstrap resamples. Momentary EG (Anger) = Momentary Anger-related Emotional Granularity. Momentary EG (Fear) = Momentary Fear-related Emotional Granularity. Momentary EG (Sadness) = Momentary Sadness-related Emotional Granularity. Momentary Emotions (Anger) = Momentary Anger-related Emotions. Momentary Emotions (Fear) = Momentary Fear-related Emotions. Momentary Emotions (Sadness) = Momentary Sadness-related Emotions. IAs = Interoceptive Sensibility.

Lagged between-category emotional granularity as a predictor of momentary pain intensity, with IAs as a moderator. In the baseline model, no effects reached statistical significance. Likewise, when covariates were added to the model, none of the main effects or interactions were significant. The models' results are reported in the Supplemental Material (Table S4).

Lagged anger-related, fear-related, and sadness-related emotional granularity as independent predictors of momentary pain intensity, with IAs as a moderator. For the anger-related cluster, lagged emotional granularity did not predict momentary pain intensity. However, the three-way interaction between lagged granularity, Δt, and IAs was statistically significant (*B*[*SE*] = -0.1[0.05], *CI*[-0.22, -0.01], $t = -2.05$, $p = 0.041$), suggesting that the joint effect of previous granularity and IAs on subsequent pain intensity depended also on the time elapsed between two consecutive pain episodes. However, this interaction effect became nonsignificant once covariates were added to the model. Additionally, both lagged arousal, *B*(*SE*) = 0.17(0.07), *CI*[0.04, 0.31], $t = 2.60$, $p = 0.010$, and lagged anger-related emotions, *B*(*SE*) = -0.18(0.08), *CI*[-0.34, -0.01], $t = -2.10$, $p = 0.036$, were significant predictors of momentary pain.

Concerning the fear-related cluster, the interaction between lagged fear-related granularity and IAs became significant after including covariates, *B*(*SE*) = 0.12(0.06), *CI*[0.00, 0.24], $t = 2.06$, $p = 0.041$, but only at very high levels of interoception (-2 *SD*: *B*[*SE*] = -0.23[0.13], $t = -1.71$, $p = 0.09$; *M*: *B*[*SE*] = 0.02[0.06], $t = 0.33$, $p = 0.74$; +2 *SD*: *B*[*SE*] = 0.27[0.14], $t = 1.95$, $p = 0.05$). Lagged arousal also emerged as a significant predictor of pain intensity, *B*(*SE*) = 0.16(0.06), *CI*[0.03, 0.29], $t = 2.52$, $p = 0.012$.

Concerning the sadness-related cluster, no effects were statistically significant, either in the baseline model or after covariate adjustment.

The models' results are reported in the Supplemental Material (Tables S5–S7).

5. Discussion

The present study aimed to investigate the within-person association between negative emotional granularity and pain intensity across different levels of dispositional IAs, both concurrently and prospectively. We explored this relationship via multiple indices of granularity: Integral granularity, between-category granularity, and three within-category indices focused on the emotion clusters of anger, fear, and sadness. We hypothesized that, across both concurrent and prospective temporal patterns and granularity indices, higher emotional granularity would be associated with lower pain intensity, particularly among individuals with low levels of IAs. The results partially supported our hypotheses.

5.1. Momentary Emotional Granularity Buffers Concurrent Pain: When and for Whom It Matters

When examining momentary predictors of pain, momentary integral granularity significantly predicted lower momentary pain within participants. However, this effect became nonsignificant after controlling for the affective tone and the intensity of negative emotions. By contrast, the interaction between momentary granularity and dispositional IAs remained significant even after adjusting for covariates, so that – as we expected – granularity was associated with lower pain intensity among participants with low IAs. Moreover, consistent with prior research (Bushnell et al., 2013; Mohr et al., 2012; Müller, 2011; Wiech & Tracey, 2009), lower affect dominance and heightened unpleasantness and negative emotions were also associated with greater pain intensity.

The novel contribution of this study lies in identifying above-average fluctuations in negative emotional granularity as a potential protective factor against chronic pain intensity for individuals with low IAs, beyond the concurrent affective and emotional experience. Negative emotions are known to significantly influence how pain is perceived (Bushnell et al., 2013; Wiech & Tracey, 2009), and research has shown that emotional and pain experiences share overlapping neural circuits and interoceptive predictive processes (Chang et al., 2015; Wager et al., 2013, 2015; Woo et al., 2015). Individuals scoring low in IAs may present a reduced attentional focus on internal bodily sensations or process such sensations in a diffuse and undifferentiated manner (Garfinkel et al., 2015). In such individuals, greater emotional granularity may facilitate a clearer conceptualization of interoceptive signals, thereby minimizing the overlap between emotional and pain experiences. In other words, emotional granularity may help prevent vague or poorly defined bodily discomfort from being mistakenly perceived as intense pain. Furthermore, a greater ability to accurately identify and label emotional states may enable individuals to reduce the emotional amplification of pain. Thus, it allows individuals to assign more appropriate meaning and intensity to their pain experiences.

Similar results emerged from the analyses using momentary between-category granularity as a predictor of pain intensity. We found that, just as the ability to differentiate negative emotional states in general, the ability to differentiate emotions among distinct clusters was also associated with lower concurrent pain intensity in women with low IAs. This similarity is not surprising given the observed strong and highly significant within-person correlation between the integral and between-category granularity indices. This finding suggests a substantial overlap between the two operationalizations of granularity, indicating that they may not capture distinct constructs. This is a convergence that has also been reported in prior research on dispositional emotional granularity (Erbas et al., 2019). The fact that our analyses were based on momentary assessments of granularity suggests that the overlap between integral and between-category granularity may not be limited to the dispositional level but may also characterize state-level emotional granularity.

By contrast, when examining within-category granularity in relation to the emotion clusters of anger, fear, and sadness, the analyses revealed a different pattern of results. After adjusting for covariates, neither within-category granularity alone nor its interaction with IAs was a significant within-person predictor of pain.

Nonetheless, emotional intensity emerged as a robust predictor: Emotions within the anger, fear, and sadness clusters were all significantly related to higher levels of pain. For all three clusters, perceived unpleasantness was also a significant predictor of pain intensity. Conversely, affect dominance was a significant predictor of pain only for the anger and fear clusters, both of which are typically considered high-arousal emotion families compared to sadness.

Overall, these findings suggest that the ability to better differentiate emotions within a single emotional cluster in a certain moment does not meaningfully influence the concurrent pain perception, even in individuals with low IAs. Affective tone and the intensity of cluster-related negative emotions appear to be more relevant than the precision of emotional labeling. Granularity can vary across time and context (Erbas et al., 2018). Thus, it is plausible that it exerts different effects depending on the level of emotional specificity. When individuals focus on differentiating between similar emotions within a single cluster, this detailed discrimination may inadvertently amplify the salience of negative emotions linked to that cluster. Consequently, the strength of negative emotions, rather than the precision of emotion differentiation, may account for pain perception. As a result, intense negative emotions within a single cluster may overshadow any protective effects of cluster-related emotional granularity. This stands in contrast to the protective role of integral emotional granularity observed among individuals with low IAs. In such cases, attention is not narrowly focused on a single emotional cluster but spans multiple domains. This suggests that the adaptive value of emotional granularity may depend on its scope – whether it is applied narrowly within a single cluster or broadly across emotional domains.

Our findings emphasize the importance of the level at which granularity is assessed. Distinguishing across negative emotion categories may help individuals with low IAs to decouple emotional distress from pain perception, thereby reducing pain intensity. By contrast, focusing on a single category may lead individuals to amplify emotional discomfort and increase its impact on pain perception. This highlights how the protective effect of granularity on pain depends not only on the ability to finely differentiate emotions but also on the degree of specificity with which those emotions are examined.

5.2. Prospective Risk Factors for Pain Chronification: Hidden Costs of Feeling Too Much

When prospective predictors of pain were examined, emotional granularity alone did not exhibit a significant main effect. Similarly, indices of granularity calculated across integral or between-category metrics showed no significant interaction with IAs. A different pattern of results was observed for granularity indices within emotion categories. Granularity within the sadness cluster showed no significant effects. The interaction of granularity within the anger cluster and IAs became nonsignificant after controlling for covariates. Finally, granularity within the fear-related cluster significantly predicted future pain intensity, but only among individuals with high levels of IAs. Thus, for individuals reporting a heightened and sustained attentional focus on interoceptive signals, momentary increases in fear-related granularity (relative to their individual mean) were associated with greater subsequent pain intensity.

This finding is especially noteworthy in light of the Fear-Avoidance Model, one of the most prominent models in the field of CPP (Alappattu & Bishop, 2011). According to this model, fear-related emotional processing is a central mechanism in the maintenance and exacerbation of chronic pain: Pain-related fear fosters hypervigilance toward bodily sensations and avoidance behaviors, which in turn contribute to pain chronification. These dynamics are further supported by predictive coding accounts of chronic pain, which conceptualize pain persistence as a function of maladaptive priors that are continually reinforced through aberrant interpretations of internal bodily signals (Ongaro & Kaptchuk, 2018). Within this integrative theoretical framework, individuals scoring high in IAs may be especially vulnerable to experiencing pain-related fear. When pain occurs, it may reinforce their fear and validate the perceived need for continuous monitoring of bodily signals to prevent future painful experiences. Consistent with this idea, our findings showed that momentary fear-related emotions significantly predicted concurrent pain, and IAs had a marginally significant effect.

Building on this, our findings showed that when individuals with high IAs exhibited heightened fear-related granularity while experiencing pain, this increased differentiation was associated with greater pain in subsequent pain episodes. Identifying and focusing on fear-related emotions may reinforce maladaptive beliefs linking interoceptive sensations with actual harm. This, in turn, may intensify pain-related fear, ultimately exerting a prospective impact on future pain experiences. In other words, in individuals with high IAs, fear-related emotional granularity may contribute to a self-reinforcing cycle that promotes the persistence and chronification of pain.

Of note, past pain intensity did not emerge as a significant predictor of subsequent pain experiences. This finding may appear counterintuitive through the lens of predictive coding models. However, this apparent discrepancy becomes more theoretically coherent when the role of arousal rather than pain intensity per se is considered. Arousal, as an index of the intensity of an affective experience, partly overlaps with pain but is not reducible to it. It represents a generalized state of physiological activation, which may then be categorized as pain, emotion, or another affective state. Affective arousal is considered to act as a key driver of pain persistence and chronicity (Ciuffini et al., 2023; Ravn et al., 2018). Consistent with this view, our results suggest that individuals who experienced high arousal during prior pain episodes were more likely to report elevated pain in subsequent episodes, regardless of whether this arousal stemmed primarily from pain itself or from associated emotional states. This finding underscores how the boundaries between pain and emotion are often blurred in the immediate experience of pain, highlighting their shared affective mechanisms (Craig, 2003).

Interestingly, although arousal played a central predictive role in shaping future pain experiences, it failed to predict concurrent pain levels. Moreover, although the affective components most closely associated with immediate pain experience were unpleasantness, affect dominance, and the intensity of negative emotions, these variables did not emerge as significant predictors in the prospective models. These discrepancies suggest that different affective mechanisms may occur depending on the temporal perspective. In the here and now, the experience of pain is shaped by affective features that are either tied to evaluative dimensions of the situation or the emotional salience of the moment. Arousal, by contrast, functions as an undifferentiated affective activation that shapes anticipatory mechanisms involved in pain chronification. Within a predictive coding framework, this undifferentiated affective activation may become embedded in prior beliefs about bodily threat, biasing the interpretation of future interoceptive input and reinforcing pain expectations (Norton & Asmundson, 2003). These findings highlight the need to distinguish between immediate correlates of pain and the longer-term affective mechanisms that underpin pain persistence.

5.3. The Conditional Role of Dispositional Interoceptive Sensibility on Pain

Dispositional IAs did not emerge as a stand-alone predictor of pain, neither concurrently nor prospectively nor for any of the granularity indices examined. This finding is particularly noteworthy in light of previous literature suggesting that individuals with chronic pain tend to report elevated levels of IAs, both within the context of CPP (Scarpina et al., 2025; Spinoni et al., 2024) and chronic pain more broadly (Horsburgh et al., 2024). However, this line of research has largely overlooked the potential role of emotional experience and its various emotional and affective correlates. Our results indicate that when within-person fluctuations in emotional and affective correlates of pain are taken into account, the predictive power of dispositional IAs alone becomes considerably less central in explaining pain intensity.

This result is theoretically consistent with the view that interoceptive processes underlie the construction of all affective experiences (Craig, 2014), whether emotional or painful (Craig, 2003; Greenwood & Garfinkel, 2024; Horsburgh et al., 2024; Poublan-Couzardot & Talmi, 2024). Given that emotional states are known to amplify pain perception (Bushnell et al., 2013; Wiech & Tracey, 2009), the role of interoception in pain may be largely accounted for by its relationship with emotional processing. In line with this, our findings suggest that IAs does not directly predict pain but rather shapes it indirectly through its interaction with emotional experience, particularly with emotional granularity. Dispositional IAs may affect how bodily signals are interpreted and categorized, biasing individuals toward either more global or more differentiated emotional representations. These representations, in turn, can distinctly modulate pain perception. Thus, IAs remains a relevant trait-level factor in the construction of pain experience. However, our findings seem to underscore the importance of considering interoception not in isolation but as part of a dynamic system of affective and emotional processes.

5.4. Limitations and Future Directions

The present study represents (to the best of our knowledge) the first attempt to investigate the role of emotional granularity in chronic pain experiences. Despite its novel contribution, some limitations should be considered when interpreting the findings.

A key limitation concerns the variability in the number of pain episodes reported by participants, which may have influenced the reliability of the momentary granularity indices. Because the denominator in the index formula was computed on the basis of variance across all observations, the stability of the momentary granularity estimate ultimately depends on the total number of measurements per participant. Although momentary granularity is calculated on a moment-by-moment basis, its reliability hinges on variance estimates aggregated across all available measurement occasions. The ecological, event-contingent design of the study, in which the measurement is inherently linked to the number of pain episodes, limited our possibility to strictly control or standardize the frequency of pain episodes across participants. Although inclusion and exclusion criteria were employed to minimize heterogeneity, the high intraindividual variability in chronic pain (Sundström et al., 2025) prevented full consistency in the number and frequency of pain episodes across participants. Moreover, the assessment period was not extended to reduce participant burden (e.g., from one to two months). Future research could address this limitation by increasing the number of pain episodes monitored, ideally selecting samples characterized by more frequent pain events.

A related limitation is the sample size. Although sixty-eight participants with at least three observations each are considered adequate on the basis of simulation studies (Maas & Hox, 2005), a larger sample would increase the statistical power and improve the robustness of the results. Thus, replication with larger samples is needed.

The absence of physiological measures represents an additional limitation. Integrating objective assessments of IAc alongside self-reported data of IAs would provide a more comprehensive understanding. The scientific literature indicates that IAs and IAc are related differently to chronic pain experiences (Horsburgh et al., 2024). Future studies could explore whether the association between emotional granularity and pain varies depending on IAc levels. Furthermore, given the prospective role of self-reported arousal in future pain experiences, measuring physiological arousal during pain episodes would offer an objective counterpart to subjective reports.

Finally, this study focused primarily on within-person dynamics, in line with recent calls and growing evidence highlighting the importance of capturing intraindividual variability in chronic pain (Sundström et al., 2025). Investigating between-person associations in future research could provide further insights. Our focus on within-person fluctuations allowed for a detailed exploration of the interplay between general affect, emotional components, and pain. However, within- and between-person approaches are not mutually exclusive, and both can yield complementary insights. Exploring between-person patterns may further enhance the understanding of chronic pain mechanisms. In particular, investigating dispositional granularity alongside dispositional variables such as interoceptive ability could provide additional valuable contributions to this field.

6. Conclusion

Overall, our findings highlight that within-person emotional granularity is a dynamic, conditional factor in the experience of neuropathic and nociplastic CPP. Moment-to-moment, broader (integral and between-category) granularity buffered concurrent pain intensity, but this effect was significant only among women with low dispositional IAs. Moreover, we found that finer fear-specific granularity prospectively amplified pain in participants with high IAs, and this result is consistent with fear-avoidance and predictive-processing accounts of pain chronification. These findings suggest that the impact of granularity on the experience of pain depends on an individual's habitual focus on bodily signals, but also on the scope of differentiation. While preliminary, these findings also suggest that interventions that foster cross-category emotion labeling, particularly when combined with strategies to temper hypervigilant interoceptive focus, may be a promising intervention strategy for alleviating CPP. Nonetheless, further studies with larger samples and more measurement occasions are warranted to replicate and extend these within-person effects.

Pain or Emotion? The Role of Negative Emotional Granularity and Interoceptive Sensibility in Neuropathic and Nociplastic Chronic Pelvic Pain

Chapter 3 Supplemental Material

List of Content:

1. Method

1.1. Description of the Full Study 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. Although 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 to ensure transparency regarding study design and implementation. A graphical overview of the full study procedure is displayed in Figure S1.

First, the participants were invited to attend an initial session, during which the objectives and structure of the study were explained in detail, eligibility was confirmed, and informed consent was obtained. Participants then completed an online baseline questionnaire assessing sociodemographic characteristics, medical history, pain intensity and affect over the past two weeks, interoceptive sensibility, psychological well-being and emotion regulation strategies. A subgroup of 25 participants also took part in additional assessments conducted in the laboratory, including the recording of psychophysiological parameters (electrocardiogram and respiration to assess respiratory sinus arrhythmia) and a task measuring interoceptive accuracy.

Following this baseline assessment, participants started the one-month experience sampling. During this phase, they were asked to complete an online diary each time they experienced a pain episode. For each episode, they were asked to answer a rating of current pain intensity, standardized measures of their affective state, and a fixed set of fourteen emotion labels. The participants also provided an open-ended narrative describing the pain episode (including details about physical sensations, emotions and feelings, contextual factors, and personal reflections) and ratings of self-generated affective adjectives, which however were not included in the present analyses. To control for potential confounding factors, we created two diary versions: In one version, affect and emotion measures were rated before providing the open-ended narrative while in the second version the participants were asked to provide the narrative before completing the emotion measures. The participants were randomly assigned to one of the two versions to counterbalance potential order effects.

After this one-month experience sampling, participants were asked to complete two additional online questionnaires. The first was administered immediately after the end of the experience sampling period (i.e., one month after baseline) and included measures of pain intensity, perceived changes in pain since the beginning of the study, interoceptive sensibility, affect, and well-being. The last assessment took place one month later (i.e., two months after baseline) and included the same set of measures.

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.

Participation in the study was voluntary and without monetary compensation.

1.2. Equations for Mixed-Effects Models Controlling for Covariates

1.2.1. Equations for Contemporaneous Mixed-Effects Models Controlling for Covariates

To investigate the concurrent association between emotional granularity and pain intensity, we specified a two-level multilevel model with random intercepts, in which pain episodes (Level 1) were nested within participants (Level 2). Momentary pain intensity was modeled as a function of momentary emotional granularity. In addition, we included interoceptive sensibility (IAs) as a Level 2 moderator of the within-person (Level 1) association between granularity and pain. We then estimated one additional contemporaneous model by adding covariates to the previous model. We included momentary affect valence, arousal, and dominance, and negative emotions as additional predictors:

Level 1 (pain episodes):

$$\text{Pain}_{\text{time } t, \text{ person } p} = \beta_{0p} + \beta_{1p} \cdot (\text{Granularity}_{tp}) + \beta_{2p} \cdot (\text{Granularity}_{tp} \cdot \text{IAs}_{p}) + \beta_{3p} \cdot (\text{Valence}_{tp}) + \beta_{4p} \cdot (\text{Arousal}_{tp}) + \beta_{5p} \cdot (\text{Dominance}_{tp}) + \beta_{6p} \cdot (\text{NegativeEmotions}_{tp}) + \epsilon_{tp}$$

Level 2 (persons):

$$\beta_{0p} = \gamma_{00} + \gamma_{01} \cdot (\text{IAs}_{p}) + u_{0p}$$

1.2.2. Equations for Lagged Mixed-Effects Models Controlling for Covariates

To test the prospective relationship between emotional granularity and pain intensity, we constructed a lagged two-level multilevel model with random intercepts, nesting pain episode within participants. Pain at pain episode (t) was predicted by emotional granularity at the previous pain episode (t-1), while simultaneously adjusting for the level of pain at the previous episode (t-1). We included interoceptive sensibility (IAs) as moderator of the lagged effect of granularity on momentary pain. As we used an event-contingent design, our observations were not equally spaced over time. To address this issue, we adjusted each within-person variable by multiplying it by a Delta Time (Δt) term, representing the time interval between consecutive observations. This approach allowed us to appropriately account for variability (both within the same participant and across participants) in the timing of assessments and control for potential time-related confounding factors. Following the same modeling logic applied in the contemporaneous analyses, we estimated one additional lagged models by sequentially adding covariates.

We added lagged affect valence, arousal, and dominance, and lagged negative emotions (i.e., the level of valence, arousal and dominance of affect, and negative emotions reported at the previous pain episode, t-1).

Level 1 (pain episodes):

$\text{Pain}_{\text{time } t,\text{ person } p} = \beta_{0p} + [(\beta_{1p} + \beta_{2p} \cdot \Delta t_{tp}) \cdot \text{Granularity}_{t\text{-}1p}] + [(\beta_{3p} + \beta_{4p} \cdot \Delta t_{tp}) \cdot (\text{Granularity}_{t\text{-}1p} \cdot \text{IAs}_{p})] + [(\beta_{5p} + \beta_{6p} \cdot \Delta t_{tp}) \cdot \text{Pain}_{t\text{-}1p}] + [(\beta_{7p} + \beta_{8p} \cdot \Delta t_{tp}) \cdot \text{Valence}_{t\text{-}1p})] + [(\beta_{9p} + \beta_{10p} \cdot \Delta t_{tp}) \cdot \text{Arousal}_{t\text{-}1p})] + [(\beta_{11p} + \beta_{12p} \cdot \Delta t_{tp}) \cdot \text{Dominance}_{t\text{-}1p})] + [(\beta_{13p} + \beta_{14p} \cdot \Delta t_{tp}) \cdot \text{NegativeEmotions}_{t\text{-}1p})] + \epsilon_{tp}$

Level 2 (persons):

$\beta_{0p} = \gamma_{00} + \gamma_{01} \cdot (\text{IAs}_{p}) + u_{0p}$

2. Tables

2.1. Table S1: Results from Mixed-Effects Models Testing the Effect of Diary Randomization on Affect and Emotional Variables

To verify that the question order (i.e., the two diary versions) did not introduce systematic differences in the results, we conducted a set of linear mixed-effects models with random intercepts. No significant order effects were observed, indicating that the order in which questions were answered did not systematically bias self-reports.

Table S1. Results from mixed-effects models testing the effect of diary randomization on affect and emotional variables.

	Est.	*SE*	*t*	*p*
Emotional Granularity (Integral)	0.27	0.66	0.41	0.680
Emotional Granularity (Between)	0.16	0.25	0.64	0.525
Emotional Granularity (Anger)	-0.05	0.27	-0.19	0.849
Emotional Granularity (Fear)	-0.09	0.29	-0.32	0.749
Emotional Granularity (Sadness)	-0.04	0.27	-0.14	0.891
Valence	-0.02	0.28	-0.07	0.947
Arousal	-0.17	0.30	-0.58	0.566
Dominance	0.18	0.30	0.58	0.565
Negative Emotions	0.39	0.30	1.27	0.208
Negative Emotions (Between)	0.40	0.31	1.28	0.205
Negative Emotions (Anger)	0.23	0.32	0.69	0.490
Negative Emotions (Fear)	0.64	0.33	1.91	0.060
Negative Emotions (Sadness)	0.33	0.33	0.98	0.392

Note: Emotional Granularity (Integral) = Integral Emotional Granularity. Emotional Granularity (Between) = Between-category Emotional Granularity. Emotional Granularity (Anger) = Anger-related Emotional Granularity. Emotional Granularity (Fear) = Fear-related Emotional Granularity. Emotional Granularity (Sadness) = Sadness-related Emotional Granularity. Negative Emotions (Between) = Mean of the cluster-specific average negative emotions ratings for anger, fear, and sadness. Negative Emotions (Anger) = Anger-related Emotions. Negative Emotions (Fear) = Fear-related Emotions. Negative Emotions (Sadness) = Sadness-related Emotions.

2.2. Table S2: Simple Slopes Analysis for the Interaction Between Momentary Cluster-related Emotional Granularity and Interoceptive Sensibility in Predicting Pain Intensity

Table S2. Results from the simple slopes analyses for the interaction between momentary anger-related, fear-related, and sadness-related emotional granularity and interoception in predicting pain intensity. For each emotion cluster, analyses from two models are presented: (1) a baseline model testing the association between emotional granularity and pain intensity, as well as its moderation by interoceptive sensibility (*Model a*); (2) a final model including momentary affect valence, arousal, and dominance, and negative emotions as covariates (*Model b*).

		Model a			*Model b*		
Predictor	IAs Level	Est.(*SE*)	*t*	*p*	Est.(*SE*)	*t*	*p*
EG (Anger)							
	-1.50 SD	**-0.26(0.10)**	**-2.71**	**0.01**	-0.12(0.07)	-1.69	0.09
	0.00 SD	-0.03(0.06)	-0.59	0.56	-0.06(0.05)	-1.23	0.22
	1.50 SD	**0.20(0.10)**	**2.03**	**0.04**	-0.01(0.07)	-0.08	0.93
EG (Fear)							
	-1.50 SD	**-0.15(0.08)**	**-2.00**	**0.05**	-0.13(0.09)	-1.46	0.15
	0.00 SD	-0.01(0.06)	-0.11	0.91	0.01(0.05)	0.22	0.83
	1.50 SD	0.14(0.08)	1.81	0.07	0.15(0.09)	1.63	0.10
EG (Sadness)							
	-1.50 SD	**-0.26(0.10)**	**-2.67**	**0.01**	-0.13(0.07)	-1.86	0.06
	0.00 SD	-0.07(0.06)	-1.22	0.22	-0.05(0.05)	-1.09	0.27
	1.50 SD	0.12(0.10)	1.22	0.22	0.02(0.07)	0.30	0.76

Note: Boldface indicates significant effects. *SD* = Standard Deviation. EG (Anger) = Anger-related Emotional Granularity. EG (Fear) = Fear-related Emotional Granularity. EG (Sadness) = Sadness-related Emotional Granularity. IAs = Interoceptive Sensibility.

2.3. Tables S3–S7: Results from Lagged Mixed-Effects Models

Table S3. Multilevel lagged models of momentary pain intensity predicted by lagged emotional granularity and its interaction with interoceptive sensibility while controlling for lagged pain (*Model a*), momentary affective valence, arousal and dominance, and momentary negative emotions (*Model b*).

	Model a				*Model b*			
	Est. (*SE*)	95% *CI*	*t*	*p*	Est. (*SE*)	95% *CI*	*t*	*p*
Intercept	**3.77 (0.12)**	**[3.54, 3.99]**	**31.38**	**<.001**	**3.76 (0.12)**	**[3.51, 3.98]**	**30.09**	**<.001**
Lagged EG (Integral)	-0.04 (0.06)	[-0.15, 0.08]	-0.61	0.543	-0.04 (0.06)	[-0.15, 0.07]	-0.75	0.454
Lagged EG (Integral) × Δt	-0.03 (0.07)	[-0.18, 0.11]	-0.43	0.667	-0.02 (0.08)	[-0.16, 0.14]	-0.25	0.801
IAs	0.22 (0.13)	[-0.03, 0.48]	1.73	0.090	0.22 (0.14)	[-0.05, 0.48]	1.60	0.116
Lagged EG (Integral) × IAs	0.07 (0.06)	[-0.04, 0.18]	1.31	0.190	0.09 (0.06)	[-0.03, 0.21]	1.58	0.115
Lagged EG (Integral) × Δt × IAs	0.01 (0.07)	[-0.13, 0.14]	0.14	0.885	0.04 (0.07)	[-0.11, 0.18]	0.51	0.614
Lagged Pain	-0.08 (0.06)	[-0.19, 0.05]	-1.29	0.198	-0.10 (0.07)	[-0.23, 0.03]	-1.51	0.132
Lagged Pain × Δt	0.08 (0.07)	[-0.04, 0.22]	1.25	0.211	0.08 (0.08)	[-0.07, 0.23]	1.05	0.297
Lagged Valence					-0.02 (0.08)	[-0.19, 0.13]	-0.28	0.780
Lagged Valence × Δt					-0.02 (0.09)	[-0.22, 0.16]	-0.25	0.804
Lagged Arousal					**0.12 (0.06)**	**[0.01, 0.25]**	**2.00**	**0.046**
Lagged Arousal × Δt					-0.00 (0.07)	[-0.15, 0.14]	-0.06	0.952
Lagged Dominance					-0.08 (0.07)	[-0.22, 0.06]	-1.09	0.275
Lagged Dominance × Δt					-0.03 (0.08)	[-0.19, 0.14]	-0.30	0.762
Lagged Negative Emotions					-0.09 (0.08)	[-0.25, 0.07]	-1.06	0.288
Lagged Negative Emotions × Δt					-0.08 (0.11)	[-0.29, 0.13]	-0.76	0.445

Note: Boldface indicates significant effects. Δt = time interval between consecutive observations. *CI* = confidence interval. CIs were estimated using 2,500 bootstrap resamples. Lagged EG (Integral) = Lagged Integral Emotional Granularity. IAs = Interoceptive Sensibility.

Table S4. Multilevel lagged models of momentary pain intensity predicted by lagged between-category emotional granularity and its interaction with interoceptive sensibility while controlling for lagged pain (*Model a*), momentary affective valence, arousal and dominance, and momentary negative emotions (*Model b*).

	Model a				*Model b*			
	Est. (*SE*)	95% *CI*	*t*	*p*	Est. (*SE*)	95% *CI*	*t*	*p*
Intercept	**3.75 (0.12)**	**[3.51, 3.99]**	**30.15**	**<.001**	**3.75 (0.13)**	**[3.49, 4.00]**	**29.17**	**<.001**
Lagged EG (Between)	-0.04 (0.06)	[-0.15, 0.08]	-0.65	0.516	-0.05 (0.06)	[-0.17, 0.07]	-0.78	0.434
Lagged EG (Between) × Δt	-0.06 (0.08)	[-0.20, 0.10]	-0.74	0.458	-0.05 (0.08)	[-0.21, 0.11]	-0.66	0.513
IAs	0.22 (0.13)	[-0.04, 0.48]	1.67	0.100	0.22 (0.14)	[-0.06, 0.48]	1.58	0.120
Lagged EG (Between) × IAs	0.06 (0.06)	[-0.05, 0.17]	1.01	0.314	0.08 (0.06)	[-0.03, 0.19]	1.34	0.181
Lagged EG (Between) × Δt × IAs	-0.01 (0.07)	[-0.15, 0.13]	-0.09	0.931	0.03 (0.08)	[-0.13, 0.18]	0.34	0.737
Lagged Pain	-0.07 (0.06)	[-0.19, 0.05]	-1.14	0.256	-0.10 (0.07)	[-0.23, 0.04]	-1.53	0.127
Lagged Pain × Δt	0.06 (0.07)	[-0.07, 0.20]	0.94	0.347	0.06 (0.08)	[-0.10, 0.21]	0.75	0.454
Lagged Valence					-0.05 (0.08)	[-0.21, 0.11]	-0.56	0.574
Lagged Valence × Δt					-0.03 (0.10)	[-0.22, 0.15]	-0.36	0.720
Lagged Arousal					0.11 (0.06)	[-0.01, 0.24]	1.80	0.072
Lagged Arousal × Δt					-0.01 (0.07)	[-0.15, 0.14]	-0.09	0.927
Lagged Dominance					-0.08 (0.07)	[-0.21, 0.07]	-1.04	0.299
Lagged Dominance × Δt					-0.06 (0.09)	[-0.22, 0.11]	-0.66	0.512
Lagged Emotions (Between)					-0.09 (0.08)	[-0.25, 0.07]	-1.03	0.303
Lagged Emotions (Between) × Δt					-0.11 (0.11)	[-0.32, 0.11]	-0.99	0.322

Note: Boldface indicates significant effects. Δt = time interval between consecutive observations. *CI* = confidence interval. CIs were estimated using 2,500 bootstrap resamples. Lagged EG (Between) = Lagged Between-category Emotional Granularity, computed using three negative emotion clusters: Anger, fear, and sadness. Lagged Emotions (Between) = Mean of the cluster-specific average lagged ratings for anger, fear, and sadness. IAs = Interoceptive Sensibility.

Table S5. Multilevel lagged models of momentary pain intensity predicted by lagged anger-related emotional granularity and its interaction with interoceptive sensibility while controlling for lagged pain (*Model a*), momentary affective valence, arousal and dominance, and momentary anger-related emotions (*Model b*).

	Model a				*Model b*			
	Est. (*SE*)	95% *CI*	*t*	*p*	Est. (*SE*)	95% *CI*	*t*	*p*
Intercept	**3.82 (0.12)**	**[3.58, 4.07]**	**30.81**	**<.001**	**3.81 (0.13)**	**[3.55, 4.07]**	**29.25**	**<.001**
Lagged EG (Anger)	-0.07 (0.06)	[-0.19, 0.04]	-1.18	0.239	-0.08 (0.06)	[-0.20, 0.04]	-1.33	0.184
Lagged EG (Anger) × Δt	-0.04 (0.07)	[-0.17, 0.10]	-0.61	0.539	-0.04 (0.07)	[-0.18, 0.11]	-0.52	0.604
IAs	0.22 (0.13)	[-0.04, 0.46]	1.68	0.098	0.21 (0.14)	[-0.07, 0.48]	1.54	0.130
Lagged EG (Anger) × IAs	-0.01 (0.06)	[-0.12, 0.10]	-0.15	0.883	0.04 (0.06)	[-0.08, 0.16]	0.64	0.524
Lagged EG (Anger) × Δt × IAs	**-0.11 (0.05)**	**[-0.22, -0.01]**	**-2.05**	**0.041**	-0.10 (0.07)	[-0.24, 0.04]	-1.40	0.161
Lagged Pain	-0.05 (0.06)	[-0.17, 0.06]	-0.90	0.371	-0.08 (0.07)	[-0.21, 0.06]	-1.12	0.263
Lagged Pain × Δt	0.11 (0.07)	[-0.02, 0.25]	1.62	0.105	0.09 (0.08)	[-0.07, 0.25]	1.17	0.245
Lagged Valence					-0.12 (0.08)	[-0.28, 0.05]	-1.40	0.162
Lagged Valence × Δt					-0.02 (0.09)	[-0.20, 0.16]	-0.24	0.813
Lagged Arousal					**0.17 (0.07)**	**[0.04, 0.31]**	**2.60**	**0.010**
Lagged Arousal × Δt					0.01 (0.08)	[-0.14, 0.16]	0.15	0.882
Lagged Dominance					-0.04 (0.07)	[-0.18, 0.11]	-0.53	0.593
Lagged Dominance × Δt					0.01 (0.09)	[-0.16, 0.18]	0.09	0.929
Lagged Emotions (Anger)					**-0.18 (0.08)**	**[-0.34, -0.01]**	**-2.10**	**0.036**
Lagged Emotions (Anger) × Δt					-0.04 (0.11)	[-0.24, 0.17]	-0.41	0.679

Note: Boldface indicates significant effects. Δt = time interval between consecutive observations. *CI* = confidence interval. CIs were estimated using 2,500 bootstrap resamples. Lagged EG (Anger) = Lagged Anger-related Emotional Granularity. Lagged Emotions (Anger) = Lagged Anger-related Emotions. IAs = Interoceptive Sensibility.

Table S6. Multilevel lagged models of momentary pain intensity predicted by lagged fear-related emotional granularity and its interaction with interoceptive sensibility while controlling for lagged pain (*Model a*), momentary affective valence, arousal and dominance, and momentary fear-related emotions (*Model b*).

	Model a				*Model b*			
	Est. (*SE*)	95% *CI*	*t*	*p*	Est. (*SE*)	95% *CI*	*t*	*p*
Intercept	**3.78 (0.13)**	**[3.53, 4.03]**	**29.95**	**<.001**	**3.75 (0.13)**	**[3.51, 4.01]**	**28.57**	**<.001**
Lagged EG (Fear)	0.01 (0.06)	[-0.11, 0.13]	0.14	0.889	0.02 (0.06)	[-0.10, 0.14]	0.33	0.745
Lagged EG (Fear) × Δt	-0.02 (0.08)	[-0.16, 0.13]	-0.26	0.791	0.00 (0.08)	[-0.15, 0.15]	0.06	0.956
IAs	0.24 (0.13)	[-0.02, 0.49]	1.81	0.075	0.23 (0.14)	[-0.03, 0.51]	1.73	0.090
Lagged EG (Fear) × IAs	0.08 (0.06)	[-0.04, 0.19]	1.35	0.179	**0.12 (0.06)**	**[0.00, 0.24]**	**2.06**	**0.041**
Lagged EG (Fear) × Δt × IAs	0.03 (0.07)	[-0.10, 0.18]	0.41	0.680	0.08 (0.08)	[-0.07, 0.23]	1.01	0.313
Lagged Pain	-0.05 (0.06)	[-0.17, 0.06]	-0.91	0.365	-0.08 (0.07)	[-0.20, 0.06]	-1.19	0.237
Lagged Pain × Δt	0.08 (0.07)	[-0.04, 0.21]	1.28	0.202	0.09 (0.07)	[-0.06, 0.23]	1.15	0.251
Lagged Valence					0.06 (0.08)	[-0.09, 0.21]	0.81	0.417
Lagged Valence × Δt					0.04 (0.09)	[-0.14, 0.22]	0.42	0.674
Lagged Arousal					**0.16 (0.06)**	**[0.03, 0.29]**	**2.52**	**0.012**
Lagged Arousal × Δt					-0.01 (0.07)	[-0.16, 0.13]	-0.15	0.880
Lagged Dominance					-0.10 (0.07)	[-0.25, 0.04]	-1.37	0.172
Lagged Dominance × Δt					-0.12 (0.08)	[-0.29, 0.06]	-1.46	0.145
Lagged Emotions (Fear)					-0.04 (0.07)	[-0.18, 0.11]	-0.48	0.629
Lagged Emotions (Fear) × Δt					-0.05 (0.09)	[-0.24, 0.12]	-0.58	0.565

Note: Boldface indicates significant effects. Δt = time interval between consecutive observations. *CI* = confidence interval. CIs were estimated using 2,500 bootstrap resamples. Lagged EG (Fear) = Lagged Fear-related Emotional Granularity. Lagged Emotions (Fear) = Lagged Fear-related Emotions. IAs = Interoceptive Sensibility.

Table S7. Multilevel lagged models of momentary pain intensity predicted by lagged sadness-related emotional granularity and its interaction with interoceptive sensibility while controlling for lagged pain (*Model a*), momentary affective valence, arousal and dominance, and momentary sadness-related emotions (*Model b*).

	Model a				*Model b*			
	Est. (*SE*)	95% *CI*	*t*	*p*	Est. (*SE*)	95% *CI*	*t*	*p*
Intercept	**3.79 (0.13)**	**[3.53, 4.05]**	**29.61**	**<.001**	**3.77 (0.13)**	**[3.50, 4.02]**	**28.90**	**<.001**
Lagged EG (Sadness)	0.06 (0.06)	[-0.06, 0.18]	1.08	0.281	0.06 (0.06)	[-0.06, 0.18]	0.99	0.325
IAs	0.20 (0.13)	[-0.07, 0.46]	1.49	0.141	0.20 (0.14)	[-0.07, 0.48]	1.47	0.148
Lagged EG (Sadness) × Δt	0.04 (0.06)	[-0.09, 0.15]	0.59	0.555	0.04 (0.06)	[-0.07, 0.16]	0.68	0.496
Lagged EG (Sadness) × IAs	0.10 (0.07)	[-0.05, 0.24]	1.33	0.186	0.12 (0.08)	[-0.04, 0.28]	1.51	0.133
Lagged EG (Sadness) × Δt × IAs	-0.05 (0.06)	[-0.16, 0.07]	-0.76	0.449	-0.09 (0.07)	[-0.22, 0.04]	-1.34	0.181
Lagged Pain	0.07 (0.07)	[-0.06, 0.21]	1.02	0.309	0.06 (0.08)	[-0.09, 0.22]	0.83	0.404
Lagged Pain × Δt	0.04 (0.06)	[-0.09, 0.15]	0.59	0.555	0.04 (0.06)	[-0.07, 0.16]	0.68	0.496
Lagged Valence					0.01 (0.08)	[-0.16, 0.18]	0.15	0.879
Lagged Valence × Δt					-0.01 (0.09)	[-0.20, 0.17]	-0.09	0.932
Lagged Arousal					0.12 (0.06)	[-0.01, 0.24]	1.85	0.065
Lagged Arousal × Δt					-0.01 (0.07)	[-0.17, 0.13]	-0.19	0.851
Lagged Dominance					-0.05 (0.08)	[-0.21, 0.09]	-0.73	0.468
Lagged Dominance × Δt					0.02 (0.09)	[-0.14, 0.20]	0.28	0.782
Lagged Emotions (Sadness)					0.01 (0.08)	[-0.14, 0.17]	0.17	0.864
Lagged Emotions (Sadness) × Δt					0.01 (0.10)	[-0.19, 0.20]	0.09	0.928

Note: Boldface indicates significant effects. Δt = time interval between consecutive observations. *CI* = confidence interval. CIs were estimated using 2,500 bootstrap resamples. Lagged EG (Sadness) = Lagged Sadness-related Emotional Granularity. Lagged Emotions (Sadness) = Lagged Sadness-related Emotions. IAs = Interoceptive Sensibility.

2.4. Results from Mixed-Effects Models Controlling for Time into the Study

2.4.1. Tables S8–S10: Results from Contemporaneous Mixed-Effects Models Controlling for Time into the Study

Table S8. Multilevel concurrent models of momentary pain intensity predicted by momentary integral emotional granularity and its interaction with interoceptive sensibility while controlling for time into the study (*Model a*), momentary affective valence, arousal and dominance, and momentary negative emotions (*Model b*).

	Model a				*Model b*			
	Est. (*SE*)	95% *CI*	*t*	*p*	Est. (*SE*)	95% *CI*	*t*	*p*
Intercept	**3.53 (0.14)**	**[3.26, 3.82]**	**25.38**	**<.001**	**3.60 (0.14)**	**[3.32, 3.86]**	**26.07**	**<.001**
Momentary EG (Integral)	**-0.11 (0.05)**	**[-0.21, -0.01]**	**-2.04**	**0.042**	**-0.08 (0.05)**	[-0.18, 0.01]	-1.74	0.082
IAs	0.26 (0.13)	[0.01, 0.52]	1.99	0.051†	0.25 (0.13)	[-0.02, 0.51]	1.84	0.070
Momentary EG (Integral) × IAs	**0.18 (0.05)**	**[0.08, 0.27]**	**3.43**	**<.001**	**0.11 (0.05)**	**[0.01, 0.20]**	**2.26**	**0.025**
Time into the Study	0.02 (0.01)	[-0.00, 0.03]	1.76	0.079	0.01 (0.01)	[-0.01, 0.02]	0.78	0.436
Momentary Valence					**-0.19 (0.06)**	**[-0.31, -0.06]**	**-2.96**	**0.003**
Momentary Arousal					0.03 (0.05)	[-0.06, 0.13]	0.65	0.517
Momentary Dominance					**-0.11 (0.06)**	**[-0.23, 0.00]**	**-1.97**	**0.049**
Momentary Negative Emotions					**0.31 (0.06)**	**[0.18, 0.43]**	**4.82**	**<.001**

Note: Boldface indicates significant effects. † indicates marginally significant effects. *CI* = confidence interval. CIs were estimated using 2,500 bootstrap resamples. Momentary EG (Integral) = Momentary Integral Emotional Granularity. IAs = Interoceptive Sensibility.

Table S9. Multilevel concurrent models of momentary pain intensity predicted by momentary between-category emotional granularity and its interaction with interoceptive sensibility while controlling for time into the study (*Model a*), momentary affective valence, arousal and dominance, and momentary negative emotions (*Model b*).

	Model a				*Model b*			
	Est. (*SE*)	95% *CI*	*t*	*p*	Est. (*SE*)	95% *CI*	*t*	*p*
Intercept	**3.51 (0.14)**	**[3.22, 3.80]**	**24.50**	**<.001**	**3.57 (0.14)**	**[3.30, 3.84]**	**25.27**	**<.001**
Momentary EG (Between)	-0.09 (0.05)	[-0.19, 0.02]	-1.60	0.111	-0.06 (0.05)	[-0.16, 0.04]	-1.30	0.194
IAs	0.25 (0.13)	[-0.01, 0.50]	1.91	0.061	0.24 (0.14)	[-0.02, 0.51]	1.80	0.077
Momentary EG (Between) × IAs	**0.18 (0.05)**	**[0.08, 0.28]**	**3.51**	**<.001**	**0.11 (0.05)**	**[0.02, 0.20]**	**2.19**	**0.029**
Time into the Study	0.02 (0.01)	[-0.00, 0.03]	1.71	0.088	0.01 (0.01)	[-0.01, 0.02]	0.86	0.388
Momentary Valence					**-0.17 (0.07)**	**[-0.31, -0.04]**	**-2.65**	**0.008**
Momentary Arousal					0.03 (0.05)	[-0.07, 0.14]	0.68	0.499
Momentary Dominance					**-0.12 (0.06)**	**[-0.24, -0.01]**	**-2.10**	**0.037**
Momentary Emotions (Between)					**0.31 (0.07)**	**[0.17, 0.44]**	**4.62**	**<.001**

Note: Boldface indicates significant effects. *CI* = confidence interval. CIs were estimated using 2,500 bootstrap resamples. Momentary EG (Between) = Momentary Between-category Emotional Granularity, computed using three negative emotion clusters: Anger, fear, and sadness. Momentary Emotions (Between) = Mean of the cluster-specific average momentary ratings for anger, fear, and sadness. IAs = Interoceptive Sensibility.

Table S10. Multilevel concurrent models of momentary pain intensity predicted by momentary anger-, fear-, and sadness-related emotional granularity and its interaction with interoceptive sensibility while controlling for time into the study (*Model a*), momentary affect valence, arousal and dominance, and momentary anger-, fear-, and sadness-related emotions (*Model b*).

	Model a				*Model b*			
	Est. (*SE*)	95% *CI*	*t*	*p*	Est. (*SE*)	95% *CI*	*t*	*p*
Emotion Cluster: Anger								
Intercept	**3.59 (0.14)**	**[3.30, 3.86]**	**25.26**	**<.001**	**3.63 (0.14)**	**[3.36, 3.91]**	**25.54**	**<.001**
Momentary EG (Anger)	-0.03 (0.06)	[-0.14, 0.07]	-0.55	0.582	-0.06 (0.05)	[-0.16, 0.03]	-1.22	0.225
IAs	0.24 (0.13)	[-0.01, 0.50]	1.92	0.060	0.24 (0.13)	[-0.03, 0.50]	1.77	0.082
Momentary EG (Anger) × IAs	**0.15 (0.05)**	**[0.05, 0.25]**	**2.81**	**0.005**	0.05 (0.05)	[-0.05, 0.15]	1.01	0.312
Time into the Study	0.02 (0.01)	[-0.00, 0.04]	1.73	0.084	0.01 (0.01)	[-0.01, 0.03]	1.06	0.289
Momentary Valence					**-0.19 (0.07)**	**[-0.32, -0.05]**	**-2.76**	**0.006**
Momentary Arousal					0.00 (0.05)	[-0.10, 0.11]	0.03	0.976
Momentary Dominance					**-0.16 (0.06)**	**[-0.27, -0.04]**	**-2.59**	**0.010**
Momentary Emotions (Anger)					**0.32 (0.07)**	**[0.19, 0.45]**	**4.87**	**<.001**
Emotion Cluster: Fear								
Intercept	**3.56 (0.15)**	**[3.27, 3.85]**	**24.31**	**<.001**	**3.62 (0.15)**	**[3.34, 3.91]**	**24.90**	**<.001**
Momentary EG (Fear)	-0.00 (0.05)	[-0.11, 0.11]	-0.04	0.964	0.01 (0.05)	[-0.09, 0.11]	0.23	0.816
IAs	**0.26 (0.13)**	**[0.00, 0.51]**	**2.00**	**0.050**	0.25 (0.13)	[-0.01, 0.52]	1.87	0.067
Momentary EG (Fear) × IAs	**0.14 (0.05)**	**[0.04, 0.24]**	**2.62**	**0.009**	0.09 (0.05)	[-0.01, 0.19]	1.82	0.069
Time into the Study	0.01 (0.01)	[-0.00, 0.03]	1.55	0.122	0.01 (0.01)	[-0.01, 0.02]	0.64	0.523
Momentary Valence					**-0.27 (0.06)**	**[-0.39, -0.14]**	**-4.19**	**<.001**
Momentary Arousal					0.09 (0.05)	[-0.01, 0.20]	1.75	0.081
Momentary Dominance					**-0.17 (0.06)**	**[-0.30, -0.06]**	**-2.85**	**0.005**
Momentary Emotions (Fear)					**0.15 (0.06)**	**[0.03, 0.26]**	**2.43**	**0.015**
Emotion Cluster: Sadness								
Intercept	**3.54 (0.15)**	**[3.26, 3.84]**	**24.00**	**<.001**	**3.59 (0.15)**	**[3.31, 3.86]**	**24.71**	**<.001**
Momentary EG (Sadness)	-0.07 (0.06)	[-0.18, 0.03]	-1.29	0.199	-0.05 (0.05)	[-0.15, 0.04]	-1.05	0.294
IAs	0.24 (0.13)	[-0.03, 0.48]	1.77	0.083	0.24 (0.14)	[-0.04, 0.50]	1.72	0.090
Momentary EG (Sadness) × IAs	**0.13 (0.05)**	**[0.03, 0.23]**	**2.43**	**0.015**	0.08 (0.05)	[-0.02, 0.18]	1.56	0.120
Time into the Study	0.02 (0.01)	[-0.00, 0.04]	1.82	0.069	0.01 (0.01)	[-0.01, 0.03]	1.01	0.312
Momentary Valence					**-0.24 (0.07)**	**[-0.37, -0.11]**	**-3.60**	**<.001**
Momentary Arousal					0.07 (0.05)	[-0.03, 0.17]	1.33	0.184
Momentary Dominance					**-0.11 (0.06)**	[-0.23, 0.01]	-1.76	0.078
Momentary Emotions (Sadness)					**0.25 (0.06)**	**[0.13, 0.38]**	**4.01**	**<.001**

Note: Boldface indicates significant effects. † indicates marginally significant effects. *CI* = confidence interval. CIs were estimated using 2,500 bootstrap resamples. Momentary EG (Anger) = Momentary Anger-related Emotional Granularity. Momentary EG (Fear) = Momentary Fear-related Emotional Granularity. Momentary EG (Sadness) = Momentary Sadness-related Emotional Granularity. Momentary Emotions (Anger) = Momentary Anger-related Emotions. Momentary Emotions (Fear) = Momentary Fear-related Emotions. Momentary Emotions (Sadness) = Momentary Sadness-related Emotions. IAs = Interoceptive Sensibility.

2.4.2. Tables S11–S15: Results from Lagged Mixed-Effects Models Controlling for Time into the Study

Table S11. Multilevel lagged models of momentary pain intensity predicted by lagged integral emotional granularity and its interaction with interoceptive sensibility while controlling for lagged pain and time into the study (*Model a*), momentary affective valence, arousal and dominance, and momentary negative emotions (*Model b*).

	Model a				*Model b*			
	Est. (*SE*)	95% *CI*	*t*	*p*	Est. (*SE*)	95% *CI*	*t*	*p*
Intercept	**3.79 (0.16)**	**[3.51, 4.09]**	**24.37**	**<.001**	**3.79 (0.16)**	**[3.46, 4.10]**	**23.80**	**<.001**
Lagged EG (Integral)	-0.03 (0.06)	[-0.15, 0.08]	-0.59	0.553	-0.04 (0.06)	[-0.16, 0.07]	-0.73	0.463
Lagged EG (Integral) × Δt	-0.03 (0.07)	[-0.17, 0.11]	-0.42	0.676	-0.02 (0.08)	[-0.16, 0.13]	-0.23	0.815
IAs	0.22 (0.13)	[-0.03, 0.48]	1.71	0.092	0.21 (0.14)	[-0.05, 0.49]	1.58	0.120
Lagged EG (Integral) × IAs	0.07 (0.06)	[-0.04, 0.18]	1.31	0.192	0.09 (0.06)	[-0.02, 0.21]	1.58	0.116
Lagged EG (Integral) × Δt × IAs	0.01 (0.07)	[-0.13, 0.15]	0.14	0.886	0.04 (0.07)	[-0.11, 0.19]	0.50	0.619
Lagged Pain	-0.07 (0.06)	[-0.19, 0.04]	-1.23	0.218	-0.10 (0.07)	[-0.23, 0.04]	-1.46	0.146
Lagged Pain × Δt	0.09 (0.07)	[-0.05, 0.22]	1.27	0.205	0.08 (0.08)	[-0.07, 0.23]	1.07	0.286
Time into the Study	-0.00 (0.01)	[-0.02, 0.02]	-0.25	0.802	-0.00 (0.01)	[-0.02, 0.02]	-0.29	0.769
Lagged Valence					-0.03 (0.08)	[-0.18, 0.14]	-0.32	0.751
Lagged Valence × Δt					-0.02 (0.09)	[-0.20, 0.17]	-0.23	0.819
Lagged Arousal					**0.12 (0.06)**	**[0.00, 0.25]**	**2.00**	**0.046**
Lagged Arousal × Δt					-0.00 (0.07)	[-0.15, 0.14]	-0.06	0.949
Lagged Dominance					-0.08 (0.07)	[-0.21, 0.06]	-1.09	0.275
Lagged Dominance × Δt					-0.03 (0.08)	[-0.19, 0.14]	-0.31	0.756
Lagged Negative Emotions					-0.09 (0.08)	[-0.25, 0.07]	-1.08	0.280
Lagged Negative Emotions × Δt					-0.08 (0.11)	[-0.29, 0.13]	-0.76	0.450

Note: Boldface indicates significant effects. Δt = time interval between consecutive observations. *CI* = confidence interval. CIs were estimated using 2,500 bootstrap resamples. Lagged EG (Integral) = Lagged Integral Emotional Granularity. IAs = Interoceptive Sensibility.

Table S12. Multilevel lagged models of momentary pain intensity predicted by lagged between-category emotional granularity and its interaction with interoceptive sensibility while controlling for lagged pain and time into the study (*Model a*), momentary affective valence, arousal and dominance, and momentary negative emotions (*Model b*).

	Model a				*Model b*			
	Est. (*SE*)	95% *CI*	*t*	*p*	Est. (*SE*)	95% *CI*	*t*	*p*
Intercept	**3.77 (0.16)**	**[3.47, 4.09]**	**23.61**	**<.001**	**3.77 (0.16)**	**[3.44, 4.08]**	**23.14**	**<.001**
Lagged EG (Between)	-0.04 (0.06)	[-0.16, 0.08]	-0.64	0.522	-0.05 (0.06)	[-0.16, 0.08]	-0.77	0.440
Lagged EG (Between) × Δt	-0.06 (0.08)	[-0.20, 0.09]	-0.73	0.464	-0.05 (0.08)	[-0.20, 0.10]	-0.64	0.520
IAs	0.22 (0.13)	[-0.04, 0.48]	1.66	0.103	0.21 (0.14)	[-0.05, 0.48]	1.56	0.124
Lagged EG (Between) × IAs	0.06 (0.06)	[-0.05, 0.17]	1.01	0.313	0.08 (0.06)	[-0.03, 0.19]	1.35	0.179
Lagged EG (Between) × Δt × IAs	-0.01 (0.07)	[-0.16, 0.13]	-0.08	0.933	0.03 (0.08)	[-0.13, 0.18]	0.33	0.740
Lagged Pain	-0.07 (0.06)	[-0.18, 0.05]	-1.09	0.277	-0.10 (0.07)	[-0.24, 0.03]	-1.48	0.140
Lagged Pain × Δt	0.07 (0.07)	[-0.07, 0.20]	0.96	0.340	0.06 (0.08)	[-0.10, 0.21]	0.77	0.439
Time into the Study	-0.00 (0.01)	[-0.02, 0.02]	-0.23	0.822	-0.00 (0.01)	[-0.02, 0.02]	-0.28	0.779
Lagged Valence					-0.05 (0.08)	[-0.20, 0.11]	-0.60	0.552
Lagged Valence × Δt					-0.03 (0.10)	[-0.22, 0.15]	-0.34	0.732
Lagged Arousal					0.11 (0.06)	[-0.02, 0.24]	1.80	0.073
Lagged Arousal × Δt					-0.01 (0.07)	[-0.15, 0.14]	-0.10	0.924
Lagged Dominance					-0.08 (0.07)	[-0.22, 0.07]	-1.04	0.298
Lagged Dominance × Δt					-0.06 (0.09)	[-0.23, 0.12]	-0.66	0.507
Lagged Emotions (Between)					-0.09 (0.08)	[-0.25, 0.08]	-1.05	0.294
Lagged Emotions (Between) × Δt					-0.11 (0.11)	[-0.32, 0.11]	-0.99	0.324

Note: Boldface indicates significant effects. Δt = time interval between consecutive observations. *CI* = confidence interval. CIs were estimated using 2,500 bootstrap resamples. Lagged EG (Between) = Lagged Between-category Emotional Granularity, computed using three negative emotion clusters: Anger, fear, and sadness. Lagged Emotions (Between) = Mean of the cluster-specific average lagged ratings for anger, fear, and sadness. IAs = Interoceptive Sensibility.

Table S13. Multilevel lagged models of momentary pain intensity predicted by lagged anger-related emotional granularity and its interaction with interoceptive sensibility while controlling for lagged pain and time into the study (*Model a*), momentary affective valence, arousal and dominance, and momentary anger-related emotions (*Model b*).

	Model a				*Model b*			
	Est. (*SE*)	95% *CI*	*t*	*p*	Est. (*SE*)	95% *CI*	*t*	*p*
Intercept	3.79 (0.16)	[3.46, 4.11]	23.71	<.001	3.78 (0.16)	[3.46, 4.09]	23.07	<.001
Lagged EG (Anger)	-0.07 (0.06)	[-0.19, 0.05]	-1.17	0.242	-0.08 (0.06)	[-0.21, 0.04]	-1.33	0.185
Lagged EG (Anger) × Δt	-0.04 (0.07)	[-0.18, 0.10]	-0.63	0.529	-0.04 (0.07)	[-0.18, 0.10]	-0.53	0.595
IAs	0.22 (0.13)	[-0.04, 0.47]	1.69	0.096	0.21 (0.14)	[-0.05, 0.48]	1.55	0.126
Lagged EG (Anger) × IAs	-0.01 (0.06)	[-0.13, 0.10]	-0.16	0.872	0.04 (0.06)	[-0.08, 0.15]	0.62	0.536
Lagged EG (Anger) × Δt × IAs	**-0.11 (0.05)**	**[-0.22, -0.00]**	**-2.08**	**0.038**	-0.10 (0.07)	[-0.22, 0.04]	-1.42	0.157
Lagged Pain	-0.06 (0.06)	[-0.18, 0.06]	-0.94	0.346	-0.08 (0.07)	[-0.22, 0.05]	-1.15	0.249
Lagged Pain × Δt	0.11 (0.07)	[-0.03, 0.25]	1.60	0.110	0.09 (0.08)	[-0.07, 0.25]	1.14	0.257
Time into the Study	0.00 (0.01)	[-0.02, 0.03]	0.38	0.703	0.00 (0.01)	[-0.02, 0.03]	0.33	0.740
Lagged Valence					-0.11 (0.08)	[-0.28, 0.05]	-1.35	0.178
Lagged Valence × Δt					-0.02 (0.09)	[-0.21, 0.15]	-0.27	0.789
Lagged Arousal					**0.17 (0.07)**	**[0.04, 0.30]**	**2.61**	**0.010**
Lagged Arousal × Δt					0.01 (0.08)	[-0.14, 0.16]	0.16	0.874
Lagged Dominance					-0.04 (0.07)	[-0.19, 0.11]	-0.54	0.591
Lagged Dominance × Δt					0.01 (0.09)	[-0.17, 0.17]	0.11	0.914
Lagged Emotions (Anger)					**-0.18 (0.08)**	**[-0.35, -0.01]**	**-2.08**	**0.039**
Lagged Emotions (Anger) × Δt					-0.05 (0.11)	[-0.26, 0.17]	-0.43	0.667

Note: Boldface indicates significant effects. Δt = time interval between consecutive observations. *CI* = confidence interval. CIs were estimated using 2,500 bootstrap resamples. Lagged EG (Anger) = Lagged Anger-related Emotional Granularity. Lagged Emotions (Anger) = Lagged Anger-related Emotions. IAs = Interoceptive Sensibility.

Table S14. Multilevel lagged models of momentary pain intensity predicted by lagged fear-related emotional granularity and its interaction with interoceptive sensibility while controlling for lagged pain and time into the study (*Model a*), momentary affective valence, arousal and dominance, and momentary fear-related emotions (*Model b*).

	Model a				*Model b*			
	Est. (*SE*)	95% *CI*	*t*	*p*	Est. (*SE*)	95% *CI*	*t*	*p*
Intercept	**3.78 (0.16)**	**[3.45, 4.09]**	**23.22**	**<.001**	**3.77 (0.17)**	**[3.45, 4.09]**	**22.68**	**<.001**
Lagged EG (Fear)	0.01 (0.06)	[-0.11, 0.13]	0.14	0.890	0.02 (0.06)	[-0.10, 0.14]	0.32	0.748
Lagged EG (Fear) × Δt	-0.02 (0.08)	[-0.16, 0.13]	-0.26	0.792	0.00 (0.08)	[-0.15, 0.15]	0.06	0.955
IAs	0.24 (0.13)	[-0.00, 0.49]	1.81	0.076	0.23 (0.14)	[-0.03, 0.50]	1.72	0.092
Lagged EG (Fear) × IAs	0.08 (0.06)	[-0.03, 0.19]	1.35	0.179	**0.12 (0.06)**	**[0.01, 0.24]**	**2.06**	**0.040**
Lagged EG (Fear) × Δt × IAs	0.03 (0.07)	[-0.11, 0.17]	0.41	0.680	0.08 (0.08)	[-0.07, 0.23]	1.01	0.315
Lagged Pain	-0.05 (0.06)	[-0.17, 0.06]	-0.90	0.371	-0.08 (0.07)	[-0.21, 0.06]	-1.16	0.245
Lagged Pain × Δt	0.08 (0.07)	[-0.05, 0.22]	1.28	0.202	0.09 (0.07)	[-0.06, 0.23]	1.16	0.248
Time into the Study	-0.00 (0.01)	[-0.02, 0.02]	-0.02	0.986	-0.00 (0.01)	[-0.02, 0.02]	-0.13	0.897
Lagged Valence					0.06 (0.08)	[-0.09, 0.21]	0.79	0.431
Lagged Valence × Δt					0.04 (0.09)	[-0.15, 0.22]	0.42	0.672
Lagged Arousal					**0.16 (0.06)**	**[0.03, 0.29]**	**2.52**	**0.012**
Lagged Arousal × Δt					-0.01 (0.07)	[-0.16, 0.14]	-0.15	0.880
Lagged Dominance					-0.10 (0.07)	[-0.25, 0.04]	-1.37	0.172
Lagged Dominance × Δt					-0.12 (0.09)	[-0.29, 0.05]	-1.47	0.144
Lagged Emotions (Fear)					-0.04 (0.07)	[-0.18, 0.11]	-0.49	0.622
Lagged Emotions (Fear) × Δt					-0.05 (0.09)	[-0.24, 0.13]	-0.58	0.562

Note: Boldface indicates significant effects. Δt = time interval between consecutive observations. *CI* = confidence interval. CIs were estimated using 2,500 bootstrap resamples. Lagged EG (Fear) = Lagged Fear-related Emotional Granularity. Lagged Emotions (Fear) = Lagged Fear-related Emotions. IAs = Interoceptive Sensibility.

Table S15. Multilevel lagged models of momentary pain intensity predicted by lagged sadness-related emotional granularity and its interaction with interoceptive sensibility while controlling for lagged pain and time into the study (*Model a*), momentary affective valence, arousal and dominance, and momentary sadness-related emotions (*Model b*).

	Model a				*Model b*			
	Est. (*SE*)	95% *CI*	*t*	*p*	Est. (*SE*)	95% *CI*	*t*	*p*
Intercept	**3.81 (0.16)**	**[3.51, 4.15]**	**23.35**	**<.001**	**3.79 (0.17)**	**[3.46, 4.10]**	**22.78**	**<.001**
Lagged EG (Sadness)	0.07 (0.06)	[-0.05, 0.18]	1.09	0.275	0.06 (0.06)	[-0.06, 0.18]	1.00	0.320
IAs	0.20 (0.13)	[-0.06, 0.46]	1.48	0.144	0.20 (0.14)	[-0.08, 0.47]	1.46	0.151
Lagged EG (Sadness) × Δt	-0.07 (0.08)	[-0.22, 0.08]	-0.96	0.336	-0.06 (0.08)	[-0.22, 0.10]	-0.78	0.438
Lagged EG (Sadness) × IAs	0.03 (0.06)	[-0.08, 0.15]	0.58	0.563	0.04 (0.06)	[-0.08, 0.17]	0.68	0.500
Lagged EG (Sadness) × Δt × IAs	0.10 (0.07)	[-0.06, 0.24]	1.31	0.190	0.12 (0.08)	[-0.04, 0.27]	1.49	0.136
Lagged Pain	-0.04 (0.06)	[-0.16, 0.07]	-0.71	0.480	-0.09 (0.07)	[-0.22, 0.05]	-1.30	0.194
Lagged Pain × Δt	0.07 (0.07)	[-0.07, 0.21]	1.03	0.302	0.07 (0.08)	[-0.10, 0.22]	0.85	0.398
Time into the Study	-0.00 (0.01)	[-0.03, 0.02]	-0.21	0.830	-0.00 (0.01)	[-0.02, 0.02]	-0.16	0.877
Lagged Valence					0.01 (0.08)	[-0.15, 0.17]	0.13	0.897
Lagged Arousal					0.12 (0.06)	[-0.00, 0.24]	1.84	0.066
Lagged Dominance					-0.06 (0.08)	[-0.20, 0.09]	-0.73	0.466
Lagged Valence × Δt					-0.01 (0.09)	[-0.20, 0.18]	-0.08	0.936
Lagged Arousal × Δt					-0.01 (0.07)	[-0.16, 0.13]	-0.19	0.848
Lagged Dominance × Δt					0.02 (0.09)	[-0.15, 0.19]	0.27	0.787
Lagged Emotions (Sadness)					0.01 (0.08)	[-0.13, 0.15]	0.15	0.878
Lagged Emotions (Sadness) × Δt					0.01 (0.10)	[-0.19, 0.20]	0.09	0.931

Note: Boldface indicates significant effects. Δt = time interval between consecutive observations. *CI* = confidence interval. CIs were estimated using 2,500 bootstrap resamples. Lagged EG (Sadness) = Lagged Sadness-related Emotional Granularity. Lagged Emotions (Sadness) = Lagged Sadness-related Emotions. IAs = Interoceptive Sensibility.

3. Figures

3.1. Figure S1: Graphical Overview of the Full Study Procedure

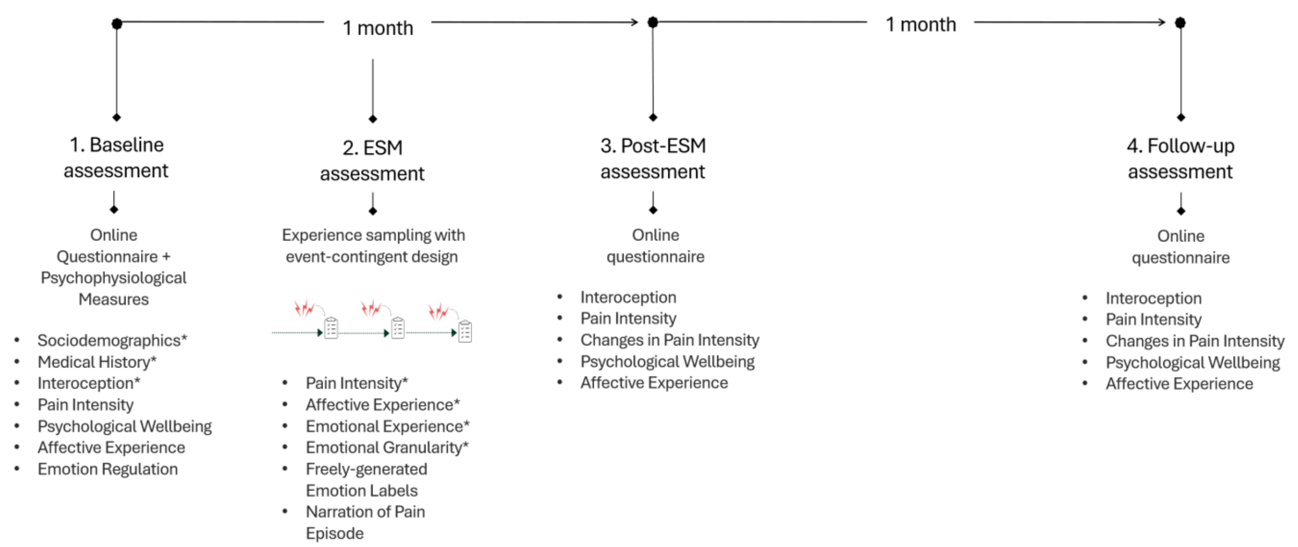

Figure S1. Graphical overview of the full study procedure.
Note: The data used in the present study were collected as part of a larger study on affective experience and chronic pelvic pain. The primary focus of the present study is on data collected during the one-month experience sampling assessment. * indicates the measures used for the purpose of the present study.

Conclusion

The present doctoral dissertation originated from a basic, primigenial question: What do we truly mean when we talk about emotional granularity within the complex system of experiences embedded in human functioning? This prompted an inquiry into the conceptual roots of this construct: How it has been theorized within broader affective dynamics; what is already known regarding its antecedents and implications for everyday lived experience; and conversely, which blind spots or inconsistencies persist in the existing literature and may therefore represent meaningful directions for future research. Inevitably, this also foregrounded a further, foundational issue, that of operationalizing the construct.

The population of emotional categories and emotion concepts inhabiting an individual can be more or less variegated, as can the degree of experiential overlap and entanglement among those concepts. The richer and more fine-grained one's conceptual knowledge is, the greater the ability to differentiate one's emotional experience in a fine-grained manner. Language is a fundamental tool through which it becomes possible to access the structure of an individual's conceptual knowledge of emotion. Unsurprisingly, language, as a shared symbolic artifact that renders emotional experience categorizable and communicable, is the primordial footprint that makes the observation of emotional granularity possible. Yet, despite this seemingly straightforward premise, it entails a number of nontrivial implications concerning both the study (and thus measurement) of granularity, and the way in which granularity is nested within the broader architecture of affective functioning.

Emotion concepts, in fact, are situated, multimodal simulations constructed from past experience and inherently predictive in nature, integrating interoceptive signals and sensory inputs regarding the state of one's body in the world. These concepts are ultimately constructed in service of allostatic regulation, in a context-sensitive manner. This implies that an affective event categorized as an emotion may involve a multitude of differentiated experiential components (sensations, behaviors, thoughts, memories, attunements, movements, action tendencies), which, only taken together and in context, constitute that specific emotional instance. Such situated instances constitute complex representations that both reflect and transcend the linguistic label used to denote them. It follows that an individual's allostatic functioning enters into a dynamic, bidirectional dialogue with affective (and emotional) experiences that may be more or less blurred; in turn, the conceptual categories and lexical resources available to identify and articulate one's current experience likewise actively participate in this dialogue.

The emotional lexicon mobilized to express (whether in communicating an emotional instance outwardly to others or in inwardly articulating it to oneself) a given emotional instance may contain a broad range of inter- and intra-individual conceptual nuances. This variability spans from the macro-level, that is, the language and culturally embedded emotion concepts (for instance, a French emotion word may carry somewhat different conceptual universes depending on whether it is used in France, Guadeloupe, or the Congo); to the micro-level, namely, the individual's learning history and experiential background, through which a personally constructed conceptual and emotional repertoire takes shape (as an example, the word *compassion* may, for one person, connote a positively valenced orientation grounded in kindness and sensitivity toward the other, whereas for another it may be closer to "pietas", carrying connotations of concern, benevolent involvement, or even a dimension of protective assistance). To complicate matters further, emotions may be lived in strongly bodily terms for some people or contexts, whereas in others they may not be represented as bodily at all. This variability is not only interindividual (on both large-scale cultural and small-scale personal levels) but can also emerge intraindividually across situations. Despite the TCE's premise that emotion is always embodied within a holistic mind–body system, such experiences may be represented and lived with greater emphasis on either bodily or mentalistic correlates. Last but not least, multiple emotion concepts may occasionally be merged or combined to represent a novel or particularly complex experience. In this case, individuals may need to combine multiple concepts and lexical items to express what a single language-specific term might otherwise capture. The absence of a single lexical label to represent a complex emotional state does not diminish the authenticity of the experience.

Language, therefore, actively shapes the communicated form of the emotional experience itself, contributing to at least a partial renegotiation of its boundaries. As such, the nature of the emotional lexicon is far from negligible, as it inevitably encodes (even if not fully exhaustive) the richness and specificity of the emotional experience it seeks to denote. All of this complexity converges on the profound subjectivity with which individuals recognize, categorize, and label emotional events in a given context. Theoretically, the more fine-grained and context-specific the emotional concepts are, the greater the resulting emotional granularity. Yet, once this assumption is translated into the concrete task of measuring granularity within broader affective functioning, one immediately encounters a number of implications and limitations rooted in the extreme subjectivity through which emotional experience is constructed and lived. It becomes clear that this complexity poses substantial challenges for research on emotions, and on emotional granularity in particular.

The present doctoral dissertation took its first steps from these reflections, undertaking an initial, preliminary effort to suture together the complex issues of measuring emotional granularity and its interweaving within the affective dynamics. This resulted in two complementary lines of inquiry: One methodological in nature, realized in the form of a systematic review of the current state of the art and the prevailing issues in the measurement of granularity; and one empirical, focused on the adaptive function of granularity within intraindividual variability in affective–emotional processes, accounting for correlates of allostatic functioning.

It emerged that research on granularity, despite its commendable efforts, still struggles to achieve a rigorous operationalization of the construct. The marked methodological heterogeneity in its assessment undoubtedly reflects both the complexity of the construct and its inherent elusiveness, which makes it challenging to capture in a valid and reliable manner. Yet, without assigning blame, it is important to acknowledge that such heterogeneity may have repercussions for the reliability and robustness of the findings currently available in the literature and cannot be dissociated from concerns regarding the generalizability of these results. One cannot hope to fully understand a phenomenon without first exploring where it is rooted, and insofar as it remains abstract and latent unless shared tools are used to render it observable, it becomes essential to interrogate the very nature of those tools. This is especially true when the phenomenon under scrutiny is an emotional experience and, more specifically, its subtle nuances subjectively and arbitrarily perceived by the experiencer. Assessing the subjectivity of another's lived experience, which exists only insofar as it is recognized and appraised as meaningful by the perceiver themselves, is a delicate endeavor that risks falling into fallacy if not approached with appropriate caution.

Although language is the primordial medium, the shared artifact, the privileged and most immediate vehicle through which emotional experience and its associated meaning may be communicated (with greater or lesser granularity), an emotion word is not an exact or isomorphic mirror of the concept it represents. It therefore becomes necessary to reflect critically on how language is used in the measurement of emotional granularity. While this challenge is undeniable, my hope is that the scientific community, animated by its profound passion for this topic, may engage in a rigorous and fertile discussion on the alignment between the conceptualization and the operationalization of granularity, keeping firmly in view of its roots in mind–body integration and holism.

In line with this final consideration (that of conceiving the mind and body as a unified whole), the present work sought to provide a glimpse into the role of emotional granularity within the moment-to-moment dynamics of individuals' affective experiences, accounting for factors at the very core of allostatic functioning. From a macro-level perspective and offering a general reading of the overall pattern of findings presented herein, it appears that the adaptive function of granularity is intricately interwoven with broader modulators of allostatic regulation and exhibits intraindividual variability contingent upon temporal framing. Specifically, the pattern of associations between the ability to differentiate emotions with nuance and other correlates of affective experience seems to shift depending on dispositional features of allostatic functioning, as well as by whether such dynamics are examined as a snapshot of the here-and-now or as processes unfolding over time. Moreover, subtle and distinct associative pathways become evident, displaying considerable variability depending on the specific characterization or facet of granularity under investigation. First, cross-valence effects are observed, rather than processes being confined solely to the positive or negative domain. Second, the influence of granularity on overall affective functioning appears to be contingent upon its scope, namely whether it reflects differentiation across emotion categories or within specific categories. Collectively, these preliminary findings suggest that the adaptive function of emotional granularity is neither uniform nor universally beneficial, but rather conditional and context-dependent.

Emotional granularity does not appear to constitute a monolithic, uniform, or fixed competence. It is therefore both necessary and desirable that future research on granularity strive to embrace a transparent and as comprehensive as possible perspective, one that fully accounts for its variability and multifaceted nature, in order to capture the essence of the construct more deeply. Only from such a standpoint can research be effectively oriented toward understanding the mechanisms underlying the potential role of granularity in adaptive functioning across the full spectrum of affective processes. This approach may involve, for instance, integrating modulators of allostatic regulation into context-sensitive models of affective and emotional functioning; systematically examining the multiple facets of granularity, such as valence or specificity across distinct emotion categories; conducting these investigations across diverse temporal perspectives; and, beyond capturing intraindividual fluctuations, extending the scope to account for interindividual differences. These represent only a few (although by no means the only) promising trajectories toward a more complete understanding of how granularity interrelates with other emotional components and contributes to the characterization of broader affective dynamics.

I conclude this dissertation on an entirely personal note. Throughout my doctoral journey, I have had the opportunity to grow ever closer to the complexity of the construct of emotional granularity. This process was accompanied, unfortunately yet perhaps inevitably, by moments of profound frustration or discouragement: Not so much (contrary to what one might assume) due to the demands of study and research, but rather because the deeper I went, the more it seemed that the scientific efforts devoted to the study of such a complex construct, situated within an equally intricate theoretical framework, were destined to be powerless in the face of such vast complexity. Standing now at the conclusion of this path, I instead feel able to affirm (with a hope that is not merely illusory optimism) that it is precisely in this complexity that the beauty of this object of inquiry resides. And that such complexity is not an insurmountable mountain, but rather an ocean of richness still waiting to be explored.

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