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The role of emotional granularity in emotional regulation, mental disorders, and well-being

Edited by
Jennifer Marie Binzak Fugate, Maria Gendron and Yasemin Erbas

Published in
Frontiers in Psychology

ISSN 1664-8714
ISBN 978-2-83250-916-6
DOI 10.3389/978-2-83250-916-6

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The role of emotional granularity in emotional regulation, mental disorders, and well-being

Topic editors
Jennifer Marie Binzak Fugate — Kansas City University, United States
Maria Gendron — Yale University, United States
Yasemin Erbas — Tilburg University, Netherlands

Citation
Fugate, J. M. B., Gendron, M., Erbas, Y., eds. (2022). *The role of emotional granularity in emotional regulation, mental disorders, and well-being*. Lausanne: Frontiers Media SA. doi: 10.3389/978-2-83250-916-6

Table of contents

04 Editorial: The role of emotional granularity in emotional regulation, mental disorders, and well-being
Yasemin Erbas, Maria Gendron and Jennifer M. B. Fugate

07 Is Negative Emotion Differentiation Associated With Emotion Regulation Choice? Investigations at the Person and Day Level
Mia S. O'Toole, Emma Elkjær and Mai B. Mikkelsen

18 Emotional Granularity Increases With Intensive Ambulatory Assessment: Methodological and Individual Factors Influence How Much
Katie Hoemann, Lisa Feldman Barrett and Karen S. Quigley

31 Negative Emotion Differentiation Predicts Psychotherapy Outcome: Preliminary Findings
Gal Lazarus and Aaron J. Fisher

46 Emotion Differentiation and Youth Mental Health: Current Understanding and Open Questions
Erik C. Nook

64 Negative Emotion Differentiation Attenuates the Within-Person Indirect Effect of Daily Stress on Nightly Sleep Quality Through Calmness
Tanja Lischetzke, Lea Schemer, Julia A. Glombiewski, Tina In-Albon, Julia Karbach and Tanja Könen

78 Emotion Differentiation in Current and Remitted Major Depressive Disorder
Renee J. Thompson, Daphne Y. Liu, Ella Sudit and Matt Boden

91 The Role of Interoceptive Sensibility and Emotional Conceptualization for the Experience of Emotions
Carlos Ventura-Bort, Julia Wendt and Mathias Weymar

106 From Knowledge to Differentiation: Increasing Emotion Knowledge Through an Intervention Increases Negative Emotion Differentiation
Evgeniya Vedernikova, Peter Kuppens and Yasemin Erbas

117 Cultivating Emotional Granularity
Christine D. Wilson-Mendenhall and John D. Dunne

124 Feel to Heal: Negative Emotion Differentiation Promotes Medication Adherence in Multiple Sclerosis
T. H. Stanley Seah, Shaima Almahmoud and Karin G. Coifman

132 Emotional Nuance: Examining Positive Emotional Granularity and Well-Being
Tse Yen Tan, Louise Wachsmuth and Michele M. Tugade

138 Operationalizing undifferentiated affect: Validity and utility in clinical samples
Sean P. Lane and Timothy J. Trull

frontiers | Frontiers in Psychology

TYPE Editorial
PUBLISHED 17 November 2022
DOI 10.3389/fpsyg.2022.1080713

Check for updates

OPEN ACCESS

EDITED AND REVIEWED BY
Florin Dolcos,
University of Illinois at
Urbana-Champaign, United States

*CORRESPONDENCE
Yasemin Erbas
y.i.erbas@tilburguniversity.edu
Jennifer M. B. Fugate
Jfugate@kansascity.edu

SPECIALTY SECTION
This article was submitted to
Emotion Science,
a section of the journal
Frontiers in Psychology

RECEIVED 26 October 2022
ACCEPTED 28 October 2022
PUBLISHED 17 November 2022

CITATION
Erbas Y, Gendron M and Fugate JMB
(2022) Editorial: The role of emotional
granularity in emotional regulation,
mental disorders, and well-being.
Front. Psychol. 13:1080713.
doi: 10.3389/fpsyg.2022.1080713

Editorial: The role of emotional granularity in emotional regulation, mental disorders, and well-being

Yasemin Erbas[1,2]*, Maria Gendron[3] and Jennifer M. B. Fugate[4]*

[1]Tilburg School of Social and Behavioral Sciences, Tilburg University, Tilburg, Netherlands, [2]Faculty of Psychology and Educational Sciences, KU Leuven, Leuven, Belgium, [3]Department of Psychology, Yale University, New Haven, CT, United States, [4]Department of Health Service Psychology, Kansas City University, Kansas City, MO, United States

KEYWORDS

emotions, emotion granularity, emotion differentiation, emotion regulation, well-being, mental disorders

Editorial on the Research Topic
The role of emotional granularity in emotional regulation, mental disorders, and well-being

Imagine having a conversation with a friend. At the end of the conversation, you feel bad about it, but are not quite sure why. Now imagine having the same conversation, but afterwards you feel very guilty. In the second example, you have labeled your feelings with a high degree of specificity, and in contrast to the first example, this will aid you in dealing effectively with the situation: you might give your friend a call and apologize. This precise and context-sensitive way of labeling feelings is referred to as emotional granularity.

Two decades of research show that high emotional granularity (EG) positively relates to a wide range of well-being outcomes (Kashdan et al., 2010; Smidt and Suvak, 2015; O'Toole et al., 2020; Seah and Coifman, 2022). First, this research shows that EG is lower in individuals with various forms of psychopathology [e.g., borderline personality disorder (BPD), affective disorders, major depressive disorder]. Second, this research suggests that high EG is a protective factor, meaning that it can help to protect individuals from maladaptive behaviors or outcomes. For instance, high EG is associated with less self-harm in individuals with BPD (Zaki et al., 2013). In addition, individuals with high EG are less prone to maladaptive behaviors, such as binge eating (Dixon-Gordon et al., 2014), alcohol abuse (Kashdan et al., 2010), and physical aggression (Pond et al., 2012). Finally, there is emerging research linking EG to emotion regulation: individuals with high EG tend to report regulating their emotions more frequently (Barrett et al., 2001), while individuals with low EG are less successful in downregulating their negative emotions (Kalokerinos et al., 2019).

Together, the research on EG shows that individuals with more granular emotions have more beneficial outcomes than those individuals having undifferentiated emotions. So then why is a Research Topic on emotional granularity still necessary? One critical reason is that the general construct of emotional granularity (i.e., its nomological network) and its exact utility beyond existing ways of characterizing emotions (i.e., incremental validity) are still unclear. In addition, little is known about how EG can be cultivated, and how this could have implications for therapeutic outcomes or treatment. This Research Topic aimed to shed light on these issues, as well as to point to future directions. To summarize these aims, we have divided the papers in this Research Topic into four themes.

The first theme extends our knowledge about the relationship between high EG and improved well-being. O'Toole et al. show that EG does not predict which emotion regulation strategies at the day-level individuals use to downregulate their negative emotions. In line with earlier work at the between-person level (Kalokerinos et al., 2019), this finding suggests that the relationship between EG and well-being might have a pathway through emotion regulation that is more complex than simply the frequency or intensity of use of adaptive or maladaptive strategies. Ventura-Bort et al. provide evidence that higher granularity is related to beliefs about one's accuracy in detecting internal states—physiological and emotional—, which in turn predicted higher well-being. Furthermore, Lischetzke et al. show that higher granularity buffers against the negative effects of stress on sleep quality. Interestingly, Thompson et al. show that EG was not only low in individuals with depression, but also in those who are in remission. This finding sheds light on why individuals who have had depression in the past might be vulnerable to remission. Likewise, this finding implies that EG is thus not only a target for interventions in depressed individuals, but also in individuals who are currently in remission.

The second theme extends the benefits of having high EG to the context of therapeutic outcomes and treatment. Lazarus and Fisher find that individuals with high (compared to low) EG, especially for negative emotions, benefit more from psychotherapy. Similarly, Seah and Coifman show that individuals with Multiple Sclerosis who exhibit high EG are less likely to stop treatment when experiencing negative emotions. Together, these studies show that high EG is not only beneficial by itself, but it can also increase the likelihood to adhere to other treatment protocols.

A third theme is the malleability of EG, especially focusing on increasing low EG to affect mental well-being. Hoemann et al. show that engaging in experience sampling increases the level of EG. Likewise, Vedernikova et al. show that increasing emotion concept knowledge increases the level of negative (but not positive) granularity, with changes persisting over time. Finally, Wilson-Mendenhall and Dunne theorize how mindfulness-based interventions could cultivate EG and the specific mechanisms future research should explore.

A final theme is the continued exploration of the EG construct as it is affected by methodology, scope, and across development. Lane and Trull point out that most EG research has so far been conducted at the between-person level. However, as EG is also expected to fluctuate within individuals, they propose a new paradigm that allows to measure within-person changes in EG. Second, Nook reviews how EG develops throughout the lifespan, and the possible link to psychopathology during adolescence. Finally, a review by Tan et al. shows that positive emotion differentiation, a previously under-explored aspect of granularity, also has beneficial effects.

Together, the papers in this Research Topic showcase the different pathways through which EG can benefit emotional regulation and adherence to treatment, how EG can be cultivated, as well as identifying the existing gaps in current research with suggestions for the future. While there is consensus about the utility of EG for well-being, the pathways underlying this relationship still require study. In addition to expanding on these Research Topics, future efforts should focus on the distinction between emotional granularity and related constructs, which might help explain why retrospective survey measures about emotion vocabulary or emotional knowledge are not always strongly correlated with EG, as derived from experiential sampling methodology measures. The current Research Topic contributes to the EG literature by trying to fill parts of these gaps, but at the same time by proposing important avenues for future research.

Author contributions

The Research Topic was proposed by JF. All editors worked collaboratively to invite potential authors and reviewers, to edit and review the manuscripts, and decide on acceptance/rejection of manuscripts. The Editorial was drafted by YE, MG, and JF. All authors contributed to the article and approved the submitted version.

Acknowledgments

We want to thank all the authors who contributed to the Research Topic, all the reviewers for their feedback, and the Frontiers team for their support.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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frontiers in Psychology

ORIGINAL RESEARCH
published: 09 July 2021
doi: 10.3389/fpsyg.2021.684377

Is Negative Emotion Differentiation Associated With Emotion Regulation Choice? Investigations at the Person and Day Level

Mia S. O'Toole*, Emma Elkjær and Mai B. Mikkelsen

Department of Psychology and Behavioural Sciences, Aarhus University, Aarhus, Denmark

Negative emotion differentiation (ED) has been suggested to be important for adaptive emotion regulation (ER). However, knowledge concerning how ED may impact specific ER strategy choice remains surprisingly sparse. We therefore investigated (1) if person-level negative ED was associated with habitual use of individual ER strategies, (2) how person-level negative ED was associated with daily use of individual ER strategies, and finally (3) how within-person daily fluctuations in negative ED were associated with daily use of individual ER strategies. During a 10-day experience sampling study, 90 healthy participants rated their momentary emotions and their ER efforts in response to those emotions. ER strategies included four putatively adaptive strategies (reflection, distancing, non-reactivity, reappraisal) and four putatively maladaptive strategies (rumination, experiential avoidance, expressive suppression, worry). Results revealed that negative ED at the person level was neither associated with habitual nor daily ER strategy endorsement when controlling for negative emotions. Likewise, associations between within-individual daily variation in negative ED and daily ER did not remain statistically significant after controlling for negative emotions. The results thus point to no or weak associations between negative ED and ER choice above and beyond negative emotions. Future experimental studies addressing ED at the momentary level and teasing out the ED–ER causal timeline are needed to further evaluate ED–ER associations. Findings from such research may represent an important step toward refining psychotherapeutic interventions aimed at improving emotional problems.

Keywords: emotion differentiation, emotion regulation, emotion regulation choice, experience- sampling method, emotion granularity

OPEN ACCESS

Edited by:
Jennifer Marie Binzak Fugate, University of Massachusetts Dartmouth, United States

Reviewed by:
Anne Gärtner, Technische Universität Dresden, Germany
Elise Kalokerinos, The University of Melbourne, Australia

****Correspondence:***
Mia S. O'Toole
mia@psy.au.dk

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: *23 March 2021*
Accepted: *15 June 2021*
Published: *09 July 2021*

Citation:
O'Toole MS, Elkjær E and Mikkelsen MB (2021) Is Negative Emotion Differentiation Associated With Emotion Regulation Choice? Investigations at the Person and Day Level. Front. Psychol. 12:684377. doi: 10.3389/fpsyg.2021.684377

INTRODUCTION

Across theoretical positions, emotions are said to arise in the face of something personally relevant in a given situation (Gross and Barrett, 2011). The majority of emotion theories also converge on the idea that one of the most prominent features of emotions is their functionality, evidenced as the enactment of this personal relevance, preparing the individual to approach, or avoid an object (Frijda, 2007; Scherer and Moors, 2019). As such, emotions provide the individual with information about themselves in relation to the world, and point to whether or not their needs and goals are being met (Frijda, 2007; Gross and Barrett, 2011; Gross, 2014). Therefore, the ability to become aware of one's emotions is deemed important for healthy emotional functioning (Lindquist and Barrett, 2010; Grühn et al., 2013; Kashdan et al., 2015; Grossmann et al., 2016b). Individuals may gain such awareness, and thus experience their emotions, in different ways. One indicator of emotion experience that has received considerable theoretical and empirical attention is emotion differentiation (ED). Emotion differentiation refers to the individual's ability to experience distinct emotions (e.g., anxiety, sadness) in a granular manner, independent of each other (Kashdan et al., 2015; Grossmann et al., 2016b). Emotion differentiation has often been operationalized as the inverse consistency between either negative or positive emotions over a number of occasions, typically derived empirically from experience-sampling studies conducted over a set number of days (Kashdan et al., 2015; O'Toole et al., 2020). It has been argued that because ED entails a detailed or rich experience of emotions, the good differentiator will have access to more information about themselves in relation to the world and thus a better foundation upon which to base their subsequent emotion regulatory efforts (Gohm and Clore, 2002; Demiralp et al., 2012; Kircanski et al., 2012; Kuppens and Verduyn, 2015; Mennin and Fresco, 2015; Kalokerinos et al., 2019; Seah and Coifman, 2021; Thompson et al., 2021).

Empirical evidence supports the assumption that ED—in particular negative ED—is associated with overall better mental health (Smidt and Suvak, 2015) and with specific positive outcomes pertaining to situational responding (for a review see Kalokerinos et al., 2019), including reduced alcohol consumption (Kashdan et al., 2010), less impulsivity (Tomko et al., 2015), more empathetic attunement to one's partner (Erbas et al., 2016), and less aggression (Pond et al., 2012). Thus, there appears to be a direct, attenuating effect of ED on a range of maladaptive behaviors. In addition to such direct effects, ED also appears to act as a moderator by attenuating the negative consequences of specific emotion regulation (ER) strategies. For instance, Zaki et al. (2013) used an experience-sampling protocol on individuals with borderline personality disorder and found that the association between rumination and both acts and urges of non-suicidal self-injury was negative for those with higher levels of ED, whereas it was positive for those with lower levels. Starr et al. (2017) investigated ED as a moderator of associations between daily perseverative self-focused ER (i.e., brooding and savoring) and daily depressive symptoms in both young healthy adults and veterans from primary care. Across the two populations, both negative and positive ED moderated the associations between perseverative self-focused strategies and depressive symptoms such that low ED was associated with an enhanced association. Seah et al. (2020) examined if negative ED moderated the positive association between rumination and frequency of social avoidance within the context of social anxiety disorder. Across two studies, negative ED was indeed found to moderate the relationship between rumination and social avoidance. Specifically, they found that the positive association between rumination and social avoidance was significant for low but not moderate to high negative ED. Finally, Liu et al. (2019) conducted a 6-month prospective longitudinal study, examining the moderating role of ED on the association between rumination and depression. They found that ED of positive and negative emotions together interacted with rumination to predict significant changes in depression, after controlling for mean levels of emotion. Together, these studies may point to a protective factor of, in particular, negative ED, such that the negative consequences of a specific ER strategy are weakened when the individual is adept at differentiating their emotional experience.

Knowing how negative ED may alter the effect of specific ER strategies (e.g., rumination) on certain desired or undesired outcomes (e.g., depressive symptoms) is clearly important for honing instances in which improved negative ED may play a role in alleviating clinical conditions or reducing maladaptive behavior. However, little is known about how negative ED influences overall ER choice. The first study to evaluate the association between ED and a variety of ER strategies was conducted in 2001 by Barrett and colleagues. In a 14-day diary study of 53 participants, emotions and ER were rated within the context of the most intense emotional experiences. The study authors hypothesized that the ED–ER relationship would be strongest in this context. This hypothesis was rooted in the assumption that the press for ER is greatest in situations characterized by negative emotions. Specifically, negative emotions are believed to have greater informational value in signaling the need to change or adjust one's current state or activity, and a failure to respond to a negative signal can prevent the individual from taking steps to avoid potential harm (Barrett et al., 2001, p. 715). Consistent with their hypothesis, the authors found that individuals with higher negative ED reported stronger regulatory efforts in response to negative emotions, operationalized as the combined use of nine ER strategies. Kalokerinos et al. (2019) recently extended this research taking into account important limitations. First, Barrett et al. (2001) averaged all ER strategies. However, the individual's habitual use of certain strategies appears to be differentially associated with well-being and healthy functioning. For instance, Aldao et al. (2010) found that habitual use of so-called putatively maladaptive strategies (i.e., rumination, suppression), compared to adaptive strategies (i.e., reappraisal, problem solving), were more strongly associated with psychopathology (i.e., symptoms of anxiety, depression, and eating disorders). Second, the ER strategies in the study by Barrett et al. (2001) were averaged retrospectively according to how much participants indicated that they had used the strategies over the previous 2 weeks. Such assessment method may not capture the dynamics of the individual's choice of ER strategies from moment to moment. Kalokerinos et al. (2019) concluded that a strategy-specific approach, evaluating ER at the momentary level, was needed. Accordingly, they examined how negative ED was related to the momentary selection of a variety of ER strategies in two experience-sampling studies. Contrary to their hypothesis, they found only few relationships between negative ED and the selection of putatively adaptive or maladaptive strategies. However, consistent with the studies mentioned above on the moderating role of ED, they found that among low differentiators, regulatory strategies were more strongly associated with increased negative emotion than they were among high differentiators.

In the studies by Kalokerinos et al. (2019), ED was operationalized as is typically the case, namely as the inverse average consistency [i.e., intra-class correlation (ICC)] between emotion ratings across all measurement occasions for each individual. As such, ED was conceptualized as a matter of individual differences, that is, a stable, person-level variable. However, it is increasingly acknowledged that ED has both stable and variable parts (Tomko et al., 2015; Grossmann et al., 2016b; Erbas et al., 2018; O'Toole et al., 2020). ED may both vary within person from day to day or moment to moment (Erbas et al., 2018), and may even improve overall following psychotherapy (Van Der Gucht et al., 2019; Mikkelsen et al., 2021). Accordingly, ED should be investigated both at the person level, where ED is averaged across all measurement occasions (i.e., between persons), and as fluctuations from this average (i.e., within-person change; Tomko et al., 2015; Erbas et al., 2018). As with ED, ER may also be conceptualized at the person-level, reflecting habitual regulatory tendencies, from which point the individual may fluctuate from day to day or moment to moment (Gross, 2014; Aldao et al., 2015; Kalokerinos et al., 2019). At this point, it remains unknown how ED—at the between and within-person level—may be differentially associated with the use of particular ER strategies. We therefore wanted to add to this rather sparse literature on the ED–ER association, investigating associations between both person-level negative ED and within-person daily deviations from this person-level on the one side, and daily ER on the other.

The Present Study

This study was an experience-sampling study (involving two samples; $N = 51$ and 39), in which participants were asked to rate both emotions and ER efforts three (i.e., Sample 1) or four (i.e., Sample 2) times a day over 10 days. With this design, we were able to evaluate both the person- and day-level association between negative ED and daily ER strategy choices. At baseline, we also inquired about habitual ER as well as overall positive and negative affect. We employed a strategy-specific approach, exploring (1) if person-level negative ED was associated with habitual use of individual ER strategies. We then explored (2) how person-level negative ED was associated with daily use of individual ER strategies, and finally (3) how within-person daily fluctuations in negative ED were associated with daily use of individual ER strategies. Our first aim serves as an extension of the study by Barrett et al. (2001), exploring the association between negative ED and average ER, however, from a strategy-specific approach. The second and third aim represent an endeavor to follow up on the studies by Kalokerinos et al. (2019) by not only addressing the association between person-level ED and daily choice of ER strategies, but also adding to this research by investigating the association between within-person daily fluctuations in ED and daily ER. For all three aims, we hypothesized that higher negative ED would be positively associated with putatively adaptive ER strategies and negatively associated with putatively maladaptive ER strategies. Following recent findings and recommendations (see Dejonckheere et al., 2019; Kalokerinos et al., 2019), we wanted to assess the unique contribution of ED to ER strategy selection and therefore evaluated the extent to which ED was associated with ER above and beyond negative emotions.

METHODS

Participants and Procedures

Participants were students recruited from the local university through advertisements on social media and lectures at the university. To participate, individuals had to be above the age of 18 years, proficient in the Danish language, and able to provide written consent to participate. Participants were excluded if they were not able to engage in the daily monitoring procedures over the following 10 days. Written consent was obtained upon participants having received written information about the study where it was underscored that participation was voluntary with no consequences in case of declining to participate or dropping out. After completing a baseline questionnaire, an experience-sampling study was conducted. Participants received three (Sample 1) or four (Sample 2) text messages every day for 10 days containing a link to an online questionnaire. They received the text messages on their personal smart phone. The link and questionnaire was created and distributed via the software SurveyXact. The text messages were sent at random times between 10 a.m. and 9 p.m. in 1-h intervals. The baseline questionnaire had a completion time of 20 to 30 min, whereas the daily measures had one of 2–3 min. Participants were compensated with a gift voucher (250 DKK/app. 40 USD)[1].

Measures

Baseline Person-Level Measures of Emotions

Baseline negative emotions were measured with seven negative emotion words (i.e., guilty, ashamed, nervous, sad, disgusted, angry, frustrated) and positive emotions were measured with seven positive emotion words (i.e., happy, appreciative, satisfied, amused, curious, proud, enthusiastic). These emotion categories have often used in experience sampling studies (e.g., Kashdan and Steger, 2006; Demiralp et al., 2012; O'Toole et al., 2014; Kashdan et al., 2015). Each emotion was rated on a 5-point Likert Scale (1 = not at all; 5 = very much).

Baseline, Person-Level Measures of Emotion Regulation

Eight ER strategies were evaluated. The different strategies were chosen based on (1) obtaining an equal number of putatively adaptive and maladaptive strategies and (2) typically investigated ER strategies (Aldao et al., 2010). The four putatively adaptive

[1]Additional measures that were included in Study 1 at baseline were the Positive and Negative Affect Schedule (Watson et al., 1988), the Hospital Anxiety and Depression Scale (Bjelland et al., 2002), and the Satisfaction With Life Scale (Diener et al., 1985). At the daily level, additional measures included the Depicted Action Tendencies (O'Toole and Mikkelsen, 2021), single item rating of well-being, and two items concerning current activities. In Study 2, Toronto Alexithymia Scale (TAS-20; Bagby et al., 1994) was included at baseline. Data from these questionnaires were not analyzed for the present study.

strategies included *reappraisal* which was evaluated with the 6-item subscale (rated from 1 to 7) from the Emotion Regulation Questionnaire (ERQ; Gross and John, 2003, α = 0.79), *distancing* which was evaluated with the 11-item subscale (rated from 1 to 5) from the Experiences Questionnaire (EQ; Fresco et al., 2007, α = 0.86), *non-reactivity* which was evaluated with the 7-item non-reactivity subscale (rated from 1 to 5) of the Five Facet Mindfulness Questionnaire (FFMQ; Baer et al., 2008, α = 0.90), and *reflection* which was evaluated with the 12-item reflection subscale (rated from 1 to 5) from the Reflection and Rumination Questionnaire (RRQ; Trapnell and Campbell, 1999, α = 0.93). The putatively maladaptive strategies included *expressive suppression,* measured with the 4-item subscale (rated from 1 to 7) from the ERQ (Gross and John, 2003, α = 0.78), *experiential avoidance* evaluated with the 7-item experiential avoidance subscale (rated from 1 to 7) of the Acceptance and Action Questionnaire (AAQ; Bond and Bunce, 2003, α = 0.56), *worry* which was evaluated with the 16-item Penn State Worry Questionnaire (rated from 1 to 5) (PSWQ; Meyer et al., 1990, α = 0.89/0.83), and *rumination* evaluated with the 12-item rumination subscale (rated from 1 to 5) from the RRQ (Trapnell and Campbell, 1999, α = 0.93).

Day-Level Measures

Daily Emotions

Daily emotions were assessed with the same seven negative and seven positive emotion words used at baseline (e.g., Kashdan and Steger, 2006; Demiralp et al., 2012; O'Toole et al., 2014; Kashdan et al., 2015). For each emotion, participants rated the degree to which it reflected the way they felt at that moment of the day on a 5-point Likert Scale.

Daily ER

Daily ER was measured with items reflecting the eight strategies measured at baseline. Specifically, each strategy was evaluated with two items, which were chosen based on the highest factor loading as obtained in validation studies while considering the ability for the item to be meaningfully repeated within a daily context (cf. Kashdan and Steger, 2006; O'Toole et al., 2017). All items were rated on a 5-point Likert Scale and changed into present tense to assess the extent to which the strategy was employed in the *present moment*. Specifically, participants were instructed to "Think about the emotional experience you just rated. Now rate the extent to which you applied each of the following strategies to handle this emotional experience." The items were all rated from 1 to 5 and included:

Daily Putatively Adaptive Emotion Regulation Strategies

Reflection: "I am exploring my 'inner' self" and "I am looking at my life in a philosophical perspective" (RRQ; Trapnell and Campbell, 1999). Reappraisal: "I am changing the way I am thinking of the situation" and "I am changing the way I am thinking of my feelings" (ERQ; Gross and John, 2003). Distancing: "I am treating myself kindly" and "I am observing my feelings without being drawn into them" (EQ; Fresco et al., 2007). Non-reactivity: "I am perceiving my feelings and emotions without having to react to them" and "I am noticing thoughts or images without reacting" (FFMQ; Baer et al., 2008).

Daily Putatively Maladaptive Emotion Regulation Strategies

Worry: "My worries are overwhelming me" and "I am worrying and can't stop worrying" (PSWQ; Meyer et al., 1990). Rumination: "I am ruminating over or dwelling on things that are happening to me" and "I'm playing back over in my mind how I acted in a past situation" (RRQ; Trapnell and Campbell, 1999). Expressive suppression: "I am controlling my emotions by not expressing them" and "I am keeping my emotions to myself" (ERQ; Gross and John, 2003). Experiential avoidance: "I am afraid of my feelings" and "I am trying to suppress thoughts and feelings that I don't like by just not thinking about them" (AAQ; Bond and Bunce, 2003).

Reliability and Validity of Daily ER Strategy Items

Reliability between the two items was evaluated by calculating the correlation coefficient for each individual across the study period. Correlation coefficients (r) $\geq$ 0.5 were taken to be indicative of satisfactory internal reliability. This criterion was met for all ER strategies except distancing and experiential avoidance, which were correlated to a moderate degree (rs = 0.3). The validity of the daily ER strategies was evaluated in a multilevel model (MLM), where the baseline measure of the ER strategy served as predictor of the daily measure (see description of MLMs below). Associations of a medium strength ($r \geq 0.3$) were taken to be indicative of satisfactory validity (Kashdan and Steger, 2006; O'Toole et al., 2014). This criterion was met for all ER strategies except reappraisal (see **Table 1**). Two sets of analyses were then conducted, serving as further validation of the chosen ER strategies as putatively adaptive (when associated with more positive emotions) and putatively maladaptive (when associated with more negative emotions), including correlation analyses between baseline ER strategies and baseline negative or positive emotions, in addition to MLMs exploring daily associations between person mean-centered daily ER and positive and negative emotions (see description of MLMs below). Results from correlation analyses at baseline, see **Table 2**, revealed positive and statistically significant correlations between putatively adaptive strategies and positive emotions, and negative and statistically significant correlations for negative emotions, all of a small to medium magnitude. This was with the exception of reflection. Concerning the putatively maladaptive strategies at baseline, worry and rumination showed the expected pattern where correlations were statistically significant and of a small to medium magnitude. However, experiential avoidance was only correlated at the statistically significant level with positive emotions, and although in the expected direction, both correlations were non-significant for expressive suppression. Concerning the daily measures, person mean-centered daily putatively adaptive ER strategies showed statistically significant positive associations with positive emotions of medium and large magnitudes except for reappraisal, where the association was non-significant. Associations with negative emotions were negative, statistically significant and of a large magnitude for distancing and non-reactivity. For reappraisal the association

TABLE 1 | Correlation coefficients between the two ER items and associations between baseline and daily measures of ER.

	Within-person correlation between the two items across the study period	Associations between baseline ER and daily ER
RRQ reflection	0.59	$t = 6.1$, $p < 0.001$, $r = 0.55$
EQ distancing	0.32*	$t = 7.2$, $p < 0.001$, $r = 0.61$
FFMQ non-reactivity	0.56	$t = 6.4$, $p < 0.001$, $r = 0.57$
ERQ reappraisal	0.67	$t = 2.6$, $p = 0.011$, $r = 0.27$*
RRQ rumination	0.65	$t = 4.3$, $p < 0.001$, $r = 0.42$
AAQ experiential avoidance	0.32*	$t = 4.4$, $p < 0.001$, $r = 0.43$
ERQ suppression	0.57	$t = 7.2$, $p < 0.001$, $r = 0.61$
PSWQ worry	0.72	$t = 6.7$, $p < 0.001$, $r = 0.59$

**Value below threshold of 0.5 (within-person correlation) or 0.3 (association between baseline and daily measure of emotion regulation).*
AAQ, Acceptance and Action Questionnaire (Bond and Bunce, 2003); EQ, Experiences Questionnaire (Fresco et al., 2007); ER, emotion regulation; ERQ, Emotion Regulation Questionnaire (Gross and John, 2003), FFMQ, Five Facet Mindfulness Questionnaire (Baer et al., 2008); PSWQ, Penn State Worry Questionnaire (Meyer et al., 1990); RRQ, Rethinking Rumination Questionnaire (Nolen-Hoeksema et al., 2008).

TABLE 2 | Associations expressed as correlation coefficients between emotion regulation at baseline, person-level emotion differentiation, and negative and positive emotions at baseline (without/with mean levels of negative emotions across the study period as a covariate).

	Person-level negative ED	Positive emotions	Negative emotions
Person-level negative ED	–	0.12	−0.29**
Reflection	−0.02/−0.06	0.16	−0.02
Distancing	0.24*/0.14	0.43***	−0.40***
Non-reactivity	0.28**/0.09	0.37***	−0.34**
Reappraisal	0.18/0.08	0.25*	−0.29**
Rumination	−0.28**/−0.07	−0.38***	0.47***
Experiential avoidance	−0.17/−0.04	−0.22*	0.09
Expressive suppression	−0.04/<0.01	−0.13	0.19
Worry	−0.30**/−0.13	−0.30**	0.35**
Positive emotions	0.12	–	−0.41***
Negative emotions	−0.29**	−0.41***	–

**$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. ED, emotion differentiation.*

TABLE 3 | Associations between person mean-centered daily emotion regulation and daily positive and negative emotions.

Person mean-centered daily emotion regulation	Positive emotions	Negative emotions
Reflection	$t = 4.6$, $\mathbf{p < 0.001}$, $r = 0.44$	$t < 0.1$, $p = 0.969$, $r = 0.10$
Distancing	$t = 9.5$, $\mathbf{p < 0.001}$, $r = 0.72$	$t = -6.6$, $\mathbf{p < 0.001}$, $r = 0.58$
Non-reactivity	$t = 2.7$, $\mathbf{p = 0.009}$, $r = 0.28$	$t = -4.4$, $\mathbf{p < 0.001}$, $r = 0.43$
Reappraisal	$t = 0.8$, $p = 0.445$, $r = 0.08$	$t = 2.2$, $\mathbf{p = 0.035}$, $r = 0.23$
Rumination	$t = -4.3$, $\mathbf{p < 0.001}$, $r = 0.42$	$t = 7.4$, $\mathbf{p < 0.001}$, $r = 0.62$
Experiential avoidance	$t = -4.4$, $\mathbf{p < 0.001}$, $r = 0.43$	$t = 6.8$, $\mathbf{p < 0.001}$, $r = 0.59$
Expressive suppression	$t = -5.0$, $\mathbf{p < 0.001}$, $r = 0.47$	$t = 7.4$, $\mathbf{p = 0.008}$, $r = 0.62$
Worry	$t = -10.1$, $\mathbf{p < 0.001}$, $r = 0.74$	$t = 11.5$, $\mathbf{p < 0.001}$, $r = 0.78$

Significant results are highlighted in bold text.

with negative emotions was significant, positive, and of a small to medium magnitude. For reflection, this association was non-significant. All person mean-centered daily putatively maladaptive ER strategies showed statistically significant negative associations with positive emotions of medium and large magnitudes. Associations with negative emotions were all positive, statistically significant, and of medium and large magnitudes. See **Table 3**.

Person-Level ED and Within-Person Fluctuations

Differentiation Indicators

Negative ED was indexed by the ICC, which is a measure of the average consistency between the negative emotions. The ICC for negative emotions was obtained for each person (Demiralp et al., 2012; Erbas et al., 2018; Thompson et al., 2021). We excluded negative ICCs because these values are considered unreliable (Erbas et al., 2018). We transformed the remaining ICCs using a Fisher's Z transformation because ICCs are not normally distributed (cf. Barrett et al., 2001). To ease the interpretation of the indicators, we then reversed the Z-transformed ICC's, such that higher values indicate better differentiation. We calculated ED both at the day level (i.e., across measurement occasions within a specific day) and at the person level (i.e., across all measurement occasions (Erbas et al., 2018). For the day-level ED, we used person mean-centered variables, that is, daily within-individual fluctuations.

Statistical Analysis

The first aim was addressed with correlation analyses between person-level ED and baseline ER strategies, exploring how person-level negative ED was associated with habitual use of individual ER strategies. MLMs were conducted to evaluate aims 2 and 3, where the repeated measurements (level 1) were nested within individuals (level 2). Specifically, either person-level ED (aim 2) or person mean-centered day-level ED (aim 3) served as the independent variable with employment of each of the daily ER strategies being the dependent variable in separate models. MLMs included a random intercept, and the repeated measure (i.e., the different observation occasions) was modeled with an "Autoregressive 1" covariance type. For MLMs

TABLE 4 | Participant descriptive statistics ($N = 90$).

	Sample 1	Sample 2	Total
	M (*SD*)	*M* (*SD*)	*M* (*SD*)
Emotions			
Positive emotions	24.3 (5.2)	25.9 (4.0)	25.0 (4.8)
Negative emotions	13.9 (4.2)	13.3 (4.9)	13.6 (4.5)
Putatively Adaptive Emotion Regulation			
RRQ reflection	44.6 (10.0)	47.1 (8.3)	45.7 (9.3)
EQ decentering	37.8 (6.9)	39.2 (7.9)	38.4 (7.3)
FFMQ non-reactivity	21.3 (5.1)	22.0 (5.5)	21.60 (5.3)
ERQ reappraisal	29.5 (4.4)	30.5 (6.5)	29.9 (5.4)
Putatively Maladaptive Emotion Regulation			
ERQ expressive suppression	11.4 (5.1)	11.22 (5.1)	11.29 (5.1)
AAQ experiential avoidance	26.24 (5.9)	24.4 (6.1)	25.4 (6.0)
RRQ rumination	40.9 (9.7)	36.5 (10.6)	39.0 (10.2)
PSWQ worry	48.3 (11.7)	48.0 (9.6)	48.2 (10.8)

Means (M) and Standard Deviations (SD) from baseline measures. Scores reflect mean total scores. AAQ, Acceptance and Action Questionnaire (Bond and Bunce, 2003); EQ, Experiences Questionnaire (Fresco et al., 2007); ERQ, Emotion Regulation Questionnaire (Gross and John, 2003), FFMQ, Five Facet Mindfulness Questionnaire (Baer et al., 2008); PSWQ, Penn State Worry Questionnaire (Meyer et al., 1990); RRQ, Rethinking Rumination Questionnaire (Nolen-Hoeksema et al., 2008).

TABLE 5 | Mean total scores for daily emotions and emotion regulation strategies.

	M (*SD*)
Emotions	
Positive emotions	18.0 (3.7)
Negative emotions	10.9 (2.2)
Putatively Adaptive Emotion Regulation	
RRQ reflection	4.9 (2.2)
EQ decentering	6.9 (1.7)
FFMQ non-reactivity	6.4 (1.7)
ERQ reappraisal	5.1 (2.2)
Putatively Maladaptive Emotion Regulation	
ERQ expressive suppression	4.6 (2.2)
AAQ experiential avoidance	4.1 (1.8)
RRQ rumination	4.8 (2.3)
PSWQ worry	3.5 (1.9)

Emotion regulation strategy values reflect mean daily total scores of the two items (i.e., possible range from 2 to 10). AAQ, Acceptance and Action Questionnaire (Bond and Bunce, 2003); EQ, Experiences Questionnaire (Fresco et al., 2007); ERQ, Emotion Regulation Questionnaire (Gross and John, 2003), FFMQ, Five Facet Mindfulness Questionnaire (Baer et al., 2008); PSWQ, Penn State Worry Questionnaire (Meyer et al., 1990); RRQ, Rethinking Rumination Questionnaire (Nolen-Hoeksema et al., 2008).

with time-varying predictors (i.e., daily ED or ER), a random slope was specified for these. Following recent findings and recommendations, all analyses exploring ED–ER associations were run with and without negative emotions as a covariate, thereby exploring the extent to which ED is uniquely associated with ER, that is, above and beyond the level of negative emotions (see Dejonckheere et al., 2019; Kalokerinos et al., 2019). When exploring ED across the study period (between-person), the covariate included was the average level of negative emotions across the study period, and when exploring daily ED, the covariate referred to daily levels of negative emotions. Effect sizes were calculated as correlation coefficients (r), using t-to-r transformations (Kashdan and Steger, 2006; O'Toole et al., 2014), and values of 0.1, 0.3, and 0.5 were taken to denote a small, medium, and large effect size, respectively (Cohen, 1988). All analyses were performed in IBM SPSS Statistics Version 27.

RESULTS[2]

Participants

One participant dropped out, resulting in 90 participants in total completing the survey. In sample 1, 88.2% of the participants were women, and the mean age was 23.7 (1.7) year. In Sample 2, 74.4% of participants were women, and the mean age was 25.4 (6.02) In total, 82.2 % were women, and the mean age was 24.4, ranging from 20 to 57. There was no statistical significant difference between the two samples regarding age ($p = 0.106$), education ($p = 0.324$), or gender ($p = 0.088$). Out of the total possible observations for each person, 22.1% responses were missing on average. Baseline means for emotional outcomes and ER strategies can be found in **Table 4**. Independent samples t-tests were used to compare scores between the two samples. Only one significant difference was detected. Sample 1 scored higher on rumination than Sample 2 [mean difference = 4.4, $t_{(86)} = 2.1$, $p = 0.043$]. No significant difference was detected for person-level negative ED, $t_{(86)} = 0.3$, $p = 0.754$. These results were taken as sufficient grounds for combining the two samples. Concerning missing ED data, it was not possible to calculate person-level ED for two participants (2%), and 248 daily records were missing out of 900 possible daily records. Of the remaining 652 records, 124 ICCs (19%) were deleted due to negative values.

Associations Between Person-Level Negative ED and Habitual Use of ER Strategies

Turning to the first aim of investigating how person-level negative ED was associated with habitual use of individual ER strategies, correlation coefficients can be found in **Table 2**. Person-level negative ED showed positive and statistically significant correlations with habitual use of distancing and non-reactivity of a small to medium magnitude, and negative and statistically significant correlations with habitual use of rumination and worry, also of a small to medium magnitude. However, none of the ED–ER associations remained statistically significant after controlling for baseline negative emotions.

[2]The data have been used in another study (Elkjær et al., 2021) where the main aim was to explore emotion regulation flexibility. There are no analytic overlaps between that and the present study.

Associations Between Person-Level and Person Mean-Centered Daily Negative ED and Daily Use of ER Strategies

For the second and third aim of exploring how person-level and person mean-centered daily negative ED were associated with daily use of individual ER strategies, mean total scores for daily measures can be found in **Table 5**, and results can be found in **Table 6**. For daily putatively adaptive ER strategies, person-level ED was positively associated with all ER strategies, but none of the associations were statistically significant when controlling for mean levels of negative emotions across the study period. For person mean-centered daily negative ED, the association with daily distancing was of a small to medium magnitude and remained borderline statistically significant after controlling for daily level of negative emotions.

With regard to daily putatively maladaptive ER strategies, person-level ED was negatively associated with all strategies, but none of the associations were statistically significant when controlling for mean levels of negative emotions across the study period. For person mean-centered daily negative ED, the association with expressive suppression was of a small to medium magnitude and remained borderline statistically significant after controlling for daily level of negative emotions.

A set of *post-hoc* analyses was conducted, exploring the associations between ED and daily ER but categorizing ER categorically[3]. These analyses were conducted with the aim of approaching the research question in a similar manner but eliminating the inherent issue of including "1 s" in the average ER scores since those values represent the lack of use and not the amount of use. ER was rated as absent for scores assuming values of 1 and 2 and present for scores assuming values of 3 through 5 (i.e., mean total scores $\geq$6). Multilevel level logistic regression were run in Stata using the *melogit* command. The dependent variable was the categorical measure of ER use, with the independent variable being negative ED. A random intercept was specified in all models, and a random slope was specified for the time-varying predictor (i.e., within-person fluctuation in ED). Analyses were run with and without negative emotions. Results can be found in **Table 7**. None of the ED–ER associations were significant in models including negative emotion as a covariate. For both between-person negative ED (r range from $<$0.01 to 0.17) and within-person fluctuations in negative ED (r range from 0.1 to 0.15), all effect sizes were small.

DISCUSSION

Negative ED has been suggested to be important for adaptive ER. However, knowledge concerning the association between ED and ER strategy choice is lacking. We wanted to add to this rather sparse literature on the ED–ER association, investigating how both person-level negative ED and within-person daily deviations from this person-level were associated with daily ER strategy endorsement. Consequently, we explored (1) how person-level negative ED was associated with habitual use of individual ER strategies, (2) how person-level negative ED was associated with daily use of individual ER strategies, and (3) how daily within-person fluctuations in negative ED were associated with daily use of individual ER strategies.

Concerning the association between person-level negative ED and habitual use of individual ER strategies, results were in the expected direction, showing that a higher score for negative ED (i.e., better differentiation abilities) was positively associated with greater use of the putatively adaptive strategies, and with less use of the putatively maladaptive strategies of rumination and worry. However, none of these associations, were statistically significant when controlling for mean levels of negative emotions. Regarding the associations between person-level negative ED and daily endorsement of ER strategies, a similar pattern was found with no statistically significant associations after controlling for mean level of negative emotions. Thus, true for both habitual and daily use of ER strategies, person-level negative ED did not show unique explanatory power above and beyond the mean level of negative emotions with all effect sizes being of negligible to small magnitudes (rs $<$ 0.15). These findings replicate the main conclusion reached by Kalokerinos et al. (2019), namely that person-level negative ED and ER strategy selection are only weakly associated.

Turning to the association between within-individual fluctuations in daily negative ED and daily ER strategies, associations also decreased in effect size and became non-significant when controlling for daily negative emotions. Thus, these results also largely confirms those obtained by Kalokerinos et al. (2019). Given a number of differences between studies, this may speak to the robustness of the overall finding of no or weak associations between ED and ER strategy endorsement. Study differences include that ER was operationalized at the momentary level in the study by Kalokerinos et al. (2019) and at the daily level in the present study. Moreover, ER efforts in the study by Kalokerinos et al. (2019) were evaluated "since the last beep," where the present study inquired about ER efforts "in this current moment." We chose the latter approach in an effort to obtain a measure directly tied to the moment in which the emotions occur. A time frame "since the last beep" may risk losing the specifics of the situations as multiple instances of ER could have happened since the last beep.

Concerning specifics of the situation, there appears to be strong consensus concerning the episodic nature of emotions, lasting seconds to minutes (e.g., Frijda, 1986; Gross, 2014). Indeed, theories and derived hypotheses surrounding ED often posit that the very reason that ED is adaptive is because the experienced emotions point to potential actions to be taken in a *particular situation* (e.g., Demiralp et al., 2012; Grühn et al., 2013; Kashdan et al., 2015). When calculating ED *across* assessment points (across the whole study period or across 1 day), one is left with an index that carries little information about the situational specifics. This could be argued to be appropriate when investigating overall associations between ED and general well-being or mental health (e.g., associations between ED and psychopathology; Smidt and Suvak, 2015) or changes in

[3]These analyses were suggested in the review process and were thus not determined *a priori*.

TABLE 6 | Results from separate multilevel models evaluating the association between daily emotion regulation strategies as a continuous measure and person-level and person mean-centered daily negative emotion differentiation (ED) (without/with daily negative emotions as a covariate).

	Reflection	Distancing	Non-reactivity	Reappraisal	Rumination	Experiential avoidance	Expressive suppression	Worry
Person-level negative ED	$t = 0.6/0.2$ $p = 0.550/0.816$ $r = 0.06/0.02$	$t = 2.8/0.2$ $p = 0.006/0.840$ $r = 0.29/0.02$	$t = 2.6/0.2$ $p = 0.012/0.807$ $r = 0.27/0.03$	$t = 0.1/-0.1$ $p = 0.957/0.953$ $r = 0.01/0.01$	$t = -2.9/-0.4$ $p = 0.004/0.712$ $r = -0.30/-0.04$	$t = -2.4/-0.4$ $p = 0.019/0.655$ $r = 0.25/0.05$	$t = -1.1/0.4$ $p = 0.273/0.671$ $r = -0.12/0.04$	$t = -3.7/-1.3$ $p < 0.001/0.195$ $r = -0.36/-0.14$
Person mean-centered daily negative ED	$t = -1.2/-0.2$ $p = 0.235/0.852$ $r = -0.13/-0.02$	$t = 3.9/1.7$ $p = <0.001/0.089$ $r = 0.39/0.18$	$t = 2.9/0.8$ $p = 0.005/0.410$ $r = 0.30/0.09$	$t = -0.9/0.4$ $p = 0.363/0.710$ $r = 0.10/-0.04$	$t = -3.0/-0.4$ $p = 0.004/0.792$ $r = -0.31/-0.03$	$t = -2.2/-0.1$ $p = 0.028/0.942$ $r = -0.23/-0.01$	$t = -2.5/-1.9$ $p = 0.014/0.061$ $r = -0.26/-0.20$	$t = -4.4/-1.1$ $p < 0.001/0.282$ $r = -0.43/-0.12$

TABLE 7 | Results from separate multilevel models evaluating the association between daily emotion regulation strategies as a categorical measure (present or not present) and person-level and person mean-centered daily negative emotion differentiation (ED) (without/with daily negative emotions as a covariate).

	Reflection	Distancing	Non-reactivity	Reappraisal	Rumination	Experiential avoidance	Expressive suppression	Worry
Person-level negative ED	$z = 0.31/0.37$ $p = 0.760/0.708$ $r = 0.03/0.04$	$z = 2.69/0.12$ $p = 0.003/0.901$ $r = 0.32/0.01$	$z = 2.43/0.29$ $p = 0.015/0.769$ $r = 0.26/0.03$	$z = 0.19/-0.04$ $p = 0.845/0.965$ $r = 0.02/<-0.01$	$z = -2.67/0.16$ $p = 0.008/0.872$ $r = -0.28/0.02$	$z = -2.34/-0.38$ $p = 0.019/0.701$ $r = -0.25/-0.04$	$z = -1.32/0.80$ $p = 0.186/0.424$ $r = -0.14/0.09$	$z = -3.42/-1.62$ $p = 0.001/0.105$ $r = -0.35/-0.17$
Person mean-centered daily negative ED	$z = 1.06/1.42$ $p = 0.290/0.155$ $r = 0.11/0.15$	$z = 1.76/-0.36$ $p = 0.079/0.717$ $r = 0.19/-0.04$	$z = 2.46/0.60$ $p = 0.014/0.549$ $r = 0.26/0.06$	$z = -0.83/0.10$ $p = 0.408/0.923$ $r = -0.09/0.01$	$z = -2.09/0.79$ $p = 0.036/0.428$ $r = 0.22/0.08$	$z = -0.95/0.98$ $p = 0.343/0.326$ $r = -0.10/0.10$	$z = -1.09/-0.13$ $p = 0.276/0.897$ $r = -0.12/-0.01$	$z = -2.11/0.43$ $p = 0.035/0.668$ $r = -0.22/0.05$

general ED skills over time (e.g., as ED may improve with psychotherapy; Van Der Gucht et al., 2019; Mikkelsen et al., 2021). However, it may not be considered appropriate when it comes to evaluating the potential effect of ED on choice of particular ER strategies calibrated to the particular situation. This has led some researchers to distinguish between trait and state ED (Tomko et al., 2015; O'Toole et al., 2020; Thompson et al., 2021), where "trait" refers to ED at the person level and calculated across a number of assessment points, and "state" refers to a single, momentary rating in a particular situation. Indeed, Tomko et al. (2015) argue that ED should be evaluated both at the trait and state level, claiming that disaggregating trait-level indicators into their state occurrences is a key step in understanding how ED influences behavior. Hence, the lack of significant associations between negative ED and ER choice identified in the present study may be a result of assessing ED across multiple measurement occasions as this produces an index that does not account for the calibration of ER to the specific situational contexts.

Concerning the empirical investigation of ED at the state level, research is still in its infancy. In a systematic review and meta-analysis, O'Toole et al. (2020) identified only two studies that had investigated the association between state ED on the one side and specific situational behaviors on the other (wise reasoning; Grossmann et al., 2016a; impulsivity; Tomko et al., 2015), both finding associations in the expected direction. More research of this type is needed to evaluate the effect of ED on ER at the situational level where emotions unfold and are believed to exert their influence. Furthermore, it would be important to empirically establish the causal relationship between ED and ER strategy choice, for which the theoretical assumption in the literature primarily points to a causal link *from* ED *to* ER (Kashdan et al., 2015; Thompson et al., 2021). Here, ED is believed to facilitate access to the information that emotions carry, making them less overwhelming and easier to regulate in a context-appropriate way (Barrett et al., 2001, Kashdan et al., 2010). However, an alternative possibility is that certain ER strategies exert an influence on ED, potentially facilitating better ED. Sometimes ER efforts may be employed specifically with the purpose of gaining a nuanced awareness of current emotions. Psychotherapies such as emotion regulation therapy (ERT; Mennin and Fresco, 2015) and acceptance-based behavior therapies (e.g., Roemer and Orsillo, 2009) teach clients a range of mindfulness-based ER strategies with which to gain such awareness. In these instances, improved ER skills (e.g., improved ability to use healthy strategies such as distancing over unhealthy strategies such as worry; Mennin and Fresco, 2015) may facilitate better emotion processing (Borkovec et al., 2004; Newman and Llera, 2011), which may in turn lead to improved ED (Mikkelsen et al., 2021). For the empirical investigation of ED at the state level, different analytic approaches have been developed. Derived from the person-level ED ICC, Erbas et al. (2021) introduce a momentary ED index, concerning fluctuations in ED relative to the person's overall level of ED. In addition, Grossmann et al. (2016a,b) have quantified state ED as a combined index of the number of experienced emotions (richness) and the relative intensity of each of the emotions (evenness). Finally, Tomko et al. (2015) have proposed yet another approach. They have estimated an individual's momentary ED by using variance decomposition analyses, in which negative affect subscale (e.g., for fear, hostility, sadness) and items per subscale (e.g., 5 items per subscale) are entered as sources of variability (i.e., factors) in an ANOVA model. From this model, researchers can derive an indicator of ED capturing the consistency of ratings across negative affect subscales in a given moment.

As for the conceptualization of ER strategies as putatively adaptive or maladaptive, the detected associations between person-level ER strategies and emotions were largely as expected. The same was true when investigating person mean-centered ER with the exception of reappraisal, which was positively associated with negative emotions. Such associations could point to the emotional effect of ER strategies, however, they could also reflect that individuals are more prone to use certain strategies over others in response to either positive or negative emotions.

The present results should be viewed in light of important limitations. First, the number of daily prompts was relatively low (i.e., 3 and 4 prompts) and past studies have suggested to calculate daily ICCs only for individuals with a higher number of completed prompts per day (e.g., 6 ESM prompts per day, Erbas et al., 2018). This small number of prompts may pose a threat to the reliability of the daily ICCs. Further in regard to the ICC, we opted to delete negative ICCs. Other approaches have sometimes been used in the literature such as retaining negative ICCs by forcing them to assume a value of 0 (Thompson et al., 2021). Second, the sample size was relatively small ($n = 90$) and this number was not determined *a priori* with the present analyses in mind. In terms of statistical power, we were not able to detect effect sizes of a small to medium magnitude ($r = 0.20$) as statistically significant in the full MLM controlling for negative emotions. Future studies could look to this effect size for the determination of their sample size. Third, two samples were combined in order to increase sample size and thereby statistical power. Although they were largely similar concerning baseline characteristics, it cannot be ruled out that the slight difference in procedures may have affected the investigated ED–ER association. In addition, while the validity (i.e., association between the full ER scale at baseline and the daily scores) and reliability (i.e., within-person correlation between the two daily items across the study period) were generally acceptable, two exceptions should be noted. Validity was low for the reappraisal items, although coming close to the pre-determined criterion (0.27 vs. 0.30). In this regard, it should be mentioned that mixed results have previously been found concerning the strength of the association between trait and daily measures of ER (McMahon and Naragon-Gainey, 2020). This could both point to habitual or trait ER being differentially associated with daily ER depending on the strategy, or to measurement error in the daily measures with only few items (i.e., often only one item and in the present study two). Furthermore, reliability was low for the items pertaining to distancing and experiential avoidance. Such finding may reflect different facets of the ER strategies being measured or even different ER strategies altogether. However, although not meeting the $r \geq 0.5$ criterion, the items were moderately correlated ($rs \geq 0.3$). Finally, positive ED and other measures of emotion experience complexity (e.g., emotion covariation, emotion variability; Grühn et al., 2013) were not evaluated, leaving it unclear how the findings extend to such.

In conclusion, the results of the present study add to the sparse literature concerning the link between ED and ER. The present findings indicate weak or no associations between ED and ER strategy endorsement when controlling for negative emotions. Experimental research addressing ED at the momentary level and teasing out the causal relationship between ED and choice of ER strategies is needed to gain further insight into this matter. Such insight may represent an important step toward refining psychotherapeutic interventions aimed at improving emotion problems.

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: doi: 10.17632/bnxjdwhzh6.1.

ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

EE was responsible for preparing and conducting the experiments, MO'T and MM for analyzing the resulting data, and MO'T for writing the initial draft of this paper. All authors developed and formulated the overarching research goals, contributed to the article, and approved the submitted version. The authors state that they have reported all measures, conditions, data exclusions, and reflections on sample sizes.

FUNDING

This research was supported by Aarhus School of Business and Social Sciences (BSS) Aarhus University with a research award granted to MO'T.

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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ORIGINAL RESEARCH
published: 28 July 2021
doi: 10.3389/fpsyg.2021.704125

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Emotional Granularity Increases With Intensive Ambulatory Assessment: Methodological and Individual Factors Influence How Much

Katie Hoemann[1], Lisa Feldman Barrett[2,3,4] and Karen S. Quigley[2,5]*

[1]Department of Psychology, Katholieke Universiteit, Leuven, Belgium, [2]Department of Psychology, Northeastern University, Boston, MA, United States, [3]Department of Psychiatry, Harvard University, Boston, MA, United States, [4]Athinoula A. Martinos Center for Biomedical Imaging, Massachusetts General Hospital, Charlestown, MA, United States, [5]Bedford VA Medical Center, Bedford, MA, United States

OPEN ACCESS

Edited by:
*Jennifer Marie Binzak Fugate,
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Reviewed by:
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University of Michigan, United States*

****Correspondence:***
*Katie Hoemann
khoemann@gmail.com*

Specialty section:
*This article was submitted to
Emotion Science,
a section of the journal
Frontiers in Psychology*

Received: *01 May 2021*
Accepted: *22 June 2021*
Published: *28 July 2021*

Citation:
Hoemann K, Barrett LF and Quigley KS (2021) Emotional Granularity Increases With Intensive Ambulatory Assessment: Methodological and Individual Factors Influence How Much. Front. Psychol. 12:704125. doi: 10.3389/fpsyg.2021.704125

Individuals differ in their ability to create instances of emotion that are precise and context-specific. This skill – referred to as *emotional granularity* or *emotion differentiation* – is associated with positive mental health outcomes. To date, however, little work has examined whether and how emotional granularity might be increased. Emotional granularity is typically measured using data from experience sampling studies, in which participants are prompted to report on their emotional experiences multiple times per day, across multiple days. This measurement approach allows researchers to examine patterns of responses over time using real-world events. Recent work suggests that experience sampling itself may facilitate increases in emotional granularity in depressed individuals, such that it may serve both empirical and interventional functions. We replicated and extended these findings in healthy adults, using data from an intensive ambulatory assessment study including experience sampling, peripheral physiological monitoring, and end-of-day diaries. We also identified factors that might distinguish individuals who showed larger increases over the course of experience sampling and examined the extent of the impact of these factors. We found that increases in emotional granularity over time were facilitated by methodological factors, such as number of experience sampling prompts responded to per day, as well as individual factors, such as resting respiratory sinus arrhythmia. These results provide support for the use of experience sampling methods to improve emotional granularity, raise questions about the boundary conditions of this effect, and have implications for the conceptualization of emotional granularity and its relationship with emotional health.

Keywords: emotional granularity, emotion differentiation, experience sampling, ecological momentary assessment, daily diary, ambulatory assessment, intervention

INTRODUCTION

Individuals differ in their ability to create instances of emotion that are precise and context-specific – a skill referred to as *emotional granularity* (Tugade et al., 2004) or *emotion differentiation* (Barrett et al., 2001). The construct of emotional granularity highlights emotional experiences that are differentiated based on current or anticipated circumstances. As typically measured, emotional granularity represents the extent to which an individual distinguishes between like-valenced emotions (e.g., anger vs. sadness and excitement vs. pride) over time. Recent studies have shown that emotional granularity varies not only between but also within individuals over time (Tomko et al., 2015; Erbas et al., 2018, 2021), suggesting that it may be shaped and even improved. Moreover, accumulating evidence illustrates that higher emotional granularity is often associated with positive health outcomes in both clinical and non-clinical samples (Kashdan et al., 2015; Smidt and Suvak, 2015; Barrett, 2017a; O'Toole et al., 2020; Thompson et al., 2021). To date, however, only a few studies have examined whether and how emotional granularity might be increased (e.g., Van der Gucht et al., 2019; Widdershoven et al., 2019). The answers to these questions are critical for gaining a fuller understanding of the nature of the construct (e.g., its stability over time) as well as for charting its translational potential. In this paper, we provide an initial answer to these questions by first assessing change in participants' emotional granularity across a two-week intensive ambulatory assessment study including experience sampling, peripheral physiological monitoring, and end-of-day diaries. We then explore the relationship between within-individual change and a set of potentially influential methodological and individual factors.

Conceptualizing Emotional Granularity

Emotional granularity is one of multiple related constructs for individual differences in the experience of emotion and has similarities and differences with each. For example, emotional granularity has been described as a type or facet of emotional complexity (Kang and Shaver, 2004; Lindquist and Barrett, 2008; Grühn et al., 2013; O'Toole et al., 2020). Whereas emotional complexity can also refer to the simultaneous experience of multiple emotions or the variability or range of emotional experiences (Kang and Shaver, 2004; Grühn et al., 2013), emotional granularity refers specifically to the precision of emotional experience (Lindquist and Barrett, 2008). Accordingly, emotional granularity has been considered equivalent to (aspects of) emotional clarity (Boden et al., 2013; Cameron et al., 2013) and emotional awareness (Cameron et al., 2013; Mankus et al., 2016), as these constructs also require that individuals unambiguously identify and describe their experienced emotions. The construct of alexithymia describes the inability to identify and describe emotional experiences, and thus is inversely related to emotional granularity (Bermond et al., 1999; Edwards and Wupperman, 2017), with alexithymia equivalent to very low emotional granularity. Where emotional granularity most differs from complexity, clarity, awareness, and alexithymia (among others), however, is in its emphasis on context-specificity.

The central idea behind granularity is that emotional experiences are most adaptive when they are tailored to the needs of the situation at hand. This idea has been elaborated within constructionist, functionalist, and appraisal-based accounts of emotion (O'Toole et al., 2020). Constructionist accounts, such as the theory of constructed emotion (Barrett, 2006, 2012, 2013, 2017a,b), propose that the brain uses prior experience (i.e., concepts) to make meaning of the current situation and issue predictions about what is likely to occur next. The experience of emotion occurs when the brain issues a prediction using a concept for emotion. More context-specific predictions – which come from more precise (emotion) concepts – are more efficient because they better anticipate probable actions and upcoming energy needs (Hoemann et al., 2021). Functionalist (Goldston et al., 1992; Shiota et al., 2014; Plonsker et al., 2017) and appraisal-based accounts (Boden et al., 2013; Erbas et al., 2014, 2018, 2021; Thompson et al., 2021) of emotional granularity, in turn, hypothesize that differentiated emotional experiences are adaptive because they provide more specific or accurate information about the current situation, which enables individuals to react appropriately and engage in more effective emotion regulation (Kalokerinos et al., 2019).

To study the context-specific precision of emotional granularity, scientists need situated emotional experience data that are obtained across multiple contexts. These data are most commonly collected using experience sampling methods (Csikszentmihalyi and Larson, 1987) or ecological momentary assessment (Stone and Shiffman, 1994; see also Thompson et al., 2021), in which participants are prompted to report on multiple emotional experiences per day over the course of multiple days (e.g., Tugade et al., 2004). In principle, this measurement approach allows researchers to examine patterns of responses over time using real-world events. In practice, however, a participant's emotional granularity is usually operationalized as the extent to which their intensity ratings for various emotion adjectives covary across all assessments [e.g., using an intra-class correlation (ICC; Shrout and Fleiss, 1979)], thereby representing an aggregate (i.e., trait) estimate of granularity. Recently, researchers have begun to estimate granularity at the momentary and/or day level (Tomko et al., 2015; Grossmann et al., 2016; Erbas et al., 2018, 2021) and have found that lower emotional granularity within individuals is predictive of behavioral tendencies (e.g., self-reported impulsivity; Tomko et al., 2015) and predicted by current distress and negative affect (Erbas et al., 2018). Furthermore, recent studies have leveraged this within-person variability to examine whether emotional granularity can be increased. For example, Van der Gucht et al. (2019) showed that a mindfulness-based intervention led to improvements in granularity both immediately following the intervention and at a follow-up assessment several months later. The possibility of increasing emotional granularity *via* intervention becomes especially relevant when considering the relationship between higher emotional granularity and various positive mental, behavioral, and social outcomes.

Associations With Positive Outcomes

Reviews and meta-analyses describe a generally positive relationship between emotional granularity and health outcomes (Kashdan et al., 2015; Smidt and Suvak, 2015; Barrett, 2017a; O'Toole et al., 2020; Thompson et al., 2021). Briefly, individuals higher in emotional granularity are less likely to be diagnosed with a range of mental disorders (e.g., Frewen et al., 2008; Suvak et al., 2011;

Erbas et al., 2013; Selby et al., 2013; Kimhy et al., 2014), including depression (Demiralp et al., 2012) and anxiety disorders (Mennin et al., 2005; Kashdan and Farmer, 2014). Higher granularity in non-clinical samples is also related to fewer symptoms associated with depression (Erbas et al., 2014, 2018; Starr et al., 2017; Willroth et al., 2019) and anxiety (Mennin et al., 2005; Seah et al., 2020). Correspondingly, higher granularity is linked to healthier coping behaviors. Individuals with higher granularity report less alcohol consumption during negative emotional experiences (Kashdan et al., 2010), fewer urges to binge eat (Dixon-Gordon et al., 2014), and lower incidence of drug relapse (Anand et al., 2017). Higher emotional granularity also results in fewer negative social outcomes, including decreased urges to physically aggress when provoked (Pond et al., 2012), and reduced neural responses to social rejection (Kashdan et al., 2014). These positive outcomes are more consistently associated with emotional granularity for negative emotions than for positive emotions (O'Toole et al., 2020; Thompson et al., 2021). Nevertheless, there is evidence that higher positive emotional granularity is linked to greater psychological resilience (Tugade et al., 2004).

In addition, increases in emotional granularity, writ broadly, appear to covary with improvements in mental health and other positive outcomes over time. Putting feelings into specific words has been shown to enhance psychotherapeutic efficacy (Kircanski et al., 2012), whereas the inability to do so (i.e., alexithymia) is a negative predictor of success across many disorders (Samur et al., 2013). In a prospective study of individuals with major depressive disorder, those whose alexithymia decreased over the course of a year were more likely to have reduced depressive symptoms (Honkalampi et al., 2001). Emotion-related training in children and adolescents resulted in better self-regulation, social functioning, and academic performance (Hagelskamp et al., 2013; Rivers et al., 2013). In adults, brief emotional granularity training has been shown to improve participants' ability to make nuanced distinctions between emotions and to better understand how their emotions impacted judgments (Cameron et al., 2013). Finally, and compellingly, a recent study by Widdershoven et al. (2019) demonstrated that experience sampling improved emotional granularity in depressed individuals – effectively suggesting that this common method of assessment may serve both empirical and interventional functions (see also Myin-Germeys et al., 2016). However, it is not yet known whether the benefits of experience sampling or other forms of ambulatory assessment (Trull and Ebner-Priemer, 2013) may extend to non-clinical samples, or whether certain methodological and individual factors may facilitate increases in granularity over time.

The Present Study

In the present study, we sought to replicate and extend the findings from Widdershoven et al. (2019) in a non-clinical sample. To do so, we used existing data from an intensive ambulatory assessment study including experience sampling, peripheral physiological monitoring, and end-of-day diaries (Hoemann et al., 2020a, 2021). Participants completed approximately 14, 8-h days of ambulatory assessment, during which their electrocardiogram (ECG), impedance cardiogram (ICG), electrodermal activity, movement, and posture were recorded. Participants responded to experience sampling prompts in the moment, and then elaborated on these responses in end-of-day diaries. As part of these diary entries, participants rated their experience of each event on a set of 18 emotion adjectives and described what was happening and how they were feeling at the time they received each prompt. This data set provided us with the opportunity to test for change in emotional granularity across a longer ambulatory assessment period than used in other studies (e.g., Erbas et al., 2018; Van der Gucht et al., 2019; Widdershoven et al., 2019). This data set also provided a unique opportunity to investigate a range of methodological, behavioral, and physiological variables that may facilitate increases in emotional granularity over time.

Based on the prior literature, we identified seven factors that might distinguish individuals who showed larger increases in granularity over the course of ambulatory assessment. Four of these were "methodological" factors, in that they were directly related to participants' engagement with the study protocol. The first two factors were the number of ambulatory assessment days completed by each participant and the mean number of experience sampling prompts responded to each day – the latter of which provided for a "dose-response" analysis (following Widdershoven et al., 2019). The third and fourth factors were derived from the event descriptions participants provided in the end-of-day diaries: the mean length of these entries and the mean percentage of affective language used in these entries. These factors were motivated, respectively, by evidence linking expressive writing (e.g., Pennebaker and Chung, 2011) and affect labeling (e.g., Torre and Lieberman, 2018) to positive health outcomes. Writing longer event descriptions may reflect more time spent attending to daily emotional events and may also facilitate the formation of more coherent narratives about these events (see also Burton and King, 2004; Baikie and Wilhelm, 2005). Similarly, using more affective language (including emotion words) to describe experience may reflect increased emotional awareness and meaning-making (Lane et al., 1990; Ottenstein and Lischetzke, 2019).

The final three factors we identified were "individual" factors, which reflected differences in participants' affective experience and peripheral physiological activity that were not directly related to the study protocol. Two of these factors were participants' mean self-reported positive and negative affect (following Van der Gucht et al., 2019). Prior work has shown that differences in affect are related to differences in emotional granularity both within (Erbas et al., 2018) and across individuals (e.g., Demiralp et al., 2012), and that measures of mean affect are strongly predictive of psychological health (Dejonckheere et al., 2019). Lastly, to examine the potential relationship between emotional granularity and peripheral physiological activity, we included resting respiratory sinus arrhythmia (RSA) as our seventh factor. RSA is the variation in heart rate due to respiration and is typically measured as heart rate variability occurring within a specific respiratory frequency range (0.12–0.40 Hz), which is an estimate of vagal (i.e., parasympathetic) influence on the heart (Berntson et al., 1993, 1997; Task Force European Society of Cardiology, 1996). Previous research suggests that higher resting RSA is associated with better emotional and mental health (for a review, see, e.g., Balzarotti et al., 2017) and may facilitate emotional learning (e.g., Pappens et al., 2014).

Using these data, we assessed change in emotional granularity over the course of ambulatory assessment using person-specific regression analyses. These regressions estimated, for each participant, the relationship between assessment day (e.g., day 1 and day 2) and daily values for positive and negative emotional granularity. We conducted separate analyses by valence based on the prior literature showing differential benefits of positive versus negative granularity (Thompson et al., 2021) as well as differential change over time (Widdershoven et al., 2019). We first tested for overall (i.e., group level) change in emotional granularity by comparing the resulting regression coefficients (i.e., slopes) against a null hypothesis of no change. We predicted that both positive and negative granularity would progressively increase over time. Then, in exploratory analyses, we entered the slopes as dependent variables in Bayesian multiple linear regressions including the seven selected methodological and individual factors. This approach allowed us to assess the evidence for these factors' influence on any increase in emotional granularity over time.

MATERIALS AND METHODS

The data used in the present study were collected as part of a larger study on affective experience and decision making in daily life and were previously reported in Hoemann et al. (2020b, 2021). All experimental protocols described below were approved by the Northeastern University Institutional Review Board (IRB# 16-01-13). These methods were carried out in accordance with the relevant guidelines and regulations for research with human subjects.

Participants

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

Of the 67 recruited participants, six withdrew and an additional nine were dismissed due to poor compliance with scheduling and prompt response requirements, as detailed below. Fifty-two participants completed ambulatory assessment, with two participants excluded because they did not complete the full study protocol including an in-lab session after the ambulatory assessment. The final sample size was 50 (54% female; 40% White, 2% Black, 44% Asian, and 14% other; M = 22.5 years, SD = 4.4 years). A sensitivity analysis in G*Power (version 3.1) confirmed that this data set was large enough to detect a difference from a constant (i.e., a one-sample t-test) with a medium effect size (d = 0.40–0.50), assuming $\alpha < 0.05$ and power $(1 - \beta) > 0.80$.

Procedure

Participants completed approximately 14 days (M = 14.4, SD = 0.6) of ambulatory assessment distributed across a three- to four-week period (M = 24.9 days, SD = 5.5 days). The study protocol included experience sampling with peripheral physiological monitoring, as well as end-of-day diaries, which enabled more comprehensive modeling of affective experience. Importantly, we also implemented a novel physiologically triggered experience sampling procedure, as described below, which enabled more efficient sampling of psychologically salient moments. Before and after the ambulatory assessment protocol, participants attended two in-lab sessions, in which they completed tasks and questionnaires that are not reported here (for an overview, see Hoemann, et al., 2020a).

Participants scheduled assessment days in advance according to their schedule, excluding weekends, within the allotted period. As such, not all assessment days occurred consecutively. On each day of ambulatory assessment, participants came to the laboratory to be outfitted with the peripheral physiological monitoring equipment. These sessions typically occurred between 8 and 9 am but varied between 7:30 am and 2:30 pm according to participants' schedules. Participants could not begin without functioning monitoring equipment, and so did not complete the daily protocol if they did not attend the session to be instrumented. In the event, a participant was unable to make a scheduled session, or the equipment was not functioning properly, the assessment day was rescheduled. In principle, the protocol was for 14 assessment days. If there were pervasive issues with the physiological monitoring equipment, participants were requested to complete (and compensated for) additional assessment days. To limit attrition, participants were retained in the study if they completed at least 12 days of ambulatory assessment with usable data. Participants who were unable to complete the minimum number of days within a four-week period were dismissed from the study.

Participants were outfitted with sensors and portable equipment to measure their ECG, ICG, EDA, and bodily movement and posture (*via* accelerometers). All physiological measures were recorded on a mobile impedance cardiograph from the MindWare Technologies LTD (Model # 50-2303-02, Westerville, OH), which participants wore clipped to their clothing on the hip. The cardiograph also collected continuous three-axis accelerometry data that were used to assess movement. Participants wore two inertial measurement units (IMUs) from LP-Research (Minato-ku, Tokyo, Japan) to derive measures of posture and changes in posture. One IMU was placed medially on the sternum and the other IMU was placed on the front of the thigh. See page 1 of the **Supplementary Material** for additional acquisition details. Participants were instructed to continue physiological recordings for 8 h each day, after which they could remove and recharge all equipment. Participants did not remove sensors until the end of each experience sampling day, unless instructed by the experimenters (e.g., due to equipment issues).

Physiological and accelerometric data were recorded continuously throughout the day and the recording devices communicated *via* Bluetooth to a Motorola Moto G4 smartphone. A custom smartphone application, MESA (MindWare Technologies LTD, Westerville, OH), processed the ECG and accelerometer data in real time, and initiated an experience-sampling prompt anytime a substantial, sustained change in interbeat interval (IBI; also known as heart period) was detected in the absence of movement or posture change, with a minimum interval of 5 min between prompts. Minimal movement was operationalized as any time none of the three accelerometry channels from the cardiograph (alone or in aggregate) exceeded a threshold of 10 cm/s^2 within the preceding 30 s. Absence of posture change was operationalized as any time when the relative orientation of the IMUs did not change within the preceding 30 s. On the first day of sampling, a substantial, sustained change in IBI was operationalized as a change of more than ±167 ms for at least an 8-s period. On subsequent days, this IBI parameter was manually adjusted to ensure each participant received approximately 20 prompts per day. This number of prompts was intended to ensure that participant had sufficient opportunities to respond, given that we could not guarantee the exact number of prompts that would be physiologically triggered.

Ultimately, participants received an average of 21.57 (*SD* = 6.06) prompts per day. The total number included an average of two "random" prompts each day. These prompts occurred in the absence of movement or posture change but were not contingent on a change in IBI. Random prompts were spread throughout the assessment day, such that one was sent in the first 4 h and one in the second 4 h. Participants were informed that they did not have to respond to all the prompts they received throughout a given day; they reported liking that they could be flexible in choosing when to respond with meaningful information. On average, participants responded to a prompt every 54 (*SD* = 13) min.

To remain in the study, participants were required to respond to a minimum of three prompts each day. In addition, for the purposes of incentivizing participation and limiting attrition, the ambulatory assessment protocol was broken into three pay periods (days 1–5, 6–10, and 11–14). Participants were required to respond to an average of at least six prompts per day during each period to remain in the study and received a bonus payment for each pay period where they completed an average of eight prompts per day (for details, see page 1 of the **Supplementary Material**). Compliance was assessed during instrumentation sessions: Experimenters would review participants' data from the prior assessment day and discuss any questions or concerns. Participants ultimately responded to an average of 8.65 prompts (*SD* = 1.09) per day, consistent with prior experience sampling studies that have asked participants to respond to 10 prompts per day (e.g., Tugade et al., 2004; Widdershoven et al., 2019). Days in which participants responded to more than 10 prompts were uncommon (19% of participant days) and those in which they responded to more than 15 prompts were rare (4% of participant days).

At each sampling event (regardless of whether it was physiologically or randomly triggered), participants were prompted to respond to a series of questions presented in the MESA phone application. These data were not analyzed in the present study but are summarized here to be transparent about all elements of the ambulatory assessment protocol. First, participants provided a brief free-text description of what was going on at the time they received the prompt. Second, participants rated their current valence and arousal, each on a 100-point continuous slider scale ranging from −50 (very unpleasant or deactivated) to +50 (very pleasant or activated). Third, participants provided a brief free-text description of their social context by: writing "alone," listing the initials of direct interaction partners, and/or writing "group" (to indicate the presence of a large number of other people). Fourth, participants selected a major activity from a drop-down list consisting of: "socializing," "eating," "exercising," "watching TV," "working," "commuting," "using computer/email/Internet," "preparing food," "on the phone," "praying/meditating/worship," "napping," "taking care of children," "housework," or "other." Fifth, participants self-generated words to label their current affective experience. Participants were able to provide as many words as they felt necessary but were required to input at least one. For each self-generated word, participants were asked to provide an intensity rating on a Likert-style scale from 1 ("not at all") to 5 ("very much"). Finally, participants received one of two possible single-item decision tasks: either a temporal discounting problem or a scrambled anagram problem.

Immediately upon finishing each day, participants automatically received a modified day reconstruction diary (Kahneman et al., 2004) *via* SurveyMonkey (San Mateo, CA). Participants were requested to complete the diary as soon as possible after finishing their day of experience sampling. In this diary, they were presented with some of the information provided for each prompt during the day: the event time, brief description, social context, and major activity. Of note, participants were not presented with the words they had self-generated to label their current affective experience. Using this information as a guide, participants were asked to provide additional details about each experience sampling event. First, they were asked to describe the social context of the event, including a brief description of any initials (e.g., "SB is a coworker"). Second, they were asked to provide a description of what was happening as they received the prompt. Participants were requested to choose three sampling events for which they provided a longer description (>200 words). Only three detailed descriptions were requested to limit the amount of burden imposed, as determined through pilot testing. Next, they were asked to recall their affective experience at the time of the prompt in two ways: (1) using slider scales to rate their valence and arousal and (2) using Likert-style scales from 0 ("not at all") to 6 ("very much") to rate their experienced intensity on a standard set of 18 emotion adjectives ("afraid," "amused," "angry," "bored," "calm," "disgusted," "embarrassed," "excited," "frustrated," "grateful," "happy," "neutral," "proud," "relieved," "sad," "serene," "surprised," and "worn out"). These standard intensity ratings were requested in the end-of-day diary, rather than at each experience sampling prompt, to reduce participant burden in the moment. Lastly, participants were asked to respond to a series of seven descriptive appraisal questions developed based on the Geneva Appraisal Questionnaire (Geneva Emotion Research Group, 2002). End-of-day diary data regarding events' social context, associated valence and arousal ratings, and appraisals were not analyzed in the present study but are mentioned with transparency in mind.

Data Preparation

We computed estimates of daily emotional granularity from the intensity ratings for the 18 emotion adjectives rated in the end-of-day diaries. Data from late diaries (i.e., completed the following day) were excluded from analysis (4% of participant days). Following prior literature (e.g., Tugade et al., 2004), we estimated granularity as an ICC using agreement with averaged raters ("A-k" method; Shrout and Fleiss, 1979). Higher ICC values reflected lower emotional granularity (i.e., greater shared variance among adjectives' ratings). To ensure reliable day-level ICCs (Erbas et al., 2018), we excluded days when participants responded to fewer than six prompts (8% of participant days).[1] Similarly, because negative ICC values are beyond the theoretical range, they were also excluded from analysis (following, e.g., Erbas et al., 2018).[2] We computed separate indices of daily granularity for pleasant (positive) versus unpleasant (negative) emotions, with this distinction based on normative ratings (Warriner et al., 2013). ICCs were Fisher r-to-z transformed to fit the variable to a normal probability distribution. We multiplied these transformed values by -1 to yield estimates of daily granularity that scaled intuitively, such that lower (more negative) values reflected lower granularity, and higher (less negative) values reflected higher granularity.

For each participant, we also computed a set of seven predictor variables. Six of these were derived from the end-of-day diary data. First, we counted the number of days completed by each participant and calculated the mean number of experience sampling prompts responded to each day. Next, we entered the event descriptions participants provided in the end-of-day diaries into the Linguistic Inquiry and Word Count software (LIWC; Pennebaker et al., 2015) and used this to calculate the mean length of entries and the mean percentage of affective language used (i.e., from the LIWC "affect" dictionary). Using the intensity ratings for the 18 emotion adjectives, we calculated participants' mean self-reported positive and negative affect as the average ratings of like-valenced emotion adjectives (with this distinction again based on normative ratings; Warriner et al., 2013).

The seventh predictor variable, resting RSA, was derived from the ambulatory peripheral physiological data. As reported in Hoemann et al. (2021), we first identified periods of seated rest in the ECG signal according to the following criteria: participant position was seated and not moving (i.e., no forward acceleration); participant maintained this position for at least 60 s and no experience-sampling prompt was triggered. We excluded data from the first 30 s of each period of seated rest to allow for the ECG signal to stabilize following movement. The ECG signal was processed following prior work (Hoemann et al., 2020a, 2021) using an in-house pipeline coded in Python. For each seated rest period, we derived resting RSA using 30-s bins and computed the mean across all bins. For each participant, we then took the grand mean across all seated rest periods. See page 1 of the **Supplementary Material** for additional details.

Analysis

To assess change in emotional granularity over the course of ambulatory assessment, we conducted person-specific regression analyses estimating the relationship between assessment day (reflecting "time in study") and daily granularity (i.e., inverse day-level ICCs). We fit two models for each participant: one in which assessment day predicted daily granularity for positive emotions and one in which assessment day predicted daily granularity for negative emotions. All variables were standardized prior to analysis for interpretability and comparability across participants. We operationalized change in granularity as the regression coefficient associated with assessment day (i.e., the slope of the independent variable). Positive slopes, then, indicate an increase in emotional granularity over time, whereas negative slopes indicate a decrease. We assessed group-level change in emotional granularity using separate one-sample t-tests, in which the slopes for positive and negative granularity were compared to zero, and we estimated the effect size of this change from the corresponding Cohen's d value.

In general, change over time can be modeled using mixed-effect approaches or using latent-curve approaches (for discussion, see McNeish and Matta, 2018). We broadly followed a mixed-effect approach because our models were simple, each with one outcome variable (i.e., positive versus negative emotional granularity), and because this approach can more easily accommodate small samples and missing data (McNeish and Matta, 2018). In principle, we could have used a mixed-effect approach to estimate the mean change in granularity (i.e., fixed effect) for the entire sample, along with random effects capturing each participant's deviation from the mean change. However, these random effects would not have allowed us to assess the relationship between each participant's absolute change in

[1]The data retained for analysis represented days when participants responded to at least six prompts, which could be interpreted as reflecting relatively high engagement from participants. At the same time, a six-prompt threshold is in keeping with the fact that participants were required to respond to a rolling average of six prompts per day to remain in the study.

[2]The decision to exclude negative day-level ICC values from analysis did not impact most participants: 29 of 50 (58%) participants had no such values; 13 (26%) had only one negative ICC; seven (14%) had two negative ICCs; and only one (2%) had more than two negative ICCs. Excluding the individual with more than two negative ICCs did not substantively change the results.

emotional granularity and individual differences in affective experience and engagement with the study protocol. To do this, we entered the slopes for positive and negative granularity as the dependent variables in separate multiple linear regressions with the seven selected factors as predictors. All variables were again standardized prior to analysis for interpretability. These regressions were fit with Bayesian estimation to quantify evidence in favor of or against any factor's relationship to an increase in granularity (Wagenmakers et al., 2018).

RESULTS

Both positive and negative emotional granularity increased over the course of ambulatory assessment: positive $t(49) = 3.54$, $p < 0.001$, two-tailed; negative $t(49) = 2.26$, $p \leq 0.03$, two-tailed. That is, the shared variance among participants' emotion intensity ratings decreased with more time in study.[3] The estimated effect sizes – $d = 0.50$ and $d = 0.32$, respectively – indicated that experience sampling had a medium treatment effect and that this was larger for positive than negative granularity. Nevertheless, the direction and magnitude of change in emotional granularity varied across the sample (see **Supplementary Figures 1, 2** for plots across individual participants). Participants also differed in terms of engagement in the study protocol, affective experience, and peripheral physiological activity, as represented by the predictor variables. Descriptive statistics for all variables are provided in **Table 1**.

Figure 1 depicts the results of the regressions for increases in positive and negative emotional granularity, respectively, as predicted by the methodological and individual factors (for details, see **Supplementary Tables 2 and 3**). Each panel is a violin plot of the posterior distributions (i.e., estimated βs) for the intercept and all seven factors. The likelihood of a factor's relationship to change in emotional granularity (i.e., its posterior probability) is represented by the extent to which each distribution (i.e., violin) overlaps zero (Franke and Roettger, 2019). For example, violins above zero with $\leq$ 5% of their area extending below zero represent factors that positively influence change in granularity with $\geq$ 95% probability, whereas violins below zero with $\leq$ 5% of their area extending above zero represent factors that negatively influence change in granularity with $\geq$ 95% probability.

TABLE 1 | Descriptive statistics across individuals.

Variable	Mean	*SD*	Min	Max
Dependent variables				
Change in positive emotional granularity	0.16	0.33	−0.54	0.92
Change in negative emotional granularity	0.12	0.37	−0.70	0.97
Predictor variables				
Included assessment days	13.12	1.41	8	15
Mean number of prompts per day	8.98	1.14	6.86	12.31
Mean length (words) of event descriptions	94.16	17.23	65.29	137.76
Mean percentage of affective language	5.39	1.51	2.41	9.31
Mean positive affect (0–6 scale)	2.22	0.63	1.49	4.41
Mean negative affect (0–6 scale)	1.62	0.42	1.16	3.25
Mean resting RSA (natural log; ln)	8.82	0.80	6.51	10.26

Daily emotional granularity estimated as the inverse of the intra-class correlation over the intensity ratings for positively- and negatively-valenced emotion adjectives, respectively. Change in positive and negative emotional granularity operationalized as the regression coefficient associated with assessment day when used to predict daily granularity, such that positive values reflect increases in granularity over time and negative values reflect decreases in granularity over time.

As illustrated in the left panel of **Figure 1**, there is a 98% likelihood that the mean number of experience sampling prompts per day was positively associated with increase in positive emotional granularity [β = 0.32, 95% Credible Interval (CI) = (0.04, 0.61)], such that participants who responded to more prompts showed larger granularity increases over the course of ambulatory assessment. There is also a 99% likelihood that resting RSA was positively associated with an increase in positive emotional granularity [β = 0.34, 95% CI = (0.05, 0.53)], such that participants with higher seated resting RSA values showed larger granularity increases over the course of ambulatory assessment.[4] There is no evidence that increase in positive emotional granularity was associated with the number of days of ambulatory assessment included [β = 0.11, 95% CI = (−0.18, 0.41)], the mean length of event descriptions provided in end-of-day diaries [β = −0.09, 95% CI = (−0.37, 0.20)], the mean percentage of affective language used in event descriptions [β = −0.02, 95% CI = (−0.30, 0.26)], or mean self-reported positive [β = −0.13, 95% CI = (−0.46, 0.20)] or negative [β = 0.06, 95% CI = (−0.27, 0.40)] affect.

[3]Recent studies suggest that emotional granularity might be indexed by the words used to label affective experience (e.g., Ottenstein and Lischetzke, 2019). Affect labeling is also related to emotion regulation (e.g., Torre and Lieberman, 2018). As such, it is possible that the number of words participants used to label their current experience at each experience sampling prompt was related to changes in emotional granularity over time. We observed that the number of words used per prompt/day decreased over time (mean person-specific slope = −0.21, SD = 0.35). However, we also observed that the total number of words each participant used across the study was positively correlated with their overall positive (r = 0.21) and negative (r = 0.23) emotional granularity. Given these observations, the number of words used per prompt/day may not have a straightforward relationship with changes in emotional granularity. A full test of this hypothesis, with appropriate control for other important covariates, awaits future research.

[4]Respiratory sinus arrhythmia (RSA) is the phenomenon of respiratory-modulated variation in the time interval between successive heart beats or the interbeat interval (IBI). In the present study, substantive and sustained changes in IBI were used to trigger the majority of experience sampling prompts, leading to the question of whether the relationship between IBI and RSA could influence our findings. We consider this possibility unlikely. We derived estimates of resting RSA for each participant based on periods of seated rest during which no experience sampling prompts were triggered. In this way, we separated IBI changes associated with specific, triggered prompts from ongoing, natural respiratory-related variation. More broadly, experience sampling prompts could be triggered by decreases or increases in IBI (cardiac acceleration or deceleration, respectively; prompts could also be random). Momentary changes in IBI may reflect sympathetic and/or parasympathetic effects on the heart, whereas resting RSA reflects overall parasympathetic influence. Thus, these variables have distinct physiological bases and would not be expected to directly predict one another, even if measured during the same periods.

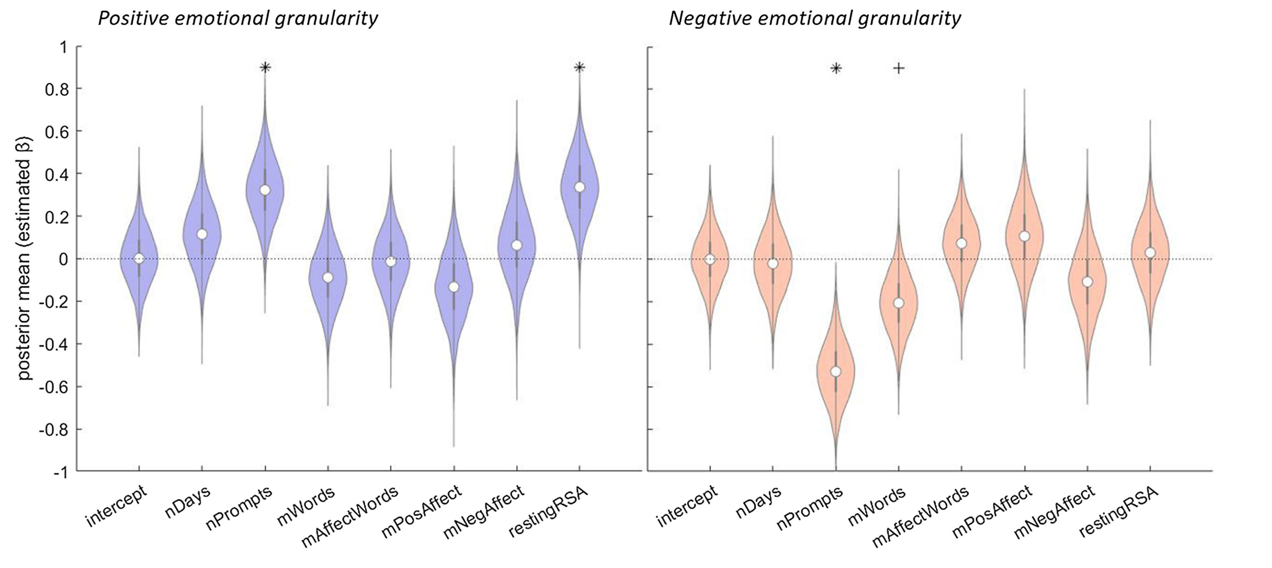

FIGURE 1 | The relationship between methodological and individual factors and change in emotional granularity over the course of ambulatory assessment. *Left panel:* positive granularity as the dependent variable. *Right panel:* negative granularity as the dependent variable. The results of Bayesian multiple regressions are shown. Violins represent the posterior distributions (i.e., estimated βs) for each factor based on 10,000 Monte Carlo samples. In the boxplots, the center dots represent medians, and the thick gray lines extend to the first and third quartiles. The whiskers extend from the quartile to 1.5 times the interquartile range. The likelihood of a factor's relationship to change in emotional granularity (i.e., its posterior probability) is represented by the violins' extents around zero, with zero indicated by the dotted horizontal black line. Factor names: nDays, number of days of ambulatory assessment included; nPrompts, mean number of experience sampling prompts responded to per day; mWords, mean length of event descriptions provided in end-of-day diaries; mAffectWords, mean percentage of affective language used in event descriptions; mPosAffect, mean self-reported positive affect; mNegAffect, mean self-reported negative affect; and restingRSA, mean respiratory sinus arrhythmia value across all periods of ambulatory seated rest. *probability ≥ 95%; + probability ≥ 90%.

As illustrated in the right panel of **Figure 1**, there is a > 99% likelihood that the mean number of experience sampling prompts per day was negatively associated with an increase in negative emotional granularity [$\beta = -0.53$, 95% CI = (−0.80, −0.24)]. In other words, participants who responded to more prompts showed smaller increases (or even decreases) in negative granularity over the course of ambulatory assessment. There is also a 94% likelihood that the mean length of event descriptions was negatively associated with an increase in negative emotional granularity [$\beta = -0.21$, 95% CI = (−0.48, −0.07)], such that participants who wrote more about each event showed smaller increases (or even decreases) over the course of ambulatory assessment. There is no evidence that increase in negative emotional granularity was associated with the number of days of ambulatory assessment included [$\beta = -0.02$, 95% CI = (−0.31, 0.27)], the mean percentage of affective language used in event descriptions [$\beta = 0.07$, 95% CI = (−0.20, 0.35)], mean self-reported positive [$\beta = 0.11$, 95% CI = (−0.21, 0.43)] or negative [$\beta = -0.11$, 95% CI = (−0.43, 0.22)] affect, or resting RSA [$\beta = 0.03$, 95% CI = (−0.27, 0.33)].

DISCUSSION

In a sample of healthy adults, we found that both positive and negative emotional granularity increased over the course of an intensive, two-week ambulatory assessment study that included peripheral physiological monitoring and end-of-day diaries. Subsequent exploratory analyses suggested that methodological factors, such as engagement with the study protocol (i.e., number of experience sampling prompts responded to each day and length of end-of-day event descriptions), and individual factors, such as affective experience and peripheral physiological activity (i.e., resting RSA), were related to the observed effects, and differentially influenced changes in positive and negative granularity. These findings broadly replicate and extend recent work (Widdershoven et al., 2019), providing further support for the use of ambulatory assessment methods to improve emotional granularity. These findings also raise questions about the boundary conditions associated with increases in emotional granularity and have implications for the conceptualization of emotional granularity and its relationship with emotional health.

Experience sampling, the most common method used to obtain a measure of emotional granularity (Thompson et al., 2021), allows researchers to examine patterns of emotion adjective co-occurrence over time using real-world events. It also requires participants to attend repeatedly to their emotional experiences, thereby providing a context that may facilitate increases in emotional granularity. Indeed, it has been hypothesized that higher emotional granularity may reflect habitual processing of affective stimuli in a differentiated and more complex manner (Lee et al., 2017), and that emotional granularity may be increased by intentionally reflecting upon and diversifying affective experiences (Cameron et al., 2013, 2014; Barrett, 2017a). It is possible that ambulatory assessment protocols such as that used here assist in these endeavors by asking participants to observe their emotions more frequently and/or thoroughly than they would otherwise. Although we did not systematically assess participants' experiences with the current protocol, we did gather anecdotal evidence during daily check-ins and at the final study debriefing. In these informal reports, many participants indicated feeling more aware of their emotions and more "mindful" after completing the ambulatory assessment protocol and found this beneficial. These comments are consistent with the idea that experience sampling may direct or focus attention on emotional experience.

Several study design choices can influence whether and by how much emotional granularity increases over the course of a given ambulatory assessment protocol. Studies can differ in terms of protocol length (i.e., number of days) and intensity (i.e., the number of experience sampling prompts per day, the average duration between prompts, and the number of emotion terms rated; Thompson et al., 2021; see also Kirtley et al., 2021). Two of these parameters – length of protocol and number of prompts administered – varied among participants in the current study and could be assessed for their impact. The results of our exploratory analyses suggest that the number of prompts responded to each day may be a key factor in the extent to which emotional granularity increases with time in study. We also found that this factor had the opposite effect on positive and negative emotional granularity. There was evidence that more prompts facilitated increases in positive granularity, suggesting a dose-response relationship, yet there was also evidence that more prompts reduced increases (or even facilitated decreases) in negative granularity. The effect on negative granularity in our results may be due to increased sampling fatigue which, by increasing distress or negative affect, could have reduced granularity for negative emotions (Erbas et al., 2018). However, recent work by Eisele et al. (2020) provides evidence against this possibility. That team found that longer prompts increased participant burden, whereas higher prompt frequency was not associated with negative consequences. Because we allowed participants to choose (beyond a necessary minimum) how many prompts they responded to, the effect of number of prompts may not be observable in studies that stipulate a specific number of prompts to be answered.

In addition, this study was the first to use a two-step approach to assess emotional granularity, in which participants received experience sampling prompts during the day and provided additional information (including emotion intensity ratings) for each prompt in end-of-day diaries. The combination of momentary and daily diary assessment has precedent in the literature (e.g., Businelle et al., 2016); it is also not uncommon to assess emotional granularity using daily diary methods in which participants rate emotional events from earlier in the day (e.g., Barrett et al., 2001; Dasch et al., 2010; for a review, see Thompson et al., 2021). It is possible that a two-step approach influenced the data obtained at end of day by, for example, providing an opportunity for initial emotion regulation in the moment (e.g., *via* affect labeling; Torre and Lieberman, 2018) or introducing some recall bias (e.g., Levine and Safer, 2002; but see Schneider et al., 2020). However, the end-of-day diaries provided participants with details recorded at the time of the experience sampling prompts, in theory allowing them to re-instantiate earlier experiences with greater fidelity. More broadly, a two-step approach raises the question of which aspect of ambulatory assessment was responsible for the observed increases (i.e., the events captured during the day versus the reflection on these events in the evening). Future studies can address these considerations by testing the effect of ambulatory assessment on healthy adults using a more typical experience sampling protocol (e.g., Tugade et al., 2004), without the addition of peripheral physiological monitoring or end-of-day diaries. In this respect, the present study design represents an upper bound of study complexity and cannot be used to determine the minimum necessary protocol elements that are needed to observe increases in emotional granularity.

In this study, we sought to replicate and extend recent work by Widdershoven et al. (2019). The authors of that study found that experience sampling improved both positive and negative emotional granularity in depressed individuals. In contrast to the present study, however, the change in positive granularity did not reach significance. Widdershoven et al. (2019) also did not find evidence of a dose-response relationship between number of experience sampling prompts and increase in granularity. Those authors attributed the latter result to a relatively small sample size (N = 55), yet a dose-response relationship was found in the present study, which was also limited by a similar sample size (N = 50). These differences in results could be due to differences in the method of ambulatory assessment used. For example, participants in the present study completed approximately 14 days of assessment across a three- to four-week period, whereas participants in Widdershoven et al. (2019) completed 18 days of experience sampling across a six-week period (at a rate of three consecutive days per week). Participants in Widdershoven et al. (2019) also completed separate baseline and post-intervention measures of emotional granularity, whereas in the present study, changes were assessed continuously over the course of the ambulatory assessment period. As noted previously, the present study was not expressly designed with replication in mind, and so it may not be representative of the kinds of parameter settings that may be used in more typical ambulatory assessment studies.

These considerations notwithstanding, the present findings have implications for the conceptualization of emotional granularity. Until fairly recently, emotional granularity has been operationalized as a trait, using a single aggregate estimate per person (Tugade et al., 2004). The observation that emotional granularity changes over the course of experience sampling is consistent with other evidence that documents meaningful within-person variability in granularity over time (Tomko et al., 2015; Grossmann et al., 2016; Erbas et al., 2018, 2021). In particular, our finding of increases in emotional granularity as a function of study engagement supports the hypothesis that granularity is a skill that can be acquired and improved (Kashdan et al., 2015). The idea that emotional granularity may be enhanced through practice has been advanced by constructionist accounts of emotion, which propose that intentional focus on emotional experience may help to elaborate and diversify emotion concepts (Barrett, 2017a; see also Averill, 1999; Hoemann, et al., 2020b). However, it is not yet clear what form this practice should take.

As discussed above, we found that participants who responded to more experience sampling prompts per day showed larger increases in positive emotional granularity but smaller increases (or even decreases) in negative emotional granularity. This finding may be related to differential effects of attending to positive versus negative experience. For example, attending to positive experiences more often or more deliberately may encourage savoring, or adaptive forms of rumination. This possibility is supported by prior studies that have instructed participants to reminisce about past experiences or focus on the present moment as a means of intensifying or prolonging positive feelings, with corresponding benefits for wellbeing (e.g., Smith et al., 2014). This possibility is further consistent with prior work linking positive granularity with the broaden-and-build framework for positive emotions and effective coping (Tugade et al., 2004). However, there is also evidence to suggest that higher positive granularity may impede savoring (Starr et al., 2017). Research is needed to further investigate the relationship between positive granularity and real-world outcomes, and the circumstances in which positive granularity is beneficial (for discussion, see Thompson et al., 2021).

In contrast, increased attention to negative experiences may encourage maladaptive forms of rumination. This possibility is supported by prior studies that have found associations between low negative granularity and rumination (e.g., Di Schiena et al., 2011; Starr et al., 2017). It is also supported by findings from the expressive writing literature suggesting that the use of negative emotion words is non-linearly related to improved wellbeing, such that a moderate number of negative emotion words is associated with greatest benefit (for review, see Pennebaker et al., 2003). Indeed, in the present study, we also found that participants who wrote longer event descriptions in the end-of-day diaries showed smaller increases in negative emotional granularity. Taken together, these findings suggest that, past a certain point, attending more often or at greater length to one's negative emotional experiences may reduce the benefits of practice. This possibility, and the long-term effects of practice on both positive and negative emotional granularity, remains to be tested by future research.

The present findings also contribute to our understanding of the relationship between emotional granularity, affective experience, and peripheral physiological activity. Our finding that larger increases in positive emotional granularity were associated with higher resting RSA is especially noteworthy given prior evidence of a positive relationship between resting RSA and both emotional and mental health (e.g., Balzarotti et al., 2017), and the potential role of RSA in facilitating emotional learning (e.g., Pappens et al., 2014). Our finding is also consistent with studies demonstrating associations between higher resting RSA and stable positive affect (Oveis et al., 2009; Koval et al., 2013) and builds on recent work with this same sample showing a positive relationship between overall emotional granularity and resting RSA in daily life (Hoemann et al., 2021). The exact nature of the link between emotional granularity and resting RSA is an open question. Both emotional granularity (Barrett et al., 2001; Kalokerinos et al., 2019) and resting RSA (e.g., Appelhans and Luecken, 2006; Geisler et al., 2010; Williams et al., 2015; Mather and Thayer, 2018) are associated with better self-regulation and adaptive coping strategies. Positive emotional granularity, although receiving less attention than negative granularity (O'Toole et al., 2020), has specifically been linked to psychological resilience (Tugade et al., 2004). The hypothesized mechanisms underlying these connections vary depending on the theoretical framework used, with some emphasizing neurobiological pathways and dynamics of RSA (Thayer and Lane, 2000; Porges, 2007), some highlighting functional advantages of positive emotions (Fredrickson, 2001; Shiota et al., 2014), and others proposing more domain-general models of psychological and physiological regulation (Barrett, 2017b; Gianaros and Jennings, 2018). Although the present findings cannot directly address questions of mechanism, they inform future studies by suggesting that emotional granularity is amenable to the experimental manipulation necessary to gain insight into causality.

This study, like Widdershoven et al. (2019), was inspired by accumulating research that uses experience sampling and other ambulatory assessment methods as a form of mental health intervention [i.e., ecological momentary interventions (EMIs; e.g., Myin-Germeys et al., 2016, 2018)]. The causal paths by which emotional granularity and emotional or mental health are related are not yet known. However, emotional granularity is a compelling potential target for intervention given growing evidence of associations between higher emotional granularity and positive health outcomes (reviewed in Kashdan et al., 2015; Smidt and Suvak, 2015; Barrett, 2017a; O'Toole et al., 2020; Thompson et al., 2021), as well as conceptual links between higher granularity and adaptive situated functioning (e.g., Barrett, 2017a; Erbas et al., 2021; Thompson et al., 2021). In this study, we have shown that emotional granularity can be increased in the absence of explicit instructions, suggesting that intensive ambulatory assessment can increase both positive and negative emotional granularity, perhaps by shifting attention to emotional experience in daily life. These findings join others (Cameron et al., 2013; Van der Gucht et al., 2019; Widdershoven et al., 2019) in laying a foundation for a line of transformative research on how emotional granularity training may shape everyday emotional experiences, with the potential for positive impacts on wellbeing and health.

DATA AVAILABILITY STATEMENT

Publicly available data sets were analyzed in this study. This data can be found at https://osf.io/dk569/.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Institutional Review Board, Northeastern

University. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

KH assisted with data collection and pre-processing, analyzed the data, and wrote the manuscript. KH and KQ designed the analysis. All authors reviewed and revised the manuscript. All authors contributed to the article and approved the submitted version.

FUNDING

KH was supported by the National Heart, Lung, and Blood Institute (grant number 1F31HL140943-01) and a P.E.O. International Scholar Award. This work was further supported by the US Army Research Institute for the Behavioral and Social Sciences (grant number W911NF-16-1-0191 to KQ and Dr. Jolie Wormwood, Co-PIs). The views, opinions, and/or findings contained in this paper are those of the authors and shall not be construed as an official Department of the Army position, policy, or decision, unless so designated by other documents.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at https://www.frontiersin.org/articles/10.3389/fpsyg.2021.704125/full#supplementary-material

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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frontiers in Psychology

ORIGINAL RESEARCH
published: 02 August 2021
doi: 10.3389/fpsyg.2021.689407

Negative Emotion Differentiation Predicts Psychotherapy Outcome: Preliminary Findings

Gal Lazarus and Aaron J. Fisher*

Department of Psychology, University of California, Berkeley, Berkeley, CA, United States

Emotion differentiation (ED), the extent to which same-valenced emotions are experienced as distinct, is considered a valuable ability in various contexts owing to the essential affect-related information it provides. This information can help individuals understand and regulate their emotional and motivational states. In this study, we sought to examine the extent to which ED can be beneficial in psychotherapy context and specifically for predicting treatment response. Thirty-two prospective patients with mood and anxiety disorders completed four daily assessments of negative and positive emotions for 30 days before receiving cognitive-behavioral treatment. Depression, stress, and anxiety symptoms severity were assessed pre- and post-treatment using self-reports and clinical interviews. We conducted a series of hierarchical regression models in which symptoms change scores were predicted by ED while adjusting for the mean and variability. We found that negative ED was associated with greater self-reported treatment response (except for anxiety) when negative emotional variability (EV) was included in the models. Probing negative ED and EV's interactive effects suggested that negative ED was associated with greater treatment response (except for anxiety) for individuals with lower EV levels. Results were obtained while controlling for mean negative affect. Our findings suggest that negative ED can benefit psychotherapy patients whose negative emotions are relatively less variable. We discuss the meaning of suppression and interactive effects between affect dynamics and consider possible clinical implications.

Keywords: emotion differentiation, dynamic assessment, psychotherapy outcome, patient factors, affect dynamics

OPEN ACCESS

Edited by:
Yasemin Erbas,
KU Leuven, Belgium

Reviewed by:
Erik Nook,
Harvard University, United States
Meng Yu,
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Stanley Seah,
Kent State University, United States

****Correspondence:***
Gal Lazarus
gal.lazarus@gmail.com

Specialty section:
This article was submitted to Psychology for Clinical Settings, a section of the journal Frontiers in Psychology

Received: *01 April 2021*
Accepted: *02 July 2021*
Published: *02 August 2021*

Citation:
Lazarus G and Fisher AJ (2021) Negative Emotion Differentiation Predicts Psychotherapy Outcome: Preliminary Findings. Front. Psychol. 12:689407. doi: 10.3389/fpsyg.2021.689407

INTRODUCTION

Emotion differentiation (ED), the extent to which emotions are experienced (and labeled) as distinct, has been found to be associated with various positive outcomes (for a meta-analysis, see Seah and Coifman, 2021). It is considered a valuable ability in multiple contexts, providing individuals with essential affect-related information that can guide their behavior in an adaptive manner (Schwarz, 2012; Kashdan et al., 2015). The present study set out to examine whether ED can be beneficial in the context of psychotherapy, and specifically, to what extent those with greater ED respond better to a personalized cognitive-behavioral treatment. We first review findings tying emotion-related constructs to psychotherapy response and then note limitations with their current operationalizations.

Subsequently, we explain how ED, obtained using dynamic assessment, can function as a promising predictor of such response.

Patients vary significantly in their response to psychotherapeutic interventions (e.g., Lambert, 2013; Boswell et al., 2016). Traditionally, this variance has been attributed to three classes of factors: treatment factors (Marcus et al., 2014; Firth et al., 2019; e.g., technique), therapist factors (Baldwin and Imel, 2013; e.g., experience), and patient factors (Bohart and Wade, 2013; e.g., personality traits). Among these classes, leading researchers (e.g., Wampold, 2010; Norcross and Lambert, 2011) estimate that a large portion of the treatment response variance can be explained by patient factors, that is, by pre-existing individual differences between patients.

Identifying which patients are likely to respond poorly to treatment and which factors underlie this response can have important clinical implications regarding treatment planning. Such factors can sometimes be addressed by therapists employing specific psychotherapeutic interventions. Moreover, these factors can inform caregivers regarding the intensity of the recommended treatment or indicate a need to employ other treatment modalities (e.g., group psychotherapy and psychopharmacology).

For many years (e.g., Luborsky et al., 1971), clinicians and researchers have attempted to discover specific patient characteristics that are predictive of therapeutic improvement (for review, see Bohart and Wade, 2013). Some characteristics, such as demographic variables (e.g., gender or age), have failed to show consistent associations with therapy outcomes (Cuijpers et al., 2009; Bohart and Wade, 2013). Other characteristics, such as symptom severity (e.g., Firth et al., 2019) or patients' therapy-related expectancies and motivational factors (e.g., Newman et al., 2006; Constantino et al., 2011), have been identified as more consistent predictors.

Emotional experience, expression, and regulation have all been proposed as key patient factors that can affect psychotherapy outcome (e.g., Greenberg and Safran, 1989; Thoma and McKay, 2015; Fisher et al., 2016), with theoretical and empirical work pointing to the importance of monitoring, processing, and regulating emotions as integral psychotherapeutic process factors (e.g., Pascual-Leone and Greenberg, 2007; Pinna et al., 2020). Though compromised to some extent in many psychopathological conditions (e.g., Dryman and Heimberg, 2018), these abilities are considered vital for patients to be able to benefit from the psychotherapeutic process (e.g., Watson et al., 2011). Specifically, they allow for deeper examination and reflection over one's experience, creating new meanings, and personally meaningful problem resolution (e.g., Watson and Bedard, 2006; Aafjes-van Doorn and Barber, 2017). In line with these notions, the quality of patients' emotional processing during sessions was found to be tied to improved treatment outcomes (Pos et al., 2009; Aafjes-van Doorn and Barber, 2017; Pascual-Leone and Yeryomenko, 2017).

Whereas session-based emotional processing and regulation have been shown to be robust predictors of therapy outcome, the predictive validity of pre-treatment emotional processing or regulation indices have been less consistent. In particular, a recent systematic review by Pinna et al. (2020, p. 1) indicated that the links between self-reported alexithymia, an inability to identify and communicate emotions, and treatment outcomes are "complex." Though in some studies alexithymia was tied to poorer treatment response (e.g., Quilty et al., 2017), this association was absent in others (e.g., Spek et al., 2008).

Additional work has examined other emotional processing or regulation variables as outcome predictors. For example, patients lower in pre-treatment emotion suppression had more favorable treatment outcomes (Scherer et al., 2017; Hosogoshi et al., 2020). Interestingly, in both studies, emotion reappraisal was not predictive of treatment outcome. Lastly, a measure of psychological mindedness, defined as the tendency to turn inward seeking psychological explanations of behavior, people, and problems, has provided mixed results as a predictor of therapy outcome (Bohart and Wade, 2013).

A common limitation shared by most studies addressing the links between patients' abilities to express, process, and regulate their emotions and psychotherapy outcomes is their attempt to capture dynamic processes using a single-time static intake measurement (Fisher, 2015). This discrepancy severely hinders researchers' ability to tap the processes underlying patients' emotional difficulties accurately. The reliance on self-reports for items requiring a high level of reflective capacity further limits the measurement validity.

Though single-time clinician assessment is still considered the gold standard in psychotherapy practice and research, pre-treatment ecological momentary assessment (EMA) is increasingly being employed to assess clinically relevant factors (e.g., Lutz et al., 2018; Rubel et al., 2018; Fisher et al., 2019; Shalom et al., 2020). It allows for intensive repeated measurement of variables of interest and modeling their dynamic inter-relationships (e.g., Fisher and Boswell, 2016). Researchers and clinicians have started to capitalize on EMA's strengths to explore the extent to which dynamic indices can inform treatment processes and outcomes (e.g., Husen et al., 2016; Lutz et al., 2018; Fisher et al., 2019).

Sophisticated analytic methods can be used to translate such dynamic indices into personalized treatment plans (Fisher and Boswell, 2016; Fisher et al., 2019; Wright and Woods, 2020). At the same time, simpler methods can help identify meaningful individual differences without prescribing specific interventions (e.g., Husen et al., 2016; Lutz et al., 2018; Bosley et al., 2019). Individual differences in the dynamic unfolding of affect (Kuppens et al., 2010) are particularly appealing and relevant in the context of psychotherapy (e.g., Husen et al., 2016).

One affect dynamics index that may be highly informative regarding emotional processing and regulation is emotion differentiation (ED). ED is defined as the extent to which same-valenced emotions are experienced and labeled in a distinct or granular manner (Barrett et al., 2001). Individuals with greater ED tend to represent and describe their emotional states using specific terms (e.g., "enthusiastic," "irritable," or "tense"), rather than general or abstract terms (e.g., "good" and "bad").

Differentiation, particularly between negative emotions, has been tied to various positive outcomes in numerous studies (for a review, see Kashdan et al., 2015; for a recent meta-analysis, see Seah and Coifman, 2021). For example, negative ED has been related to greater self-esteem, lower neuroticism, and less depressive feelings (Erbas et al., 2018; Willroth et al., 2020). Additionally, negative ED was found to serve as a protective factor in the face of various daily stressors (in a community sample; Starr et al., 2017) and of the adverse outcomes of ruminations (in clinical samples; Zaki et al., 2013; Seah et al., 2020). Interestingly, in a recent study (Liu et al., 2020), only a combination of negative and positive ED (but neither independently) moderated an association between trait rumination and increases in depression.

A few candidates have been identified as possible mechanisms underlying the benefits of (mostly) negative ED. ED provides nuanced information about one's emotions which is likely to translate to more adaptive emotion regulation processes. Indeed, greater negative ED was found to be tied to greater effectiveness of negative emotion downregulation strategies (Kalokerinos et al., 2019). Moreover, affect labeling, the act of putting feelings into words, is widely regarded as a form of implicit emotion regulation technique (for review, see Torre and Lieberman, 2018), and high negative ED individuals are likely to be more accurate and thorough in labeling their emotions. Additionally, greater ED may clarify motivational processes and consequently render the allocation of attentional and behavioral resources more efficient (Kashdan et al., 2015). Lastly, greater ED may involve more accurate causal attributions that rely on better access to the origins of one's emotional experience. When adverse events are followed by more differentiated and less global emotional states, there is a greater likelihood of identifying the cause one's emotional response. Accurate attributions are likely to be less *depressive*, that is, less internal, global, and stable (Seligman et al., 1979).

Positive ED, in contrast, has not been tied consistently with adaptive outcomes (despite being moderately correlated with negative ED; Liu et al., 2020). It has been found to be associated with favorable outcomes only under specific circumstances, such as among participants with borderline personality features (Dixon-Gordon et al., 2014) or sub-clinical eating disorders (Selby et al., 2014). In other studies (e.g., Barrett et al., 2001; Demiralp et al., 2012; Kashdan and Farmer, 2014; Willroth et al., 2020), such associations did not emerge, and often they are not being examined or reported.

The impact of ED may be most pronounced and visible in conditions where emotions and their processing play diverse and fundamental roles. Working with patients' emotions has been identified as a cornerstone of the psychotherapeutic process across theoretical orientations and disorders (Barlow et al., 2011; Greenberg, 2012; Thoma and McKay, 2015). Whereas different orientations may have different foci and employ distinct techniques, they share a primary change mechanism—accessing patients' emotions and modifying their underlying cognitive-affective mental structures. Patients' ability to differentiate between their emotions, particularly their negative ones, is probably of great value for such processes.

The Present Study

The present study expanded recent work regarding the role of dynamic affective patterns (e.g., Husen et al., 2016; Bosley et al., 2019) in patients' response to psychotherapy by examining the extent to which ED is predictive of treatment outcome. Using EMA conducted prior to a personalized modular cognitive-behavioral treatment (see Fisher et al., 2019) for individuals with generalized anxiety disorder (GAD) or major depressive disorder (MDD), we prospectively estimated patients' negative and positive ED prior to therapy. These indices were then used to predict patients' symptomatic improvement from pre- to post-therapy. This study is a secondary data analysis of Fisher et al. (2019) and likewise an extension of Bosley et al. (2019). The latter work examined affect dynamics as predictors of symptoms severity and pre- to post-treatment symptomatic change but did not address ED.

Maladaptive emotional processes are at the core of the development and maintenance of both GAD and MDD. Individuals with GAD often suffer from excessive negative affect that is poorly understood and maladaptively regulated through recurrent worrying (e.g., Mennin et al., 2002). Individuals with MDD often suffer from difficulties identifying emotions, tolerating and accepting negative emotions, and effectively regulating their emotions, and tend to employ maladaptive regulation techniques (e.g., rumination and suppression; for review, see Rottenberg, 2017). These deficiencies in emotional processing are likely to be involved in cognitive biases, such as maladaptive causal attribution processes that play a key role in depression (Peterson and Seligman, 1984).

Given patients' diagnoses, the characteristics of the treatment, and the nature of ED, we hypothesized that those patients who are better at differentiating between their *negative* emotions would show greater symptomatic improvement. We also examined patients' ability to differentiate between their *positive* emotions, but we did not expect it to have a similar predictive role for two reasons. First, the evidence for associations between positive ED and adaptive outcomes is much weaker than for negative ED. Second, the context of psychotherapy for depression and anxiety, in which patients work through and around their negative emotions, probably renders their differentiation more meaningful.

Specifically, higher negative ED patients are likely to be more capable of identifying their core maladaptive emotional processes, including inefficient attempts to regulate them (e.g., worrying and ruminating). Moreover, greater negative ED can help patients reinterpret the meaning of negative situations and change maladaptive causal attributions (i.e., internal, global, and stable) that are central to the maintenance of their depressive symptoms. Lastly, the ability of higher negative ED patients to engage in psychotherapy sessions in an emotionally effective manner and regulate their emotions during the sessions is likely to allow for a more focused and efficient therapeutic process.

Notably, following recent work demonstrating limited incremental predictive validity of affect dynamics indices beyond the mean and variability (Bos et al., 2019; Dejonckheere et al., 2019; Wendt et al., 2020), we included these indices in all models. Of note, Bosley et al. (2019) found that the mean and standard deviation (SD) of negative emotions were not associated with treatment response and that the variability of positive emotions was associated with more significant symptom reduction.

MATERIALS AND METHODS

Participants

The current study utilized data from an open trial of personalized modular psychotherapy for depression and anxiety based on the unified protocol (UP; Barlow et al., 2011). In this trial, participants with GAD and MDD completed four daily self-report assessments of affect, behavior, and symptoms for 30-day period prior to treatment. Subsequently, they received psychotherapeutic interventions tailored to their symptom dynamics as assessed during the EMA. A full description of the procedures and outcomes can be found in Fisher et al. (2019).

Individuals with symptoms consistent with possible GAD or MDD diagnoses were recruited from the greater San Francisco Bay Area using referrals, flyers, and internet advertisements. One hundred and seventy-four potential participants passed a brief telephone screening and were invited to an in-person appointment. They underwent a structured clinical interview (the Anxiety and Related Disorders Interview Schedule for DSM-5; ADIS-5, Brown and Barlow, 2014) to verify their diagnosis and assess symptoms' severity. Inclusion criteria included a primary diagnosis of MDD or GAD, age of 18 to 65 years, and a mobile phone with web access. Exclusion criteria included a history of psychosis or mania, concurrent or recent (within the past 12 months) cognitive-behavioral treatment. Interrater reliabilities for diagnoses (based on video recordings of the structured clinical interviews) were high—GAD and MDD had kappa values of 0.68 and 0.84, and percent agreement of 95 and 92%, respectively.

Fifty-seven individuals (33%) met the inclusion and exclusion criteria, and of these, 40 began treatment. Seven participants withdrew from the study during treatment, and one participant did not complete a post-treatment assessment, leaving 32 participants in the present sample. As shown in Table S1 in the online supplementary material (OSM),[1] no significant differences were found in demographics, pre-treatment symptoms, and affect variables between participants who completed treatment and post-treatment assessment and those who did not. Twenty of 32 participants in the final sample (62.5%) identified as female, and the average age was 37.9 years (SD = 14.3). Sixteen participants (50%) identified as White, nine (28.1%) identified as Asian, four (12.5%) identified as Latino/a, one (3.1%) identified as Black, and two (6.2%) selected "other." Thirteen (41.6%) individuals were diagnosed with current primary GAD, 5 (15.6%) were diagnosed with current primary MDD, and 14 (43.8%) met the criteria for co-primary diagnoses of both GAD and MDD. Sixteen (50%) participants had at least one current comorbid disorder other than GAD or MDD; these comorbid diagnoses included social anxiety disorder (n = 10; 31.2%), specific phobia (n = 4; 12.5%), persistent depressive disorder (n = 3; 9.4%), agoraphobia (n = 2; 6.2%), and posttraumatic stress disorder (n = 1; 3.1%).

Measures

Hamilton Rating Scale for Depression

The Hamilton Rating Scale for Depression (HRSD; Hamilton, 1960) assesses the severity of depressive symptomatology. It is a 13-item clinician-administered scale providing severity rating of each overarching symptom cluster on a scale from 0 (not present) to 4 (very severe/incapacitating). The HRSD's internal consistency ranges from adequate to good (0.73–0.81; Steer et al., 1987; Moras et al., 1992). Its total score interrater reliabilities range from 0.78 to 0.82 (Steer et al., 1987; Moras et al., 1992). HRSD scores correlate strongly with self-report depression measures in clinical samples (Steer et al., 1983).

Depression, Anxiety, and Stress Scales

The Depression, Anxiety, and Stress Scale (DASS) is a 42-item self-report questionnaire comprised of three subscales (14 items each) developed to capture levels of anxiety, depression, and stress, as described by the tripartite model (Clark and Watson, 1991; Lovibond and Lovibond, 1995). The anxiety subscale evaluates hyper-arousal unique to some forms of anxiety, and the depression subscale evaluates anhedonia or low positive affect unique to depression. As noted by several researchers (e.g., Holmes and Newman, 2006; Campbell-Sills and Brown, 2010), the DASS stress subscale primarily evaluates tension and irritability prevalent among individuals suffering from GAD. Hence, to create a measure relevant to our entire sample, we combined the depression and stress subscales to be used as the main self-report outcome measure, and used the anxiety subscale as an additional outcome measure. Items were rated on a 4-point Likert scale ranging from 0 to 3 ("did not apply to me at all" to "applied to me very much or most of the time"). In our sample, all three subscales were highly reliable (Cronbach's alphas for the anxiety subscale were 0.84 and 0.78 for pre- and post-treatment, respectively, for the depression subscale were 0.94 and 0.94 for pre- and post-treatment, respectively, and for the stress subscale were 0.89 and 0.90 for pre- and post-treatment, respectively). The Cronbach's alphas for the combined depression-stress measure were 0.91 and 0.89 for pre- and post-treatment, respectively.

Momentary Affect

For each EMA survey, participants rated their emotional experience over the preceding hours across the survey items using a 0–100 visual analog slider with the anchors "not at all" and "as much as possible." The surveys included four positive affect items (positive, energetic, enthusiastic, and content) and seven negative affect items (angry, irritable, worthless/guilty, frightened/afraid, down/depressed, worried, and hopeless). Additional items not used for the present study consisted of various symptoms (i.e., loss of interest or pleasure, restless, difficulty concentrating, muscle tension, fatigued, dwelled on

[1]https://osf.io/vqsdb

the past, avoided people, avoided activities, procrastinated, and sought reassurance). Of note, down/depressed, frightened/afraid, and worthless/guilty were measured as couplets in a single item to reflect the language used in clinical assessment for anxiety or depression, and to prevent patients from being overly exclusive in endorsing them. The within- and between-person reliabilities for the scales were computed using procedures outlined by Cranford et al. (2006). For negative emotions, the within- and between-person reliabilities were 0.81 and 0.77, respectively; for positive emotions, they were 0.82 and 0.58, respectively.

Procedure

Clinical Interview

Following a brief telephone screening, eligible participants were invited to an in-person appointment for a structured clinical interview. The HRSD (along with other measures reported in Fisher et al., 2019) was administered by clinical psychology graduate students supervised by a doctoral-level clinical psychologist.[2] At this appointment, participants also completed a battery of self-report measures, including the DASS.

EMA Surveys

After enrolling in the study, participants' mobile phone numbers were entered into a secure web-based survey system which prompted participants to answer survey questions four times per day during pre-reported waking hours. During these hours, they received text messages (containing a hyperlink to a web-based survey) approximately every 4 h, with the exact time being randomized within a 30-min window. Each survey expired once a subsequent survey was sent. Participants were instructed to complete surveys for a minimum of 30 days (the total number of days ranged from 29 to 42; M = 34.25).

Personalized Treatment

Following the 30-day EMA period, participants started modular cognitive-behavioral psychotherapy for mood and anxiety disorders which was personalized *via* the selection of relevant modules from the unified protocol (Barlow et al., 2011) based on the EMA data (Fernandez et al., 2017; Fisher et al., 2019). The average number of sessions delivered in the study was 10.38, ranging from 4 to 14 (mode = 9). Within days of completing treatment, participants underwent an in-person follow-up assessment to evaluate change in diagnosis and symptoms severity. At this assessment, trained graduate students and postdoctoral therapists administered a structured clinical interview, and participants completed various self-report instruments, including the DASS.

Data Preparation

Data were processed and analyzed using R (version 4.0.3; R Core Team, 2020). Complete R syntax for the analyses described in this paper is available in the OSM (see footnote 1). Initially, composite positive and negative emotion scores were calculated for each time point of each participant by averaging across positive and negative emotion items. Next, means and standard deviations of these positive and negative emotions composites were calculated for each participant's time series.

Subsequently, negative and positive ED indices were calculated for each participant using the average consistency[3] intra-class correlation (ICC; Shrout and Fleiss, 1979), which is a standard procedure (e.g., Erbas et al., 2018). Resulting ICCs were transformed using a Fisher Z-transformation. To ease interpretation, we subtracted the transformed ICCs from 1.00 so that higher values will represent greater differentiation. No negative ICC values were obtained.

Data Analysis

To estimate the extent to which ED predicts treatment response, we conducted a series of hierarchical multiple regression models. In the final block, the pre- to post-treatment changes in DASS depression-stress and anxiety scales and the HRSD scores were regressed on (a) ED, (b) affect mean, (c) affect SD (representing emotional variability), and (d) the corresponding pre-treatment outcome measure scores. The means and SDs of momentary affect were included following Dejonckheere et al.'s (2019) recommendations to account for their shared variance with the ED indices.[4] They were added iteratively to the models after the ED score (and the relevant pre-treatment outcome index) was the only predictor in the first block. All variables were standardized to ease the interpretation of the results. Separate models were estimated for each outcome measure (DASS depression-stress, DASS anxiety, and the HRSD) and for each affective valence (negative and positive emotions). Hence, six models were estimated in total.

To aid the interpretation of significant results vis-à-vis the small sample size, we estimated Bayesian regression models (against an intercept-only null hypothesis) using the BayesFactor package (Morey et al., 2018) parallel to the last steps in the models. For the effects of interest, we present Bayesian credible intervals based on the posterior distribution. Bayesian credible intervals refer directly to the probability of the parameter value to be within the intervals (unlike confidence intervals which refer to the probability of the interval itself to include the true value).

RESULTS

The total number of observations per participant ranged from 90 to 151 (M = 113.19, SD = 11.83). The percentage of missing data ranged from 0 to 31.8% (M = 12.4%, SD = 8.5%). The intercorrelations among the ED indices, affect means, SDs, and outcome variables, as well as these variables' means and SDs, are presented in **Table 1**. Among the affect indices, the

[2]Inter-rater reliability was calculated only for the ADIS-5 diagnoses.

[3]We opted to use the consistency index that ignores reported items' means, as we were concerned the latter may reflect response tendencies and not true differentiation. The correlations between the consistency and absolute agreement indices were 0.95 and 0.96 for the negative and positive indices, respectively.

[4]Due to the small sample size we opted not to include additional affect dynamics indices.

TABLE 1 | Means, standard deviations, and correlations.

S. No.	Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11
1.	Negative emotion differentiation	−0.13	0.29											
2.	Negative emotion mean	40.61	14.28	−0.01										
3.	Negative emotion variability	13.42	3.56	−0.50**	0.00									
4.	Positive emotion differentiation	−0.18	0.27	0.34	0.05	−0.02								
5.	Positive emotion mean	39.24	9.59	−0.16	−0.27	0.01	−0.15							
6.	Positive emotion variability	14.50	4.14	−0.09	−0.25	0.69**	−0.29	0.19						
7.	Pre-Tx DASS depression and stress	44.34	13.29	0.27	0.48**	0.16	0.28	−0.28	0.09					
8.	Pre-Tx DASS anxiety	12.88	7.81	0.05	0.27	0.37*	0.32	−0.18	0.09	0.55**				
9.	Pre-Tx Hamilton depression	13.81	3.84	0.03	0.34	0.35	0.11	−0.10	0.20	0.46**	0.59**			
10.	Δ DASS depression and Stress	−26.28	12.80	−0.35*	−0.40*	−0.23	−0.18	0.14	−0.32	−0.72**	−0.31	−0.45*		
11.	Δ DASS anxiety	−7.69	7.10	−0.1	−0.27	−0.37*	−0.24	−0.07	−0.26	−0.47**	−0.84**	−0.56**	0.46**	
12.	Δ Hamilton depression	−8.03	3.60	−0.17	−0.15	−0.25	−0.01	−0.14	−0.39*	−0.19	−0.34	−0.67**	0.42*	0.56**

*Pre-Tx, pre-treatment. *p < 0.05; **p < 0.01.*

only significant correlations were between negative ED and negative emotional variability (EV; $r = -0.50$) and between negative and positive EV ($r = 0.69$). Of the correlations between the affect indices and pre-treatment symptoms, the correlations between negative affect mean and DASS depression-stress ($r = 0.48$; notably, correlations with the DASS anxiety and the HRSD were 0.27 and 0.34, respectively) and between negative EV and DASS anxiety ($r = 0.37$)[5] reached significance.

Of note, the dependent variable in all models was a change score calculated by subtracting pre-treatment symptoms scores from the post-treatment symptoms scores. Hence, a more positive regression coefficient indicates that the predictor is associated with lower symptom reduction. A more negative coefficient indicates that the predictor is associated with greater symptom reduction.

Negative ED and Treatment Outcome

Predicting DASS Scores

The results of the hierarchical regression models predicting changes in DASS depression-stress and anxiety symptoms by negative affect indices are presented in **Table 2**'s left and right panels, respectively.[6,7,8] For the depression-stress outcome, when negative ED was the only dynamic index in the model, it did not significantly predict change scores. After introducing the negative EV index, negative ED became a significant predictor with greater differentiation associated with greater symptom reduction. The negative EV index also predicted greater symptom reduction. Lastly, across blocks, higher levels of pre-treatment symptoms predicted greater change. These associations (except the ones with pre-treatment symptoms) did not reach significance in the model predicting anxiety symptoms change.

To further explore the apparent suppression effect, we examined the associations between negative EV and symptoms change scores while adjusting for pre-treatment symptoms scores. These too were not significant, indicating a cooperative (or mutual) suppression (Cohen and Cohen, 1975). Statistically, each of the variables suppressed irrelevant (i.e., residual) variance (in predicting treatment outcomes) in each other. To estimate the size and robustness of the suppression effects, we followed

[5]We avoided noting the simple correlations with the difference scores because the associations between the pre-treatment symptoms and (a) post-treatment symptoms ($r = 0.42$, 0.43, and 0.47 for DASS depression-stress, DASS anxiety, and the HRSD, respectively) were moderate and significant, and (b) the affect indices were non-zero. These associations make difference-scores correlations hard to interpret (Allison, 1990).

[6]We reran all models while adjusting for gender, age, and number of EMA surveys completed. Results remained essentially unchanged.

[7]To allay the concern of multicollinearity, we examined the variance inflation factor (VIF) of the predictors in all models. All the values were below 1.86, indicating that the models did not suffer from a multicollinearity problem.

[8]At the request of a reviewer, we examined additional models predicting each subscale separately and a model predicting the DASS total score. The results of these models are presented in Tables S2 and S3 in the OSM. As can be seen in Table S2 (NA indices), whereas no significant effects emerged for the separate DASS subscales, effects parallel to the combined DASS depression-stress measure emerged for the DASS total score. As can be seen in Table S3 (PA indices), no significant effects emerged for any of the outcome variables.

TABLE 2 | Hierarchical linear regressions predicting DASS pre- to post-change by negative emotion indices.

Pred./ Outcome	DASS depression-stress					DASS anxiety				
	β	*SE*	t	p	η_p^2	β	*SE*	t	p	η_p^2
Model 1				R^2:	*0.54*				R^2:	0.72
NED	−0.17	0.13	−1.28	0.211	0.05	−0.06	0.10	−0.59	0.563	0.01
Pre-Tx Sym.	−0.67	0.13	−5.15	<0.001	0.48	−0.84	0.10	−8.52	<0.001	0.71
Model 2				R^2:	*0.55*				R^2:	0.72
NED	−0.18	0.13	−1.36	0.185	0.06	−0.06	0.10	−0.59	0.562	0.01
Mean NE	−0.10	0.15	−0.67	0.511	0.02	−0.05	0.10	−0.46	0.652	0.01
Pre-Tx Sym.	−0.62	0.15	−4.07	<0.001	0.37	−0.83	0.10	−7.96	<0.001	0.69
Model 3				R^2:	*0.63*				R^2:	0.73
NED	**−0.40**	**0.15**	**−2.59**	**0.015**	**0.20**	−0.14	0.12	−1.2	0.241	0.05
Mean NE	−0.17	0.14	−1.23	0.231	0.05	−0.07	0.10	−0.64	0.528	0.01
NEV	**−0.35**	**0.15**	**−2.38**	**0.025**	**0.17**	−0.16	0.13	−1.26	0.219	0.06
Pre-Tx Sym.	−0.47	0.15	−3.05	0.005	0.26	−0.76	0.12	−6.51	<0.001	0.61
Model 4				R^2:	*0.67*				R^2:	0.75
NED	**−0.32**	**0.15**	**−2.07**	**0.048**	**0.22**	−0.09	0.12	−0.73	0.471	0.05
Mean NE	−0.19	0.13	−1.40	0.175	0.07	−0.08	0.10	−0.78	0.443	0.02
NEV	**−0.34**	**0.14**	**−2.38**	**0.025**	**0.19**	−0.15	0.13	−1.14	0.264	0.06
NED X NEV	0.24	0.13	1.80	0.084	0.11	0.16	0.12	1.39	0.176	0.07
Pre-Tx Sym.	−0.51	0.15	−3.38	0.002	0.31	−0.79	0.12	−6.77	<0.001	0.64

Pred., predictor; NED, negative emotion differentiation; Pre-Tx Sym., pre-therapy symptoms; NEV, negative emotion variability; and NE, negative emotion. Using bold font was meant to make significant results more noticeable.

recommendations by Shrout and Bolger (2002), who suggested considering suppression situations as a type of intervening variables models (e.g., mediation; see also Paulhus et al., 2004). Hence, we employed bootstrapping techniques (using the R package lavaan) to calculate the confidence intervals of the “indirect effect,” once with negative EV as the “mediator” and once with negative ED as the “mediator.” The bias-corrected bootstrapped 95% confidence intervals with 10,000 samples were above zero when EV [0.04, 0.53] and ED [0.03, 0.57] functioned as “mediators.”

Despite the small sample size, we chose to examine the non-independence of negative ED and negative EV by introducing their interaction term into the regression model. As shown in the lower panel of **Table 2**, the interaction term was below the threshold of statistical significance at alpha = 0.05 (p = 0.084) yet had medium effect sizes (η_p^2 = 0.11). Moreover, adding the interaction term to the model accounted for an additional 4% of the variance. Hence, we further explored the simple slopes of the associations between negative ED, and symptoms change for different negative EV levels (one SD below and one SD above the mean of negative EV; see **Figure 1**—the y-axis uses the non-standardized difference scores to ease interpretation). The association between negative ED and the DASS depression-stress was negative and significant for low negative EV (coefficient = −0.56, *SE* = 0.17, t = −3.24, p < 0.001) and non-significant for high negative EV (coefficient = −0.08, *SE* = 0.23, t = −0.34, p = 0.74), indicating that for low negative EV, greater negative ED was associated with greater symptom reduction, whereas for high negative EV, it was not. Exploring the simple slopes of EV for different ED levels showed that the association between negative EV and changes in DASS depression-stress was negative and significant for low negative ED (coefficient = −0.58, *SE* = 0.19, t = −3.04, p < 0.001), and non-significant for high negative ED (coefficient = −0.10, *SE* = 0.20, t = −0.34, p = 0.63), indicating that for low negative ED, greater negative EV was associated with greater symptom reduction, whereas for high negative ED, it was not.

Given the limited statistical power in the present study, the interaction results should be interpreted with caution. Notwithstanding, in the Bayesian regression model, the empirical means of negative ED and its interaction term with negative EV were −0.28 and 0.21, respectively, only slightly lower than their estimates in the original model. The respective 95% credible intervals were [−0.58, 0.02] and [−0.05, 0.47], respectively. Notably, in none of the models, negative emotion means predicted symptomatic change.

Predicting HRSD Scores

The results of the hierarchical regression models predicting changes in the HRSD by negative affect indices are presented in **Table 3**. Neither negative ED nor negative EV predicted HRSD change scores. Still, following the observed dependency between the predictors, we again added their interaction to the HRSD model. In this model, the interaction term reached statistical significance and accounted for an additional 10% of the variance. We explored the simple slopes (see **Figure 2**) and found that the effect of negative ED was negative and significant for low negative EV (coefficient = −0.48, *SE* = 0.18, t = −2.64, p = 0.01), and non-significant for high negative EV (coefficient = 0.38, *SE* = 0.28, t = 1.36, p = 0.19), indicating that for low negative EV, negative ED was associated with symptom reduction, whereas for high negative EV, it was not. In the Bayesian regression model, the empirical mean of the

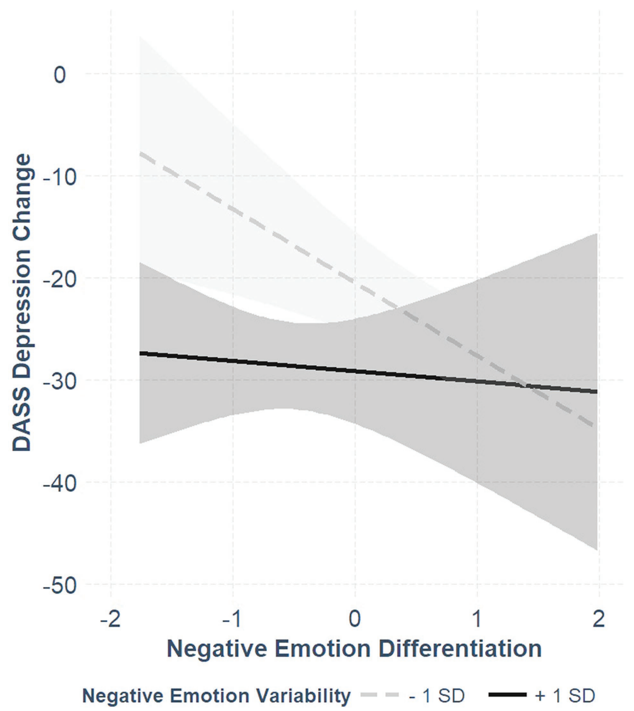

FIGURE 1 | The associations between negative emotion differentiation and DASS depression-stress change scores for high (+1 *SD*) and low (−1 *SD*) levels of negative emotion variability. More negative change scores indicate grater symptom reduction.

TABLE 3 | Hierarchical linear regressions predicting Hamilton Depression Rating Scale pre- to post-change by negative emotion indices.

Pred./ Outcome	**Hamilton Depression Rating Scale**				
	β	***SE***	***t***	***p***	η^2_p
Model 1				R^2:	*0.47*
NED	−0.15	0.13	−1.11	0.278	0.04
Pre-Tx Sym.	−0.67	0.13	−4.94	<0.001	0.46
Model 2				R^2:	*0.48*
NED	−0.15	0.14	−1.08	0.289	0.04
Mean NE	0.08	0.15	0.54	0.596	0.01
Pre-Tx Sym.	−0.69	0.15	−4.78	<0.001	0.45
Model 3				R^2:	*0.49*
NED	−0.22	0.16	−1.32	0.197	0.06
Mean NE	0.06	0.15	0.40	0.696	0.01
NEV	−0.14	0.18	−0.78	0.445	0.02
Pre-Tx Sym.	−0.64	0.16	−3.91	0.001	0.36
Model 4				R^2:	*0.59*
NED	−0.05	0.16	−0.31	0.755	0.08
Mean NE	0.07	0.14	0.51	0.617	0.01
NEV	−0.04	0.17	−0.25	0.807	0.03
NED X NEV	**0.43**	**0.17**	**2.55**	**0.017**	**0.20**
Pre-Tx Sym.	−0.84	0.17	−4.99	<0.001	0.49

Pred., predictor; NED, negative emotion differentiation; Pre-Tx Sym., pre-therapy symptoms; NEV, negative emotion variability; and NE, negative emotion. Using bold font was meant to make significant results more noticeable.

interaction term between ED and EV was 0.36, and the 95% credible intervals were [0.03, 0.69]. Notably, in none of the models, negative emotion means predicted symptomatic change.

Positive ED and Treatment Outcome

Predicting DASS Scores

The results of the hierarchical regression models predicting changes in DASS depression-stress and anxiety symptoms by positive affect indices are presented in **Table 4**'s left and right panels, respectively. Positive ED did not significantly predict change scores in either DASS depression-stress or anxiety. Positive emotion mean did predict greater changes in anxiety symptoms.

Predicting HRSD Scores

The results of the hierarchical regression models predicting changes in the HRSD by positive affect indices are presented in **Table 5**. No significant effects emerged.

DISCUSSION

The interest in pre-treatment dynamic assessment based on intensive repeated measurements taken in individuals' daily life is rapidly growing (Fisher, 2015; Piccirillo and Rodebaugh, 2019; Wright and Zimmermann, 2019; Trull and Ebner-Priemer, 2020), demonstrating the immense potential it holds for clinical science and practice. Such assessment can be used to generate idiographic treatment plans (e.g., Fisher et al., 2019; Wright and Woods, 2020), but can also be employed with a more modest yet important aim of identifying predictors of treatment response. Dynamic assessment is particularly suitable to measure affective processes that unfold in time and reflect individuals' capacity to process and regulate their emotions. The present work sought to explore one such capacity—individuals' ability or tendency to differentiate between their emotions.

We estimated ED using an EMA paradigm of 1 month prior to cognitive-behavioral psychotherapy and examined its associations with self-report and clinician-administered outcome measures. Negative ED was found to be negatively associated with negative EV (a risk for multicollinearity problems in the ensuing regression models was largely allayed by low VIF values). Zero-order correlations between negative or positive ED and pre-treatment symptoms did not reach statistical significance. These non-significant correlations may reflect no true correlation in our purely clinical sample, but also the small sample size.

Negative ED was not independently associated with changes in any of the measures. Still, after introducing negative EV into the prediction models, the associations between negative ED and changes in self-reported depression and stress symptoms became significant. Negative EV itself was also not independently associated with change scores, but when concurrently estimated alongside negative ED, it was associated with the depression and stress self-reported change score.

Negative ED and negative EV acted as mutual suppressors increasing each other's predictive validity once included in the same model (e.g., Paulhus et al., 2004). The shared variance between the two, which underlies the suppression effect, can

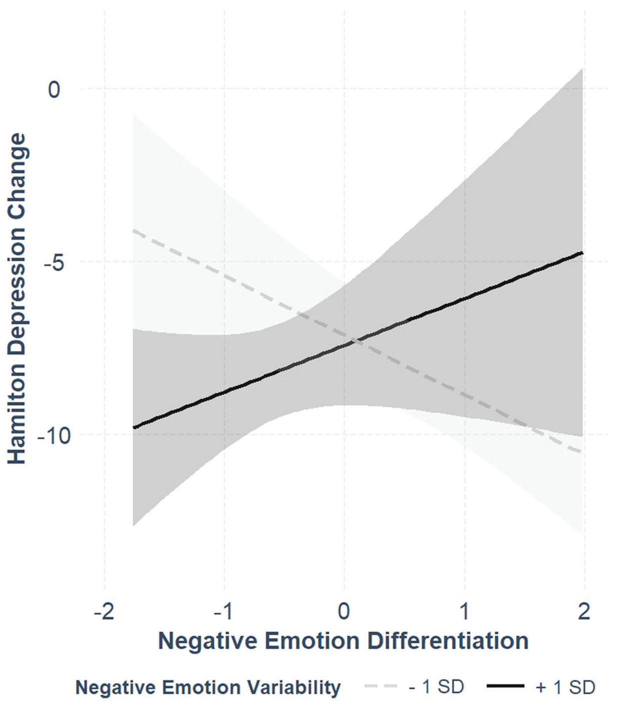

FIGURE 2 | The associations between negative emotion differentiation and Hamilton Depression Rating Scale change scores for high (+1 *SD*) and low (−1 *SD*) levels of negative emotion variability. More negative change scores indicate grater symptom reduction.

stem from their common origin in the variance of patients' momentary affect reports.[9] Their shared variance may represent their ties with changes in the external contexts patients were exposed to during the EMA period. Greater contextual variability may elicit greater EV and also create the appearance of lower ED (because such changes make it easier for emotions to change together, that is, to be less differentiated). Including ED and EV in the same model allows for examining their effects while taking into account such hypothesized between-patient differences in contextual variability so that purer operationalizations of the processes of interest can be tested. Mutual suppression effects are statistically counter-intuitive yet make much theoretical sense. For example, guilt and shame, which are similar in being "self-conscious," yet distinct in their objects (the former involves the global self, and the latter involves a specific behavior), were found to act as mutual suppressors in predicting aggression (Paulhus et al., 2004). Excluding self-conscious aggression-irrelevant variance revealed shame and guilt's "true" predictive power. Future work employing larger samples within different contexts should explore the replicability and generalizability of our suppression finding.

The ED literature contains ample evidence for ED's independent (i.e., not suppressed) associations with various wellbeing indicators (Seah and Coifman, 2021) and for its protective role in the face of daily stressors or maladaptive behaviors (e.g., Starr et al., 2017; Seah et al., 2020; Nook et al., 2021). ED's role as a predictor of change processes is yet to be established. However, preliminary findings point to more complex relationships involving interactions between romantic partners' ED (Lazarus et al., 2021a), between negative and positive ED (Liu et al., 2020), and between ED and personality traits (Oh and Tong, 2020). It seems that associations between ED and changes in outcome measures may be more specific and contingent on other factors.

To further explore the meaning of the non-independence between negative ED and negative EV in predicting self-reported symptoms changes, we added their interaction term to the prediction models. Given the small sample size, the interpretation of these interactions should be made cautiously. The interaction term did not reach statistical significance in predicting the self-report change scores but accounted for a considerable amount of their variance. Hence, we examined negative ED's effects under different levels of negative EV and found that it was associated with changes in self-reported depression and stress symptoms for low, but not high, level of negative EV. Moreover, in the model predicting clinician-rated change in depression symptoms, the interaction term reached significance, with negative ED being associated with symptoms change only for low levels of negative EV.

Taken together, these findings indicate that pre-treatment negative ED may predict more favorable treatment response for those patients whose momentary experiences of negative emotions are less variable across time. We hypothesize that those patients whose negative emotions are less variable across time have a greater need to differentiate between these emotions due to the persistent or entrenched nature of their negative emotional experiences. Conversely, patients whose negative emotions are more variable across time may be able to benefit from psychotherapy even when they are less capable of differentiating between them. For these patients, their affect and symptomatology may be relatively malleable or plastic. Supporting this hypothesis, Shalom et al. (2020) found that variability in social anxiety symptoms (that include some affective items) before psychotherapy is predictive of sudden gains during the treatment.

Positive ED was not associated with any of the treatment response measures in the current study. Importantly, this finding should not be automatically generalized to other psychopathological conditions or other types of treatments. Positive ED was found to be associated with adaptive outcomes in contexts where positive emotions are prevalent or important (e.g., the transition to parenthood; Lazarus et al., 2021a). From a functional perspective, differentiated experience of positive emotions can aid in eliciting specific and adapted motivational, cognitive, physiological, and behavioral responses to environmental opportunities (Shiota et al., 2014; Beall and Tracy, 2017). In the context of interventions targeting positive affect and reward sensitivity (e.g., Craske et al., 2019), positive ED may prove beneficial.

[9]Whereas EV represents the variance in negative affect reports attributable to differences between measurements, ED represents the variance in affect reports not attributable to differences between measurements and between specific items' means (that is, their inconsistency).

TABLE 4 | Hierarchical linear regressions predicting DASS pre- to post-change by positive emotion indices.

Pred./ Outcome	DASS depression-stress					DASS anxiety				
	β	*SE*	*t*	*p*	η_p^2	*β*	*SE*	*t*	*p*	η_p^2
Model 1				R^2:	0.52				R^2:	0.72
PED	0.02	0.13	0.16	0.876	0.00	0.04	0.10	0.40	0.692	0.01
Pre-Tx Sym.	−0.72	0.13	−5.37	<0.001	0.50	−0.86	0.10	−8.20	<0.001	0.70
Model 2				R^2:	0.52				R^2:	0.77
PED	0.02	0.14	0.11	0.909	0.00	0.02	0.10	0.18	0.86	0.00
Mean PE	−0.07	0.14	−0.48	0.635	0.01	−0.23	0.09	−2.44	0.021	0.17
Pre-Tx Sym.	−0.74	0.14	−5.26	<0.001	0.50	−0.89	0.10	−9.12	<0.001	0.75
Model 3				R^2:	0.58				R^2:	0.78
PED	−0.07	0.14	−0.53	0.601	0.01	−0.03	0.10	−0.33	0.74	0.00
Mean PE	−0.01	0.13	−0.08	0.941	0.00	−0.2	0.09	−2.16	0.04	0.15
PEV	−0.27	0.14	−2.00	0.055	0.13	−0.15	0.10	−1.55	0.132	0.08
Pre-Tx Sym.	−0.67	0.14	−4.89	<0.001	0.47	−0.86	0.10	−8.72	<0.001	0.74

Pred., predictor; PED, positive emotion differentiation; Pre-Tx Sym., pre-therapy symptoms; PEV, positive emotion variability; and PE, positive emotion.

TABLE 5 | Hierarchical linear regressions predicting Hamilton Depression Rating Scale pre- to post-change by positive emotion indices.

Pred./ Outcome	Hamilton Depression Rating Scale				
	β	*SE*	*t*	*p*	η_p^2
Model 1				R^2:	0.45
PED	0.06	0.14	0.44	0.661	0.01
Pre-Tx Sym.	−0.68	0.14	−4.91	<0.001	0.45
Model 2				R^2:	0.49
PED	0.03	0.14	0.23	0.816	0.00
Mean PE	−0.20	0.14	−1.46	0.155	0.07
Pre-Tx Sym.	−0.69	0.14	−5.11	<0.001	0.48
Model 3				R^2:	0.54
PED	−0.04	0.14	−0.28	0.783	0.00
Mean PE	−0.16	0.13	−1.18	0.248	0.05
PEV	−0.24	0.14	−1.72	0.097	0.10
Pre-Tx Sym.	−0.63	0.14	−4.66	<0.001	0.45

Pred., predictor; PED, positive emotion differentiation; Pre-Tx Sym., pre-therapy symptoms; PEV, positive emotion variability; and PE, positive emotion.

Of note, the means of patients' negative and positive emotions throughout the EMA period were not associated with symptomatic change (except for the association between positive emotion mean and changes in anxiety symptoms). These null effects partially echo previous work exploring daily affect and psychotherapy response. Specifically, Husen et al. (2016) found that mean positive and negative daily affect did not predict early response in cognitive-behavioral therapy. In Forbes et al. (2012), mean daily negative (but not positive) affect was tied to a slower rate of symptom reduction during depression and anxiety treatment for children and adolescents. In both studies, greater positive to negative emotions ratio predicted better treatment response (we did not observe a similar pattern in our data). It is notable that the significant predictors of symptomatic change (ED, EV, and positive to negative affect ratio indices) all involve within-person (co)variation, unlike the means, which represent a summary of absolute values. Absolute values may be more liable to various response biases that restrict their efficiency in predicting change scores. While the diverse research contexts and limited sample sizes (N = 39 in Husen et al., 2016; N = 66 in Forbes et al., 2012) make it difficult to draw firm conclusions, this emergent pattern may strengthen the case for the predictive validity of dynamic indices vs. mean levels.

Identifying patients who fail to sufficiently differentiate between their negative emotions in daily life can guide therapists' efforts at the first treatment stages. Therapists can employ various techniques and tools developed in the context of leading clinical approaches, including emotion-focused therapy (e.g., Pascual-Leone and Greenberg, 2007) and cognitive-behavioral therapy (e.g., Barlow et al., 2011) to help their patients attain a more differentiated emotional experience. Other capacities, such as mindfulness skills (Van der Gucht et al., 2019), or activities, such as self-monitoring (e.g., Widdershoven et al., 2019), have been shown to improve ED. Patients can then use this newly acquired ability to achieve other therapeutic goals.

Broader Considerations

This study examined a specific EMA-derived patient factor predictive of treatment response. Current efforts to identify patient factors often adopt data-driven machine learning algorithms that examine large numbers of possible predictors, with the potential to estimate nonlinear associations and higher-order interactions (e.g., Zilcha-Mano, 2019; Webb et al., 2020). Despite the advantages this approach may hold, it suffers from several limitations. First, generalizable findings require very large sample sizes (Archer et al., 2021) often unavailable in psychotherapy context. Second, the resultant models are often a black box with limited interpretability. Third, in the context of psychotherapy outcome prediction, this approach usually relies on self-reports. Arguably, the quality of any statistical model is limited by the quality of the data it includes, and single-time self-reports are inherently limited in their ability to capture dynamic processes representative of prospective patients' abilities. Due to these limitations, we believe that a theory-driven EMA-based search for specific treatment outcome predictors is necessary and valuable.

A significant advantage of dynamic assessment is that its reliance on associations between repeatedly measured self-report variables helps alleviate the risk of patients being swayed by factors, such as social desirability or experimenter demands typical of single-time self-report assessment (Sened et al., 2018). This risk may be particularly relevant in the context of pre-therapy assessment, where prospective patients may either over (Merckelbach et al., 2019) or under (Warner et al., 2011) report their psychological difficulties and symptoms. Using dynamic within individual patterns as predictors allows researchers to go beyond respondents' direct awareness and the mean levels of their reports, thus increasing these predictors' validity.

The discovered interactive effect between ED and emotional variability may suggest that greater attention to interactions between affect dynamics in their relations with other constructs is in place. After all, it is unlikely that these relations follow simple linear regularities, but rather more complex patterns (e.g., Wichers et al., 2015). It is possible that interactions between different dynamic indices will function better than single indices in representing robust interindividual differences. Notably, examining such interactive effects will require increased sample sizes.

In this study, the dynamic indices were derived from surveys collected four times a day, approximately 4 h apart. This data collection scheme was chosen to reduce patients' burden and provide a representative sample of participants waking hours, but the relatively long measurement intervals run the risk of missing the more rapid affective processes (e.g., Verduyn et al., 2009). An alternative, contextualized approach to dynamic assessment may aim to capture affect dynamics when and where they matter the most, for example, in the vicinity of a stressful event (Dejonckheere et al., 2020; Lapate and Heller, 2020). Moreover, assessment of affect dynamics can be relevant and informative also after psychotherapy has started using either EMA between sessions (e.g., Frumkin et al., 2020) or reports regarding the sessions themselves (Lazarus et al., 2019; Galili-Weinstock et al., 2020).

Lastly, for dynamic assessment of affective processes to reach its full potential, it must involve thorough consideration of the temporal dynamics of the target processes (e.g., Hamaker and Wichers, 2017; Lazarus et al., 2021b). Specifically, a time scale (e.g., Adolf et al., 2021) appropriate for capturing affective changes as they unfold in patients' daily life should be identified based on prior research (e.g., Verduyn et al., 2009) or theoretical grounds, and dictate the measurement scheme. Additionally, trends (e.g., linear and quadratic; Jebb et al., 2015) and cycles (e.g., diurnal and weekly; van de Maat et al., 2020) should be modeled and interpreted on a case-by-case basis (Fisher and Newman, 2016).

Limitations

Several limitations of the present study should be acknowledged. First, the available sample size of treatment completers provided low statistical power. Such low power may have prevented us from detecting some effects that would have emerged with a larger sample. This sample size should also suggest caution when interpreting the effects that did emerge, as they may not be generalizable to other samples. Clearly, replications with larger samples are necessary to establish the reported effects' validity. Of note, the study's procedure is highly demanding (included both EMA and psychotherapy) and makes larger samples hard to obtain. Moreover, the study did have a large number of within-individual measurements across a prolonged period, increasing the ED indices' reliability.

Second, though ED was measured prior to treatment, claims regarding its causal role in the treatment should be taken with caution. While we cannot rule out the effects of many "third variables," the inclusion of pre-treatment symptoms scores in all models narrows this concern somewhat. Future work measuring ED throughout the treatment and at its end can provide further credibility for causal inferences.

Third, the items used to estimate patients' ED suffered from two limitations stemming from the original focus and the purpose of the data collection. The PED measure was based on only four positive emotions and included one unspecific item (i.e., "positive"). This narrow measurement was meant to reduce participants burden but might have crippled our positive ED index. Given the growing interest in the role of distinct positive emotions (e.g., Weidman and Tracy, 2020), future dynamic assessment work should operationalize positive ED using a larger number of items. The NED measure was partially based on items with conjoint terms. Two of these items (i.e., down/depressed and frightened/afraid) were used to avoid patients being overly exclusive in endorsing them; the third (worthless/guilty) was used as an adaptation of one of the key DSM depression symptoms and involves clearly two distinct emotions. These issues might have added noise to our NED measurement. Specifically, endorsement of the same value for these items on different occasions may reflect different experiences for patients who could differentiate between the conjoint terms. Consequently, the ED scores of these patients might have been underestimated. The usage of such items is particularly problematic when studying ED because how individuals interpret them is a derivative of ED itself and thus runs the risk of leaving important between-individual variability in ED unaccounted for. Furthermore, the negative affect measurement included a limited number of items, and future work is necessary to assess whether findings generalize to differentiation among other emotions.

CONCLUSION

The present work took a preliminary step in demonstrating the utility of dynamic assessment to identify affect-processing patient factors predictive of treatment outcome. We found that negative ED predicted better treatment response when emotional variability was taken into account. Our findings suggest that negative ED may play an important role in the success of psychotherapeutic interventions.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material; further inquiries can be directed to the corresponding author.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Committee for Protection of Human Subjects (CPHS), University of California, Berkeley. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

GL developed the idea for the study and conducted the data analyses and interpretation under the guidance of AF. AF performed the data collection. GL drafted the paper under the guidance of AF who provided critical revisions and comments. All authors contributed to the article and approved the submitted version.

FUNDING

GL is supported by a Marie Skłodowska-Curie individual fellowship (895828) under the European Union's Horizon 2020 research and innovation program. The Berkeley Research Impact Initiative (BRII) provides funding for the publication fees. Publication made possible in part by support from the Berkeley Research Impact Initiative (BRII) sponsored by the UC Berkeley Library.

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Psychology

REVIEW
published: 06 August 2021
doi: 10.3389/fpsyg.2021.700298

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Emotion Differentiation and Youth Mental Health: Current Understanding and Open Questions

Erik C. Nook[1,2]*

[1] Department of Psychology, Harvard University, Cambridge, MA, United States, [2] Department of Psychiatry, NewYork-Presbyterian Hospital/Weill Cornell Medical Center, New York, NY, United States

A growing body of research identifies emotion differentiation—the ability to specifically identify one's emotions—as a key skill for well-being. High emotion differentiation is associated with healthier and more effective regulation of one's emotions, and low emotion differentiation has been documented in several forms of psychopathology. However, the lion's share of this research has focused on adult samples, even though approximately 50% of mental disorders onset before age 18. This review curates what we know about the development of emotion differentiation and its implications for youth mental health. I first review published studies investigating how emotion differentiation develops across childhood and adolescence, as well as studies testing relations between emotion differentiation and mental health in youth samples. Emerging evidence suggests that emotion differentiation actually *falls* across childhood and adolescence, a counterintuitive pattern that merits further investigation. Additionally, several studies find relations between emotion differentiation and youth mental health, but some instability in results emerged. I then identify open questions that limit our current understanding of emotion differentiation, including (i) lack of clarity as to the valid measurement of emotion differentiation, (ii) potential third variables that could explain relations between emotion differentiation and mental-health (e.g., mean negative affect, IQ, personality, and circularity with outcomes), and (iii) lack of clear mechanistic models regarding the development of emotion differentiation and how it facilitates well-being. I conclude with a discussion of future directions that can address open questions and work toward interventions that treat (or even prevent) psychopathology.

Keywords: emotion differentiation, development, mental health, psychopathology, adolescence

OPEN ACCESS

Edited by:
Jennifer Marie Binzak Fugate, University of Massachusetts Dartmouth, United States

Reviewed by:
Tanja Lischetzke, University of Koblenz and Landau, Germany
Carlos Ventura-Bort, University of Potsdam, Germany

Correspondence:
Erik C. Nook
enook@g.harvard.edu

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: *25 April 2021*
Accepted: *12 July 2021*
Published: *06 August 2021*

Citation:
Nook EC (2021) Emotion Differentiation and Youth Mental Health: Current Understanding and Open Questions. Front. Psychol. 12:700298. doi: 10.3389/fpsyg.2021.700298

INTRODUCTION

Some people easily label their emotional experiences using precise terms (e.g., differentiating when they feel "frustrated" from when they feel "disappointed"), but others struggle to make such fine-grained distinctions and instead focus merely on whether they feel "good" or "bad" in any given moment. This individual difference is referred to as *emotion differentiation* or *emotional granularity*. Several studies have demonstrated that people with higher emotion differentiation tend to have better mental health (see Kashdan et al., 2015; Smidt and Suvak, 2015; Trull et al., 2015; Hoemann et al., 2020a; Thompson et al., 2021 for reviews and O'Toole et al., 2020; Seah and Coifman, 2021 for meta-analyses). A substantial body of research in adult samples now shows that emotion differentiation scores are associated with healthier and more effective responses to intense negative emotions (Barrett et al., 2001; Tugade et al., 2004; Kashdan et al., 2010;

Pond et al., 2012; Zaki et al., 2013; Kalokerinos et al., 2019; Ottenstein, 2020) and that emotion differentiation scores tend to be lower in adults experiencing several forms of psychopathology (e.g., depression, anxiety disorders, eating disorders, schizophrenia, autism, and borderline personality disorder; Decker et al., 2008; Demiralp et al., 2012; Erbas et al., 2013; Dixon-Gordon et al., 2014; Kashdan and Farmer, 2014; Kimhy et al., 2014; Tomko et al., 2015; Mikhail et al., 2020). Together, this body of research suggests that the ability to specifically identify one's emotions bolsters adaptive emotional responding and protects against psychopathology.

To date, however, very few studies have examined emotion differentiation in developmental samples, constraining our knowledge of this phenomenon almost entirely to adult populations. This is a major gap in understanding, especially considering that childhood and adolescence are active windows of change in several social and emotional processes (Guyer et al., 2016; Somerville and McLaughlin, 2018; Nook and Somerville, 2019). Across childhood, people gradually learn how to define emotion words, to accurately label emotional facial expressions, to predict specific emotional responses from contextual settings, and to manage their emotional responses (Baron-Cohen et al., 2010; Widen, 2013; Silvers et al., 2017; Lagattuta and Kramer, 2019; Nook et al., 2020). In fact, the abilities to conceptualize one's own and others' emotions show protracted development, continuing to mature into adolescence (Dumontheil et al., 2010; Sebastian et al., 2012; Nook et al., 2017, 2020), and adolescence is a period of the lifespan where neural, hormonal, and social changes bring about increased stress and negative emotion compared to childhood (Larson and Ham, 1993; Larson et al., 2002; Romeo and McEwen, 2006; Steinberg, 2015). These social and emotional transitions make adolescence a period of increased risk for the onset of psychopathology, with an estimated 50% of all mental illnesses arising before age 18 (Kessler et al., 2005; Sawyer et al., 2012).

Given that transitions from childhood to adolescence are times of both substantial emotional change *and* increased risk for psychopathology, it is imperative that we clearly understand how youth might best manage their emotional experiences and healthfully navigate this period of their lives. This renders greater understanding of the development of emotion differentiation extremely important, as it could provide insight into how normative changes in affective processes relate to increased risk for psychopathology in adolescence. Such insight could then guide psychological interventions that protect youth from psychopathology. Fortunately, researchers have begun to examine how emotion differentiation develops across age, as well as how emotion differentiation scores relate to well-being in youth samples. The first goal of this paper is to synthesize this burgeoning literature, taking stock of elements of commonality and areas for future growth in our understanding of the development of emotion differentiation and how it relates to well-being in youth.

However, the scientific study of emotion differentiation (in both adult and developmental samples) is limited by several open questions, including: (i) concerns about the construct validity of current emotion differentiation measures, (ii) the presence of third variables that might explain existing relations between emotion differentiation and mental health (e.g., IQ, mean negative affect, circularity with outcome measures), and (iii) a lack of clear mechanistic models for how emotion differentiation develops and how it facilitates mental health. These topics have received some attention in the adult literature (Trull et al., 2015; Dejonckheere et al., 2019; Hoemann et al., 2020a; Thompson et al., 2021), but not in developmental populations. Therefore, the second goal of this paper is to clearly describe these limitations and discuss how they manifest in studies of emotion differentiation in youth. Even though research on youth emotion differentiation is in its infancy, there are several reasons to conduct a review at this point. First, identifying (in)consistencies in methods and results across emerging studies can provide insight into the stability of effects and generate hypotheses of potential moderating factors. Second, as noted above, studies on the development of emotion differentiation have lagged behind studies on adults, suggesting that clearly articulating the impact of a developmental approach to this phenomenon could stimulate future research in this area. Third, identifying and summarizing key open questions can improve future studies by laying out an agenda of research questions in need of study that can together work toward a clear scientific account of emotion differentiation (see **Box 1** for a summary).

This paper is organized into five sections, which together aim to articulate what we do and do not know about the development of emotion differentiation and youth mental health. The first section "Carving the Subject Matter" defines emotion differentiation and carves it away from other related phenomena. The second section "Emotion Differentiation Across Age" then synthesizes published studies examining how emotion differentiation scores vary across age to chart what we have learned about its shift from childhood into adulthood. The third section "Emotion Differentiation and Youth Mental Health" reviews studies showing how emotion differentiation scores relate to mental health variables in youth samples (i.e., participants younger than age 18). The fourth section "Key Questions for the Study of Emotion Differentiation in Youth" then identifies key open questions that limit our understanding of how emotion differentiation relates to mental health in developmental samples. The final section "Discussion and Future Directions" provides a general discussion of the paper's topics and outlines ideas for future research.

CARVING THE SUBJECT MATTER

Given the diversity of emotion constructs that exist in the literature, it is important to define what I mean by emotion differentiation and outline the scope of the current review. The field has generated a wide array of constructs that seek to quantify how aspects of affective experience differ across individuals (e.g., emotion awareness, emotional intelligence, emotional clarity, emotional intensity, emotional complexity, emotional instability, emotion comprehension, emotional inertia, emotion abstraction, alexithymia, and emodiversity (Sifneos, 1973; Lane and Schwartz, 1987; Kang and Shaver, 2004; Salovey and Grewal, 2005;

BOX 1 | Key lessons, open questions, and future directions for research on youth emotion differentiation.

Lessons from prior work	Key open questions	Avenues for future research
Two studies show emotion differentiation scores decrease from childhood to adolescence, in contrast to the common-sense assumption that this ability should strengthen with age.	Is emotion differentiation related to mental health in children? To date no published studies have tested this question.	A series of studies are needed to parse how contextual factors at the person-level (e.g., age, vocabulary, early life experiences), study-level (e.g., duration of EMA measures, which emotion words were used), and situation-level (e.g., momentary stress levels) influence emotion differentiation.
Four of six studies show that negative emotion differentiation is associated with improved mental health in youth.	Can we rule out third variables on relations between emotion differentiation and mental health? Rather than being "confounds," might they play a meaningful role in these relationships? Key candidates: IQ, mean negative affect, personality characteristics, circularity with outcome measures (e.g., fatigue).	Use of experimental approaches are needed to test causal relationships (e.g., how does facilitating or depleting access to emotion concepts influence differentiation? How do emotion differentiation interventions influence downstream mechanisms that facilitate mental health?)
Zero studies found a linear person-level relationship between positive emotion differentiation and youth mental health.	How should we measure emotion differentiation? How do we best separate it from other closely related constructs? Is there a valid measure uncontaminated by mean negative affect?	Biological-level approaches are needed (e.g., how does the brain support differentiated emotional experiences? How does this scaffold on normative brain development?)
Two of three studies show that emotion differentiation buffers youth from the impact of stress.	How do we measure emotion differentiation in children whose verbal abilities are still developing or in adults who lack access to emotion words?	Greater focus on the interpersonal aspects of emotion differentiation, especially in development are needed (e.g., could low emotion differentiation in adolescence relate to social difficulties that consequently foster internalizing problems?).
Although results converge on lessons above, some mixed results hasten a call for increased research on these relationships to generate additional effect sizes, test of moderators, and set the stage for future meta-analyses.	What would clear models for (i) the development of emotion differentiation and (ii) the relation between differentiation and mental health look like? In particular, what multi-level mechanisms explain (i) decreased differentiation from childhood to adolescence and (ii) how strong differentiation boosts healthy outcomes?	Widespread use of open science principles (e.g., preregistration, consortium-level data sharing, replication), gold-standard developmental methods (e.g., wide age ranges, continuous age models), and principles of intervention science (e.g., testing mechanisms) are crucial for a robust science.

Waugh et al., 2011; Boden et al., 2013; Quoidbach et al., 2014; Koval et al., 2016; Nook et al., 2020). Scholars debate the best way to organize these different constructs (Grühn et al., 2013; Thompson et al., 2021), with some arguing that they can be meaningfully integrated into a framework of "emotional expertise" (Hoemann et al., 2020a), while others argue that they are largely redundant in the prediction of mental health in adults (Dejonckheere et al., 2019). Regardless, these constructs are associated with psychological health in both youth and adult samples (e.g., Zeidner et al., 2012; Boden and Thompson, 2015; Trull et al., 2015; Bailen et al., 2019), and we have data on how some of them vary across age (Bailen et al., 2019; Haas et al., 2019; Reitsema et al., 2021). Although the questions of how these constructs relate to each other and how they all develop are interesting and fruitful directions of research, the current paper engages only with emotion differentiation, which is defined as *how specifically people identify their emotional experiences* (see Barrett et al., 2001; Kashdan et al., 2015).

This paper focuses on studies that operationalize emotion differentiation in its classic formulation as the intercorrelation between self-reported emotional experiences, which I refer to as *emotion differentiation scores*. The earliest studies of emotion differentiation asked participants to rate their emotions at the end of each day on 5-point scales (Barrett et al., 2001) and calculated the average of all pairwise correlations between emotion ratings. The logic of this approach is that participants who struggle to conceptualize emotions in specific emotional terms (instead representing their affect as merely "good" or "bad") will consistently endorse similar emotional states across days. For example, at the end of a "bad" day, they will provide similarly intense ratings of fear, anger, and sadness, and on a "less bad" day, they will report slightly less intense ratings of all of these emotions. By contrast, people with high emotion differentiation will select unique profiles of emotion terms that specifically describe their emotional reactions on each day (e.g., providing high fear and anger ratings on a day that elicited those specific emotions but high anger and sadness ratings on a different day). Correlations between emotion ratings will be high for the first kind of individual and low for the second kind of individual, meaning that low correlation coefficients between emotions are taken as an indication of high emotion differentiation.

This method is still widely used to measure emotion differentiation, with a few key advances. Researchers have increased the number of emotion ratings participants complete each day (i.e., using *ecological momentary assessment* [EMA] methods), and laboratory measures have also been introduced in which emotion ratings are made in response to standardized image sets (Erbas et al., 2014; Nook et al., 2018). Additionally, intraclass correlations (ICCs) are often used instead of pairwise correlations (Kalokerinos et al., 2019). Nonetheless, the logic of these methods remains identical: High consistency in emotion ratings across instances indicates poor differentiation of one's affect. Studies using this method will be reviewed in the current paper.

When possible, researchers apply these methods separately for ratings of "positive" and "negative" emotions, leading to measures for positive emotion differentiation (i.e., how specifically people differentiate emotions like happiness, gratitude, excitement, and amusement) and negative emotion differentiation (i.e., how specifically people differentiate emotions like sadness, anger, fear, and disgust). Positive and negative emotion differentiation are computed separately so that each score can represent how specifically people identify emotions *within* a class of emotions that share a similar valence, though some research has investigated overall differentiation using an ICC across both positive and negative emotions (e.g., Kimhy et al., 2014). Researchers have also recently developed methods to quantify how specifically people differentiate emotions at the *moment-level*, not just at the *person-level* (Tomko et al., 2015; Erbas et al., 2018, 2021). These studies offer compelling evidence that emotion differentiation varies *within* individuals and that these oscillations share interesting relationships with outcomes. Unfortunately, because these methods have not yet been investigated in youth, no studies using this approach are reviewed. Similarly, although researchers have attempted to measure emotion differentiation through self-report questionnaires (e.g., the Range and Differentiation of Emotional Experience Scale; Kang and Shaver, 2004), convergent validity with the canonical ICC approach has not been established. As such, the current paper will focus only on studies that use repeated assessments of experienced emotions.

EMOTION DIFFERENTIATION ACROSS AGE

If being able to specifically identify emotions helps people manage them, then it seems important to understand the normative trajectories through which this affective skill develops. Indeed, the framework of developmental psychopathology (Sroufe and Rutter, 1984; Cicchetti and Sroufe, 2000; Cicchetti and Rogosch, 2002) emphasizes four key steps in understanding and preventing psychological disorders: (i) identify how psychological processes typically emerge across age, (ii) document differences between these normative trajectories and trajectories indicative of psychopathology, (iii) elucidate the mechanisms that produce these diverging trajectories, and (iv) develop interventions that bring pathological trajectories into alignment with healthy development. To date, two published studies have investigated the typical developmental trajectory of emotion differentiation (one assessing negative emotion differentiation and one assessing both positive and negative emotion differentiation, **Table 1**).

One study asked a cross-sectional sample of 143 participants aged 5–25 to complete a laboratory measure of negative emotion differentiation (Nook et al., 2018). Participants viewed 20 negative images and rated how angry, sad, disgusted, scared, and upset they felt in response to each image, and an emotion vocabulary test was used to exclude participants who didn't comprehend these terms (Nook et al., 2020). Emotion differentiation scores (i.e., the inverse of intraclass correlations on these ratings) revealed an inverted-U relationship with age: Negative emotion differentiation scores fell from childhood to around age 15 before rising again into young adulthood. Somewhat surprisingly, this suggested that young children were actually *better* at differentiating negative emotions than adolescents. Further analyses revealed that children were more likely to report experiencing only one emotion at a time compared to older participants and that this tendency statistically explained why emotion differentiation scores fell from childhood to age 15. This finding converged with previous research showing that children tend to report emotions one-at-a-time (Harter and Buddin, 1987; Wintre and Vallance, 1994; Larsen et al., 2007). As such, the current study provided initial evidence for a non-linear developmental trajectory for emotion differentiation.

These results were partially replicated in a study of 233 adolescents aged 14–17 (Starr et al., 2020b). This study used an EMA method in which participants received four prompts each day for seven days with a survey asking them to report how strongly they felt five negative emotions (i.e., anxious, sad, annoyed, angry, worn-out) and five positive emotions (i.e., happy, proud, cheerful, lively, joyful) on 7-point scales. ICCs were again used to quantify negative and positive emotion differentiation. Here the researchers only found a significant linear decrease in negative emotion differentiation scores across age, and tests for non-linear trajectories were not significant. Positive emotion differentiation scores also showed an overall negative relationship with age, but this did not reach significance. Even though the tendency to report feeling only one negative emotion at a time was related to both negative and positive emotion differentiation scores, it did not vary across age.

Although these two studies used different methods (laboratory vs. EMA measurement of emotion differentiation and broad vs. narrow age range), they converge on the intriguing finding that younger individuals actually construct negative emotions in a *more* differentiated fashion than older individuals. This may seem surprising, given notions that children tend to focus on whether emotion concepts are merely "positive or negative" and that additional complexity in emotion concepts emerge with age (Pons et al., 2004; Widen and Russell, 2008; Widen, 2013; Nook et al., 2017; Morningstar et al., 2019). However, the story seems more complex than the takeaway that children are expert emotion differentiators. Instead, children may construct emotional experiences in entirely different ways than adults. Children tend to report experiencing emotions one at a time, potentially suggesting that they believe emotions are mutually exclusive mental states. This reveals an important nuance about the measurement of emotion differentiation, as children and adults might both achieve the same differentiation score but have entirely different "routes" to obtaining this score: Whereas children clearly identify what they are feeling by endorsing a single emotion at a time, adults can differentiate emotions even while multiple are co-experienced simultaneously. Adolescents appear to be somewhere in the middle of these two developmental processes, struggling to differentiate newly co-experienced emotions. Interestingly, other lines of research also show that youth report *greater* difficulty in labeling and describing their emotions as they age from childhood to adolescence (Haas et al., 2019; Weissman et al., 2020). These findings may all reflect overlapping psychological processes that render emotions more difficult to identify in adolescence, but future research is needed to gain clarity on relations between these constructs, as well as the down-stream impacts of this developmental shift on emotion regulation and mental health.

TABLE 1 | Published papers investigating emotion differentiation in youth.

Authors	Year	Usable *N*	Age range	Emotion differentiation measure				Relationships with:				Mean affect control?
				Method	**Valence**	**Stimuli Duration**	**Emotions**	**Age**	**Psychopathology**	**Stress buffering**	**Other**	
Nook, Sasse, Lambert, McLaughlin, and Somerville	2018	143	5–25	Lab task	Negative	20 negative images	Angry, disgusted, sad, scared, and upset	U-shaped relationship	–	–	–	Yes (from lab task)
Starr, Shaw, Li, Santee, and Hershenberg	2020	233	14–17	EMA	Negative	4 prompts/day for 7 days	Anxious, sad, annoyed, angry, and worn-out	Linear negative relationship	Significant negative relationship with depression symptoms in community sample	–	Significant negative relationships with parental depression, parental attachment, and parenting style	Yes (from EMA)
					Positive		Happy, proud, cheerful, lively, and joyful	Not significant (negative direction)	Not significantly related to depression symptoms in community sample	–	Significant negative relationships with parental depression and parental attachment	
Erbas, Ceulemans, Boonen, Noens, and Kuppens	2013	18 ASD + 26 TD	15–19	Lab task	Negative	20 negative images	Fear, worry, anxiety, nervousness, anger, irritation, disgust, rage, shame, guilt, regret, embarrassment, sadness, loneliness, unhappiness, depression, jealous, envious, and two Dutch words for inferior	–	Significantly lower in participants diagnosed with ASD compared to controls (one-tailed)	–	–	No
Lennarz, Lichtwarck-Aschoff, Timmerman, and Granic	2018	86	Not given (M = 14)	EMA	Negative	22 prompts/ weekend for 2 weekends (4 on Friday, 9 on Saturday, 9 on Sunday)	Jealous, anxious, ashamed, irritated, worried, angry, guilty, sad, and lonely	–	Not significantly related to depression symptoms in community sample	–	Significant negative association with mean negative affect and implicit theories of emotion	No
					Positive		Happy, cheerful, satisfied, relaxed, and proud.	–	Not significantly related to depression symptoms in community sample	–	Significant positive association with mean positive affect	

(Continued)

TABLE 1 | Continued

Authors	Year	Usable *N*	Age range	Emotion differentiation measure				Relationships with:				Mean affect control?
				Method	**Valence**	**Stimuli Duration**	**Emotions**	**Age**	**Psychopathology**	**Stress buffering**	**Other**	
Starr, Hershenberg, Shaw, Li, and Santee	2020	233	14–17	EMA	Negative	4 prompts/day for 7 days	Anxious, on edge, uneasy, sad, hopeless, discouraged, angry, resentful, annoyed, fatigued, worn out, and exhausted		Significant relationship with depression symptoms concurrently and 1.5 years later in community sample∗	Significantly buffered relationship between stressful events and concurrent depression symptoms, depression symptoms 1.5 years later, and momentary depressed affect	–	Yes (from EMA)
					Positive		Happy, proud, cheerful, lively, and joyful	–	Not significantly associated with depression symptoms in community sample	Significantly buffered relationship between daily hassles and concurrent depressed affect, but no longer significant when controlling for negative emotion differentiation	–	
Schreuder et al.	2020	401	15–18	EMA	Negative	10 prompts/day for 6 days	Lonely, anxious, irritated, listless, suspicious, down, insecure, guilty	–	Significantly associated with good prognosis (global severity score below cutoffs) 1 year later in community sample of twins∗∗	No interaction between negative emotion differentiation and stressful events in predicting prognosis 1 year later	–	Yes (from EMA)
Nook, Flournoy, Rodman, Mair, and McLaughlin	2021	30	15–17	Lab task	Negative	20 negative images	Angry, ashamed, disgusted, sad, and scared	–	Not significantly associated with depression or anxiety in community sample	Significantly buffers relationship between perceived stress and depressed affect (moment level), as well as relationship between stressful events and anxiety symptoms (month level)	–	Yes (from lab task)
					Positive	20 positive images	Calm, excited, happy, inspired, and interested	–	Not significantly associated with depression or anxiety in community sample	Significantly buffers relationship between perceived stress and depressed affect (moment level)	–	

EMA, ecological momentary assessment; ASD, autism spectrum disorder; TD, typically developing.
All studies used the ICC method for computing emotion differentiation scores.
∗Prospective association no longer significant when controlling for baseline depression symptoms and mean negative affect.
∗∗No longer significant after controlling for mean negative affect.

The two studies reviewed above differed in what they suggest about the trajectory of negative emotion differentiation from age 15 onward. The first suggested an increase across age, whereas the second did not find this U-shaped pattern. This could be explained by the age restriction of the second study, which may not have included enough data from older participants to capture the increase across this window. That said, the four published studies on emotion differentiation in older adults provide mixed results: Older adults' emotion differentiation scores are sometimes higher than (Mankus et al., 2016), sometimes lower than (Brose et al., 2015) and sometimes equivalent to (Grühn et al., 2013; Mikkelsen et al., 2020) younger adults. This heterogeneity in effects either suggests that emotion differentiation is largely unchanging over this age range (i.e., positive or negative correlations emerge in a given study merely due to sampling error) or that there are important study-level factors that systematically influence these results.

EMOTION DIFFERENTIATION AND YOUTH MENTAL HEALTH

Even though studies show that emotion differentiation scores track mental health in adult samples, this does not necessarily imply that the same relationship exists in younger samples, especially given that emotion differentiation scores vary normatively across age. A handful of studies have investigated both simple associations between emotion differentiation scores and mental health in youth samples as well as more complex questions of whether emotion differentiation offers resilience to youth when they face stressful life experiences (**Table 1**).

Associations Between Emotion Differentiation and Mental Health

Erbas et al. (2013) tested whether emotion differentiation differed between 18 adolescents with autism spectrum disorders (ASD, ages 15–19) and 26 typically developing adolescents (ages 15–18). Both groups completed a laboratory-based assessment of negative emotion differentiation in which they rated how strongly they felt 20 negative emotions in response to 20 negative images. Emotion differentiation scores computed from intraclass correlations were significantly lower in participants with ASD compared to controls. A second measure in which participants sorted 20 emotion words into piles also showed that participants made fewer piles than controls—suggesting less differentiation—though the result was on the margin of significance ($p = 0.06$). Hence, this study provided initial evidence that negative emotion differentiation is lower in adolescents with ASD.

A number of studies have examined how youth emotion differentiation relates to symptoms of depression. Lennarz et al. (2018) assessed both positive and negative emotion differentiation in 86 adolescents (72 included in a subset of analyses, $M_{age} = 14$). Participants completed EMA measures over two weekends (44 prompts total) and ICCs were applied to compute emotion differentiation scores. Negative emotion differentiation scores were negatively correlated with (i) the average intensity of negative affect over the EMA periods, (ii) self-reported propensity to experience negative emotions in the weeks between sampling periods, and (iii) having a "fixed mindset" regarding negative emotions (i.e., higher emotion differentiation scores were associated with more adaptive implicit theories of emotions, Tamir et al., 2007). By contrast, positive emotion differentiation scores were only associated with the average intensity of positive emotions during EMA periods, but this relationship was rendered non-significant when controlling for gender. Interestingly, neither positive nor negative emotion differentiation scores were related to self-reported depressive symptoms, though this may be due to the fact that the sample rarely endorsed symptoms ($M = 0.35$).

The Starr et al. (2020a) paper described above also included measures of both participant and parent mental health. Adolescents with higher negative emotion differentiation scores endorsed significantly fewer depressive symptoms, and a negative (but non-significant) relationship also emerged for positive emotion differentiation scores. Interestingly, adolescents with higher positive and negative emotion differentiation scores also had *parents* who were less depressed, and they reported being more securely attached to their parents. Finally, parents' self-report of parental style was significantly related to negative emotion differentiation scores such that parents who were less authoritarian had adolescents with higher negative emotion differentiation scores. Although one cannot infer causality or directionality from these correlational results, they nonetheless highlight the fact that youth emotion differentiation emerges in the context of family environments such that parental well-being and parenting styles may shape or be shaped by adolescent emotion differentiation.

Three additional studies investigated how emotion differentiation relates to internalizing symptoms in youth (Schreuder et al., 2020; Starr et al., 2020a; Nook et al., 2021a), and they also included analyses testing whether emotion differentiation buffers the impact of stress on youth (reviewed below). In Starr et al. (2020a), 233 participants aged 15–17 completed interviews assessing depression symptoms (Kaufman et al., 1997) both immediately before EMA measures used to assess emotion differentiation (labeled T1) as well as 1.5 years later (labeled T2). Negative emotion differentiation scores were significantly related to both T1 depression symptoms and T2 depression symptoms 1.5 years later. However, the prospective relationship with T2 symptoms was no longer significant when controlling for T1 depression scores and mean negative affect endorsed in EMA sampling. Positive emotion differentiation scores were not significantly related to depression symptoms at either timepoint.

Nook et al. (2021a) conducted an intensive longitudinal study of 30 adolescent girls aged 14–17 and examined relations between emotion differentiation assessed using a laboratory-based picture rating task and self-reported measures of depression and anxiety symptoms. Although positive and negative differentiation scores were negatively correlated with internalizing symptoms, they did not reach significance at the between-persons level. This was likely due to the small N, as the study was optimized to detect within-persons, rather than between-persons effects (see next section for significant within-person buffering effects).

Finally, Schreuder et al. (2020) examined prospective relations between emotion differentiation and broad indices of psychopathology over a 1-year period in 401 participants aged 15–18. They used a slightly different measure of psychopathology in which they administered the SCL-90 (Arrindell and Ettema, 1986) at the beginning and end of the study period and categorized participants into "good" or "bad" prognosis depending on how these scores had changed over time (Schauenburg and Strack, 1999). They found that negative emotion differentiation scores assessed by 6 days of EMA were significantly related to prognosis 1 year later, but not after controlling for mean negative affect.

Together, these studies extend research on the positive correlates of emotion differentiation in adults to developmental samples, with 4 of 6 finding a relationship between emotion differentiation and psychopathology (and the other 2 either finding that emotion differentiation tracks a broader index of negative affect or that it buffers the impact of stress). This suggests that emotion differentiation is indeed associated with youth mental health. However, few caveats must be kept in mind regarding this association. First, all relations with psychopathology only exist for negative emotion differentiation, and no significant relations emerge between psychopathology and positive emotion differentiation. Unfortunately, this means that the number of significant relations falls to the much less rosy 4 out of 10 when the total number of comparisons is taken into account. Although there are indeed legitimate reasons why some of these relations were null (e.g., low sample symptom prevalence, low between-subject power due to an intensive within-person design, positive emotion differentiation scores are known to be less consistently associated with outcomes; Liu et al., 2020), a 40% significance rate raises concerns about the stability of the effect. As such, further evidence is needed to gain confidence in the association between mental health and negative emotion differentiation. Additionally, although it is compelling to find in two studies that emotion differentiation has *predictive* relations with psychopathology, this relationship became non-significant after controlling for baseline symptoms and/or mean negative affect. This raises questions about the unique contribution of differentiation on youth mental health, as has been raised in the adult literature (Dejonckheere et al., 2019).

Taken together, this review suggests that negative emotion differentiation *may* track psychopathology in youth, but the evidence base is not as strong as for the adult literature. In fact, the evidence summarized here might indicate that differentiation is helpful in adolescence but with a smaller effect than in adulthood. A meta-analysis following additional data collection would greatly aid in estimating the stability and size of these relationships. Meta-analytic approaches would also allow us to clarify whether moderators might explain when we would or would not expect significant relations. As such, additional studies that estimate relations between differentiation and youth mental health are sorely needed. Most notably, there are *no* studies testing how emotion differentiation relates to *child* mental health, as no studies focused on participants less than age ∼14. Even if it seems reasonable to expect that emotion differentiation is helpful in managing emotions in childhood—as it is in adults—this remains an important open empirical question for the field to address. This is especially true considering the evidence reviewed previously showing that there are many facets of emotion construction that differ between childhood, adolescence, and adulthood. Similarly, only one study selected participants based on diagnosed levels of psychopathology (Erbas et al., 2013) and all others used community samples. Although community samples often include symptomatic individuals (e.g., at T2 in Starr et al., 2020a, 37% of participants reported clinically significant symptoms and 16% met criteria for major depressive disorder), future research should verify that these relationships exist when directly comparing youth with and without elevated symptom levels (as has been done in adults; e.g., Demiralp et al., 2012).

Emotion Differentiation as a Buffer Against Stress

A long history of scholarship has associated stressful life experiences (i.e., situations in which people experience significantly unexpected and/or threatening events that tax their available coping resources; Lazarus and Folkman, 1984) with heightened risk of psychopathology (Larson and Ham, 1993; Grant et al., 2006; McLaughlin and Hatzenbuehler, 2009; Michl et al., 2013). However, if emotion differentiation does indeed facilitate emotion regulation, then differentiation may be especially helpful in buttressing individuals during stressful experiences, when emotions run high. Indeed, relatively early studies of emotion differentiation in adults demonstrated that emotion differentiation scores were associated with healthier coping strategies specifically when negative emotions were elevated (Kashdan et al., 2010; Zaki et al., 2013), and these results have been replicated and extended more recently (Starr et al., 2017; Liu et al., 2020). To date, three published studies introduced above have extended this line of research into developmental populations.

Starr et al. (2020a) tested whether emotion differentiation buffered the impact of stress on psychopathology at two levels. First, within the EMA method that assessed emotion differentiation, participants also indicated if any stressful events (defined as daily hassles across several life domains; Cohen et al., 2005) had occurred since the last prompt and rated the intensity of this event. Both positive and negative emotion differentiation scores moderated the relationship between these stressors and concurrent reports of depressed mood (i.e., the average EMA rating of feeling sad, hopeless, and discouraged), though the interaction for positive emotion differentiation scores was no longer significant when controlling for negative emotion differentiation scores. Nonetheless, these results suggest that adolescents with higher emotion differentiation felt less depressed in response to daily stressors compared to adolescents with low emotion differentiation, just as has been found in two studies with adult participants (Starr et al., 2017). Second, this moderation was also discovered outside of EMA measures. Participants completed interviews assessing stressful life events (Hammen et al., 2000) and depression symptoms

(Kaufman et al., 1997) immediately before the EMA assessment (T1) and approximately 1.5 years later (T2). Somewhat astoundingly, negative emotion differentiation scores moderated the cross-sectional relationship between stressful life events and depressive symptoms at T1 and it also moderated the impact of T1 stress exposure on prospective T2 depression symptoms 1.5 years later, even after controlling for baseline depression symptoms. In fact, participants with high emotion differentiation scores demonstrated no significant relationship between stress exposure and later depression symptoms. Thus, this study provided evidence at two levels of analysis that emotion differentiation buffers adolescents from the deleterious impacts of stress.

These results were largely replicated in a parallel study by Nook et al. (2021a). This study utilized a year-long intensive longitudinal design that included a smaller number of participants ($N = 30$) but greatly increased within-subjects monitoring. Like Starr et al. (2020a), this study structured measures at two levels. First, participants completed 12 weeks of EMA sampling split into four waves across the year, and although this study used a laboratory-based (rather than EMA-based) measure of emotion differentiation, both positive and negative emotion differentiation scores moderated the concurrent relationship between momentary ratings of perceived stress and depressed affect. Second, participants completed interviews each month in which experimenters coded participants' exposure to stressful life events and self-report questionnaires assessing depression and anxiety symptoms. Negative emotion differentiation scores also buffered the concurrent association between objective exposure to stressful life events and anxiety symptoms at the monthly level. Similar to the previous study, participants with high emotion differentiation scores actually had no significant relationship between stress and symptoms. Consequently, this study also found that adolescents who are better able to differentiate their emotions appear to be more resilient to stress.

By contrast, Schreuder et al. (2020) did not find a significant moderating impact of emotion differentiation in protecting against psychopathology 1 year later. This lack of replication may have arisen for a few reasons. First, the measure of psychopathology was much broader (i.e., a broad symptom checklist rather than focused assessments of internalizing symptoms; Arrindell and Ettema, 1986). Second, the measure of psychopathology was dichotomized into good vs. bad prognosis, rather than kept continuous, which could have reduced power to find small effects. Third, the measure of stressful life events was administered *retrospectively* at the 1-year follow-up rather than at baseline, potentially clouding measurement of proximal stressors.

Together, these studies offer two points of evidence that emotion differentiation might facilitate adaptive stress coping in adolescents, and one point of evidence against this hypothesis. The replication across the Starr et al. (2020a) and Nook et al. (2021a) papers is compelling given that they differed in methods. The former used a relatively brief EMA measure to assess emotion differentiation and found that it buffered longitudinal changes in depression 1.5 years later in a large sample. The second used a laboratory measure to show the same conceptual finding using an intensive assessment of within-persons fluctuations in internalizing symptoms in a smaller sample. It is also interesting that both found that positive emotion differentiation scores moderated stress-pathology relationships only when measured at the EMA level and not at a monthly or interview-based level, suggesting that the null person-level positive emotion differentiation results reviewed in the previous section might be masking a relationship that exists at a finer level of analysis. It is not obvious why exactly the Schreuder et al. (2020) study did not show a similar replication, but perhaps methodological details (focus on broad prognosis rather than granular changes in internalizing symptoms or timing of the stress measure) may play a role.

Regardless, just as described above, these studies offer glimmers for the adaptive role of emotion differentiation in youth, but a lack of consistent findings suggests that a clear picture is still emerging. Future research should take these discrepant findings into account when scrutinizing the question of whether (and *how*) differentiation protects against psychopathology in youth. Specifically, it seems that continuous (rather than categorical) measures of psychopathology and using concurrent stress measures may be important for detecting this effect. Interestingly, a recent paper using a 4-year longitudinal EMA design in young adults (i.e., college students) found that negative emotion differentiation scores did not moderate the relationship between stress and the emotion regulation strategies participants reported using (Brown et al., 2021). Although it's possible that the study did not include a measure of the specific strategies that are "active ingredients" in explaining how differentiation buffers the impact of stress (or that these patterns will differ in younger populations), this finding complicates the theoretical picture for how differentiation offers resilience to stress. As described in the Section "Key Questions for the Study of Emotion Differentiation in Youth," studies like these that work toward clear mechanistic models are sorely needed. Nonetheless, this review highlights what evidence we have assembled so far, as well as the many open questions that must be addressed to arrive at a complete picture of youth emotion differentiation.

KEY QUESTIONS FOR THE STUDY OF EMOTION DIFFERENTIATION IN YOUTH

Recent reviews and empirical studies have generated important discussions of key concerns and limitations in the study of emotion differentiation in adults (Trull et al., 2015; O'Toole et al., 2020; Seah and Coifman, 2021; Thompson et al., 2021). In the previous sections, I reviewed papers on youth emotion differentiation and noted that overall, more data are needed for firm conclusions both about how emotion differentiation develops and how it relates to youth mental health. In this section, I expand this discussion to outline what I believe are three of the most pressing issues that loom in our understanding of emotion differentiation beyond the gaps in the literature identified above. Where relevant, I outline how these limitations manifest specifically in the context of youth populations, but many of the concerns raised here also apply to adults. Addressing these and other open questions will be crucial for generating a clear account of emotion differentiation that can spur actionable interventions for improving mental health across development.

Gaining Consensus on What We're Measuring and How to Measure It

Eörs Szathmáry once said that linguists "would rather use each other's toothbrushes than their terminology," and I fear the same is true of psychologists. Several researchers have already commented on the fact that there are a large set of metrics that fall under the umbrella of "affective dynamics" (e.g., Trull et al., 2015; Dejonckheere et al., 2019; Jeronimus, 2019; Reitsema et al., 2021) and that there may be more effective ways to integrate them into a common framework (Hoemann et al., 2020a). A proliferation of terms is not necessarily a bad thing. If each name matches a distinct construct that is clearly specified at the conceptual and operational level, then our field will have a detailed and precise sense of how affective dynamics function. Unfortunately, though, this is likely not the case, as many of these constructs share conceptual (and even statistical) overlap, and some have gone so far as to say that dynamic measures beyond mean affect contribute little to our understanding of mental health (Grühn et al., 2013; Dejonckheere et al., 2019). So how exactly do we define emotion differentiation in the midst of these manifold constructs, and are our current techniques the best measures for this ability?

Unfortunately, creating a clear taxonomy of constructs is easier said than done. One reason it is difficult to declare which constructs provide unique vs. redundant information is that *context* influences (i) how specific operationalizations map onto the underlying affect dynamics they aim to measure, (ii) how different measures relate to each other, and (iii) how these measures relate to outcomes of interest (Aldao, 2013; Lapate and Heller, 2020; see also Grieve, 2021). This makes it difficult to conclude from any single study—which only captures a single or a small set of contexts—what the taxonomy ought to be. To address this problem, it may be helpful to dissect contextual factors into three levels, specifically study-level, person-level, and situation-level factors. Identifying how factors at each level influence emotion differentiation is an important step in working toward a precise understanding of what any individual's emotion differentiation score might be capturing and how it should behave.

First, "study-level factors" (i.e., the specific methods through which emotion differentiation is measured in a study) influence emotion differentiation estimates. For example, the predictive power of emotion differentiation measures is influenced by which emotion terms are administered (Erbas et al., 2019), and merely having a longer duration of self-monitoring influences participants' mean emotion differentiation scores (Widdershoven et al., 2019). Second, "person-level factors" also shape how the same emotion differentiation scores should be interpreted. For example, in Nook et al. (2018) *age* is one such feature, as even if a 5-year-old and a 25-year-old achieve the same score on a laboratory measure of emotion differentiation, these two individuals likely have a radically different profile of emotional experiences. Other person-level variables like vocabulary size or trauma history also likely influence emotion differentiation scores (Nook et al., 2017; Weissman et al., 2020). Third, "situation-level factors" shape how we should interpret emotion differentiation measures. For example, momentary levels of stress influence emotion differentiation scores (Erbas et al., 2018, 2021). Similarly, one would imagine that the literal situations in which one measures participants' emotional responses would affect emotion differentiation scores and how well they predict psychopathology (e.g., people who avoid fear-inducing situations during sampling periods may never have the opportunity to endorse feeling fear, even though measuring differentiation in these settings might be the most powerful assay of symptom levels). Consequently, further descriptive evidence is needed to fill in the many unknowns of how these factors influence mappings between measures, constructs, and outcomes if we are to develop a replicable and accurate taxonomy for affective dynamics measures that are not confounded by these contextual factors (see Grieve, 2021 for a related argument in linguistics). Once these patterns have been documented, we can work toward a data-driven taxonomy that accurately situates emotion differentiation within the broader network of other constructs.

In this spirit, it seems that there is open space for developing novel measures of emotion differentiation that do not rely on the ICC measure of repeated emotion ratings. Two studies have recently aimed to do just that by coding the granularity of the emotion words participants used when they narrate their emotional reactions (Ottenstein and Lischetzke, 2020; Williams and Uliaszek, 2021). This method aims to directly assess how nuanced or specific participants are when labeling their emotional experiences by coding their language as more undifferentiated (e.g., "bad," "unpleasant") or more differentiated (e.g., "frustrated," "disappointed") using a coding scheme similar to the Levels of Emotional Awareness Scale (LEAS; Lane et al., 1990). Although this linguistic method offers a face-valid approach to the construct of emotion differentiation, the data surprisingly show that it is not related to the ICC measure and is overall less strongly connected to outcomes (Ottenstein and Lischetzke, 2020; Williams and Uliaszek, 2021). As such, the construct validity of this approach has not been established, and we have little clarity on how actual verbal reports can be used to measure the psychological processes that the ICC method appears to capture. Nonetheless, this line of research affords an opportunity to circumvent some of the context problems raised above, as this method could be applied to standardized vignettes presented in controlled lab environments.

One other looming measurement issue concerns how to measure emotion differentiation in very young populations (and some adult populations) who lack emotion words (see also Shablack and Lindquist, 2019). Emotion vocabulary is constrained to simple words in very young children, and most emotion words are learned across the first ~10 years of life (Baron-Cohen et al., 2010; Nook et al., 2020; Grosse et al., 2021). Researchers have developed creative designs to test emotion perception in very young children, including pre-verbal infants (e.g., looking time, children's behavioral responses to maternal facial expressions, and sorting paradigms; Sorce et al., 1985;

Widen and Russell, 2008; Wu et al., 2017; Ogren and Johnson, 2020b). Although these paradigms can indeed test whether individuals discriminate between stimuli, they primarily focus on differentiating *emotional stimuli* (e.g., others' facial expressions, affective utterances), which is not the same as differentiating *one's own emotions*. Formulating how to measure differentiation of actual emotion experiences in non-verbal individuals is a puzzle in need of a solution.

Ruling Out Third Variables

A second major threat to a clear understanding of emotion differentiation is the looming specter of untested third variables. These undermine both the question of how emotion differentiation relates to age and how it relates to mental health outcomes. One key third variable has already been identified and discussed: Mean negative affect. In a large study of 1,777 individuals, Dejonckheere et al. (2019) showed that many different affective dynamic measures are either no longer associated with mental health measures (or their associations are drastically reduced in size) when mean negative affect is added as a control variable. Interestingly, emotion differentiation scores remained a significant predictor of psychological well-being even after controlling for mean negative affect. However, the size of the relationship fell from $R^2 = 0.04$ to $R^2 = 0.005$, and controlling for mean negative affect rendered the relationship between differentiation scores and depressive symptoms non-significant. This suggests that a large portion of covariance between emotion differentiation scores and well-being is explained merely because people who endorse more negative affect both have worse mental health and have more homogeneous reports of negative emotion.

There are two very different ways to interpret this finding at the conceptual level: (i) emotion differentiation may merely be an artifact of a "true" relationship between heightened negative affect and psychopathology, or (ii) low emotion differentiation may produce elevated endorsements of emotions (e.g., people may anchor ratings on their strongest emotion and then provide similarly strong endorsements for other emotions of the same valence). If the latter is true, controlling for mean negative affect removes true signal produced by emotion differentiation. Adjudicating between these explanations is an important future direction, as one implies that emotion differentiation is epiphenomenal while the other implies that controlling for negative affect metaphorically "throws the baby out with the bathwater." One way to sidestep this concern is to develop methodological innovations that allow emotion differentiation to be measured separate from daily mean negative affect (e.g., from verbal reports or in response to standardized lab stimuli rather than daily experiences; e.g., Erbas et al., 2014; Nook et al., 2018; Ottenstein and Lischetzke, 2020; Williams and Uliaszek, 2021). Another possibility is to develop experimental methods for shifting emotion differentiation (see "Discussion and Future Directions") and testing whether this has a causal impact on shifting mean endorsement of negative affect (i.e., empirically testing the mediation model implied above).

Beyond mean negative affect, there are several other third variables that remain underexplored. Overall cognitive abilities (e.g., IQ; Wechsler, 1981; Deary, 2012; Nisbett et al., 2012) are an especially important untestedse of 3rd variables. Both fluid reasoning and verbal knowledge (the two major components of IQ) are associated with emotion and mental health (De Stasio et al., 2014; Opitz et al., 2014; von Salisch et al., 2015; Nook et al., 2017; Miller et al., 2018; Zelazo, 2020), and it stands to reason that they are likely associated with the ability to use words to specifically parse one's affect. These abilities typically increase across age, but their relations with normative shifts in differentiation scores haven't been explored in youth samples. As such, it's possible that cognitive abilities could explain both age-differentiation and mental health-differentiation relationships.

Personality variables (e.g., neuroticism, extraversion, conscientiousness) could similarly serve as third variables for these relationships. For example, highly conscientious individuals may carefully ponder their reactions to each emotion item and provide more nuanced descriptions of their emotions (generating higher emotion differentiation scores) and also be more likely to engage in behavioral habits that promote mental health (e.g., building social relationships; Cohen and Wills, 1985; Bendezú et al., 2019). Two studies reported by Erbas et al. (2014) demonstrated weak relationships between emotion differentiation scores and most personality variables ($|r|$s < 0.06) except for neuroticism ($-0.27 < r$s < -0.17). Although these correlations did not reach significance in either study, they are sizeable enough that future research should seek to ensure they do not confound the research question at hand.

Finally, it is possible that there is a subtle circularity in measures of emotion differentiation and mental health outcomes. Although not truly a "third variable," it's important to rule out the possibility that mental health issues could *produce* emotion ratings that would be scored as low differentiation but are actually reflecting the mental health issue itself. For example, fatigue and low motivation are hallmark symptoms of depressive disorders (American Psychiatric Association, 2013). These symptoms could produce low engagement in the research study, especially if they require many repeated emotion ratings. A lack of engagement could produce similar numerical ratings across scales, a high ICC across emotions, and ultimately low differentiation scores. Consequently, if participants with low motivation in fact experienced highly differentiated emotional experiences but provided homogenous emotion ratings due to a lack of task engagement, this could produce a spurious correlation between emotion differentiation scores and depression symptoms.

We also know that people with mental health difficulties are more likely than controls to (i) make decisions that increase their exposure to stressful situations and (ii) be exposed to systemic adversities (e.g., racism, ostracism, low socioeconomic resources; Adrian and Hammen, 1993; Meyer, 1995; Cole et al., 2006; Sheridan and McLaughlin, 2014; Wadsworth et al., 2016; Vaid and Lansing, 2020). Both of these pressures may shift the typical situations that these individuals are in, potentially generating different profiles of emotion responding in which emotions are naturally co-experienced more intensely than for individuals without these experiences. If so, this could similarly create a natural bias in emotion differentiation score computations that also generate a circular result. The possibility that measures of emotion differentiation may tap externalities of mental health difficulties—rather than the individual's ability to differentiate emotions—is a thorny issue that similarly requires conceptual and methodological innovation to address.

One important note to keep in mind when pursuing these third variables is that it is important to differentiate whether they are operating as true deflationary confounds versus potential mechanisms in a more complex model. For example, it is possible that verbal knowledge operates *either* as a true deflationary confound or as an interesting variable in a mechanistic explanation of the relationship between emotion differentiation and mental health. Having a larger vocabulary may produce more differentiated emotional experiences and facilitate mental health *without* there being any relationship between differentiation and mental health. Conversely, emotion differentiation might actually *explain why* vocabulary is associated with mental health (i.e., people with larger vocabularies can use more specific terms to label their emotions, boosting regulation and ultimately mental health). This distinction becomes especially interesting in a developmental context, where language may contribute to growths in emotion conceptualization (Nook et al., 2017; Hoemann et al., 2019, 2020b; Nook and Somerville, 2019). Similarly, as hinted above, mean negative affect may confound the relationship between differentiation and health, or it may *mediate* this relationship. Studies that engage in careful and thorough adjudication between these different possibilities are needed.

Clarifying Mechanisms and Developing Causal Models

At present, there are not clearly specified causal models that explain either (i) how emotion differentiation develops or (ii) why emotion differentiation is associated with mental health. On the one hand, this is understandable given the developmental stage of our science. The first formulation of emotion differentiation was just 20 years ago (Barrett et al., 2001) and the current review revealed only seven papers focusing on emotion differentiation in youth. It is consequently understandable for us to still be in a *descriptive* stage of scientific discovery, in which scientists focus merely on describing the general properties of emotion differentiation (e.g., its correlates). This stage has generated enthusiasm in the field, and above I advocated for continued effort at the descriptive stage of discovery, given the number of open questions regarding how to conceptualize and measure emotion differentiation. However, the world is desperate for improved techniques to bolster mental health (Kazdin and Blase, 2011; Sawyer et al., 2012; Kazdin and Rabbitt, 2013) and although intervening on emotion differentiation could contribute to mental health efforts, fully realizing this goal will require that we move beyond mere description into formulation of precise theories and thoroughly tested causal models (Eronen and Bringmann, 2021; Robinaugh et al., 2021).

The findings from Nook et al. (2018) summarized above provide an initial step in formulating a model of how emotion differentiation develops, but it is by no means complete. First, it only captures variation across ages 5–25, leaving the early ontogeny of this process unclear. Are emotions at even younger ages also clearly understood in a mutually exclusive fashion? Emotion representation processes from birth to age 5 need to be clarified for a complete theory of emotion differentiation development (see Ogren and Johnson, 2020a; Ruba and Repacholi, 2019 for recent reviews on early emotion development). Second, we have very little insight into the psychological and neural *mechanisms* that explain why these two processes would unfold as they do. Do children indeed *experience* only one emotion at a time, or is this effect produced by how they respond to rating scales? If it does indeed reflect their actual emotional experiences, is this because their actual physiology only triggers affect for one emotion at a time or is it because they have a higher-level belief that leads them to only parse their affect into one emotion type at a time?

Answering these questions will also likely elucidate the mechanisms underlying why adolescence is a period of low emotion differentiation: Does this emerge because of changes in the physiological generation of affect (i.e., hormonal or neural changes producing "messier" affective signals), changes in higher-order beliefs (e.g., the recognition that emotions can occur leading to more complex constructions of what emotions they are feeling), or perhaps some other psychological change (e.g., growing mentalizing skills that could influence how stimuli are interpreted or protracted developments in how the emotion words used in these tasks are interpreted)? Working toward a multilevel causal model may also clarify whether the normative decrease in differentiation across age reflects maladaptive shifts that expose adolescents to increase risk for psychopathology or whether they reflect natural adaptations that overall promote well-being during this developmental period.

The field has also assembled a similarly reasonable, though underspecified, model for why emotion differentiation scores are associated with improved mental health revolving around the idea that being able to specifically identify one's emotions facilitates (i) more effective regulation of negative emotions and/or (ii) selection of more adaptive regulatory strategies. However, it is largely unclear *why* differentiation would afford more effective or healthier regulation: What psychological beliefs, processes, abilities, or computations explain these relations? Research on language and emotion suggests that activating emotion words can influence how people construct emotional experiences (Lindquist et al., 2006; Gendron et al., 2012; Lindquist et al., 2015; Nook et al., 2015; Satpute et al., 2016), that merely labeling emotions can reduce the intensity of those emotions (Lieberman et al., 2011; Kircanski et al., 2012; Torre and Lieberman, 2018), and that people who lack abilities to verbalize their emotions also struggle to effectively manage them (Taylor and Bagby, 2004; Leweke et al., 2011; Weissman et al., 2020). These lines of data suggest that applying specific emotion language should facilitate later regulation. However, tight empirical investigations have actually found the opposite: Labeling emotions makes subsequent regulation *less* effective (Nook et al., 2021b), and labeling emotions using many emotion words leads people to select more *maladaptive* regulatory strategies than if they had used just a few emotion words (Vine et al., 2019). There are certainly ways to iron out the logic to make these findings fit (e.g., perhaps precise labeling boosts regulation at longer time horizons than these experiments tested?), but right now they run counter to theoretical intuitions that emotion language boosts regulation. As such, close scrutiny is needed to more fully understand how the simple act of labeling our emotions affects regulation if we hope to address the bigger question of why differentiation is associated with mental health.

There are several other aspects of this theoretical model that can be further refined, and addressing these open questions is likely to require collaboration across psychological subdisciplines. For instance, even though a handful of studies have used neuroimaging or psychophysiological approaches to study emotion differentiation (Lee et al., 2017; Wang et al., 2020a,b; Hoemann et al., 2021), the biological mechanisms that explain why emotion differentiation boosts regulation remain largely unclear. Additionally, the clinical question of *multifinality* has yet to be addressed (e.g., why are some people with low emotion differentiation prone to alcohol use, while others engage in non-suicidal self-injury?). Although it seems that low emotion differentiation generates *transdiagnostic* risk, how exactly does it do so, and what forces push someone with low differentiation to experience specific forms of pathology? Emerging models of psychopathology are shifting away from a categorical model in which specific illnesses have unique discrete essences toward frameworks where syndromes reflect underlying dimensions of dysregulation and/or networks of interacting symptoms (McNally et al., 2015; Kotov et al., 2017). Incorporating these theoretical approaches into studies on emotion differentiation and including samples that are selected to include elevated levels of psychopathology could help address these questions. Finally, potential *interpersonal* mechanisms that might explain the benefits of emotion differentiation have only begun to be explored. For example, emotion differentiation may facilitate empathy (Erbas et al., 2016; Israelashvili et al., 2019) and accurate prediction of others' emotions is associated with relationship quality (Zhao et al., 2020), potentially explaining why low emotional awareness is associated with worse mental health in adolescent girls (Weissman et al., 2020).

Answering these open questions through a specific, testable, and multilevel theory (that also rules out the third-variables noted above) will greatly advance the translational impact of research on emotion differentiation. To summarize this section, this would ideally lead to a clear model with two parts. First, a precise explanation of *what psychological processes* produce any given individual's emotion differentiation score taking into account person-level factors (e.g., age), study-level factors (e.g., the emotion words they rated), and situation-level factors (e.g., the settings in which they reported on their emotions). Second, a precise explanation of how these psychological processes then produce their level of psychological functioning. At present, both parts of this model are not clearly articulated, rendering low emotion differentiation scores something of akin to a "maintenance required" light in a car: Low scores suggest that *something* might not be quite right with a person's level of psychological functioning, but we don't really know what mechanisms are producing the scores or why they have deleterious impacts. Moving from this "maintenance required" indicator stage to a clear understanding of the mechanistic psychological components that are operating "under the hood" is an exciting and important horizon of future research.

DISCUSSION AND FUTURE DIRECTIONS

Scientific understanding of youth emotion differentiation is in its infancy, and this review has unearthed many unanswered questions (see **Box 1**). Below I outline general guidelines that can help future researchers interested in advancing this understanding. In particular, I describe strategies for maximizing reproducibility, addressing the open questions raised above, and working toward interventions.

Beyond the obvious advice of using sample sizes that are well-powered to reliably detect small-to-medium effects (Richard et al., 2003; Open Science Collaboration, 2015), open science practices offer clear strategies for enhancing replicability of findings (Kathawalla et al., 2021). Preregistration—where researchers commit to their data collection procedures, inclusion/exclusion criteria, analytic plan, and hypotheses—reduce the possibility that published findings include only cherry-picked significant associations that may actually be false-positives. Individual replication studies or planning internal replications within papers (either by conducting additional studies or through a split-sample approach) can generate additional data for testing the stability of effects. Data sharing can allow future researchers to verify results as well as compile datasets to assess replicability and test moderators that might explain heterogeneous effects across studies. Indeed, cross-group collaborations in which datasets are shared across research labs, as is done in genetics (e.g., Smeland et al., 2019), could greatly speed progress on the many open questions raised in this review. Fortunately, researchers have begun to compile and publicly share EMA datasets[1]. All of these open science practices are likely to pay dividends in the future. Additional considerations for maximizing reproducibility in developmental studies include using a wide age range, measuring potential explanations for age-related effects, and ensuring that study procedures are suitable for diverse ages (e.g., controlling relevance of stimuli).

The open questions raised above can help organize and inform future research on emotion differentiation in development. However, it should be assumed that *substantial* additional information is needed to address these questions, and a single study is unlikely to accomplish this task. As such, scientists should consider issues of measurement at both the conceptual and methodological levels when designing studies. For example, consider what other affective dynamics measures can be extracted and have a plan for analyzing how these measures relate (e.g., through factor or network analyses; Lange et al., 2020). Also consider how selection of specific emotion terms should either intentionally match prior research or include a larger set to test whether the emotions that are measured influence the results. Studies should also intentionally focus on the third variables highlighted previously, testing both whether they confound relationships between emotion differentiation and age as well as relations between emotion differentiation and mental health. However, analyses should explore the multiple pathways through

[1] https://emotedatabase.com/

which these third variables could influence results (i.e., as confounds that create spurious relationships or as mechanisms in a larger model).

Longitudinal and *experimental* paradigms will likely prove invaluable in disentangling the influence of potential third variables and working toward causal models. For instance, demonstrating that vocabulary development longitudinally precedes changes in emotion differentiation can help test the causal direction of influence. Similarly, using paradigms that facilitate or interfere with access to emotion concepts (see Halberstadt, 2005; Lindquist et al., 2006; Gendron et al., 2012; Nook et al., 2015; Barker et al., 2020; Satpute et al., 2020) could hone in on the causal influence of emotion differentiation on downstream processes. Relatedly, developing effective interventions that boost emotion differentiation can then be used to causally test mechanisms thought to explain both (i) the genesis of strong differentiation skills and (ii) how differentiation improves mental health.

However, developing these interventions would benefit from incorporating emerging trends in intervention science. Ideally, these interventions would borrow from mechanisms outlined in basic research as well as theoretical models. For example, they might target enhancing mindfulness to the affect generated during different emotional experiences (Van der Gucht et al., 2019), equipping individuals with emotion vocabulary (Nook et al., 2017), or educating individuals in how to have refined conceptual representations of different emotions (Hoemann et al., 2019). Conversely, studies can reverse-engineer potential intervention targets and mechanisms of influence by analyzing if and how existing interventions (e.g., psychotherapy) increases differentiation (Linehan, 1993; Barlow et al., 2011). Intervention scientists have developed clear guidelines for structuring these experiments to maximize knowledge not only concerning *what* interventions work but *why* they work (Kazdin, 2007; Ng and Weisz, 2016). In fact, a recent paper shows that Emotion Regulation Therapy (Mennin, 2004; Mennin and Fresco, 2015) improves negative emotion differentiation, setting the stage for a line of research that dissects the mechanisms underlying this effect (Mikkelsen et al., 2021). Finally, the notion of single-session interventions have recently gained heightened interest (Schleider and Weisz, 2017), motivating the question of what *dose* of intervention is needed effectively shift differentiation and mental health.

Though challenging, it seems apparent that partnerships between affective, developmental, and clinical psychologists could produce a promising set of tools for explaining, detecting, treating, and potentially even preventing psychopathology. Indeed, given the number of open questions, it seems wise to maintain a sense of patience, optimism, and collaboration in this pursuit for clarity. The current review aims to summarize both what we do and do not know about emotion differentiation in youth, with the ultimate goal of achieving a clear science of how emotions go awry and what we can do to prevent these experiences.

CONCLUSION

Although emotion differentiation is consistently associated with mental health in adults, there are substantial open questions concerning *how* this ability arises and *why* it is associated with well-being. Taking a developmental perspective on both questions offers a powerful opportunity for disentangling potential causal processes and developing strategies for intervening early to minimize the public health burden of psychopathology. Only by addressing open questions concerning measurement and looming third variables can we develop a clear and useful theoretical model.

AUTHOR CONTRIBUTIONS

EN developed the manuscript's thesis, conducted the literature review, and wrote the manuscript.

FUNDING

The Sackler Scholarship in Psychobiology supported publication fees.

ACKNOWLEDGMENTS

Sincere thanks to Leah H. Somerville and the Cambridge Writing Group for their constructive feedback while drafting this manuscript.

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Conflict of Interest: The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Psychology

ORIGINAL RESEARCH
published: 11 August 2021
doi: 10.3389/fpsyg.2021.684117

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Negative Emotion Differentiation Attenuates the Within-Person Indirect Effect of Daily Stress on Nightly Sleep Quality Through Calmness

Tanja Lischetzke, Lea Schemer, Julia A. Glombiewski, Tina In-Albon, Julia Karbach and Tanja Könen*

Department of Psychology, University of Koblenz-Landau, Landau, Germany

The ability to differentiate between negative emotional states [negative emotion differentiation (NED)] has been conceptualized as a trait that facilitates effective emotion regulation and buffers stress reactivity. In the present research, we investigated the role of NED in within-person processes of daily affect regulation and coping during times of stress (the first COVID-19-related pandemic lockdown in April 2020). Using intensive longitudinal data, we analyzed whether daily stress had an indirect effect on sleep quality through calmness in the evening, and we tested whether NED moderated this within-person indirect effect by buffering the link between daily stress and calmness in the evening. A non-representative community sample (n = 313, 15–82 years old) participated in a 21-day ambulatory assessment with twice-daily surveys. The results of multilevel mediation models showed that higher daily stress was related to within-day change in calmness from morning to evening, resulting in less calmness in the evening within persons. Less calmness in the evening, in turn, was related to poorer nightly sleep quality within persons. As expected, higher NED predicted a less negative within-person link between daily stress and calmness in the evening, thereby attenuating the indirect effect of daily stress on nightly sleep quality through calmness. This effect held when we controlled for mean negative emotions and depression. The results provide support for a diathesis-stress model of NED, and hence, for NED as a protective factor that helps to explain why some individuals remain more resilient during times of stress than others.

Keywords: negative emotion differentiation, negative emotional granularity, daily stress, stress reactivity, calmness, sleep quality, COVID-19, multilevel mediation analysis

OPEN ACCESS

Edited by:
Yasemin Erbas,
Tilburg University, Netherlands

Reviewed by:
Katie Hoemann,
KU Leuven, Belgium
Michaela Rohr,
Saarland University, Germany

***Correspondence:**
Tanja Lischetzke
lischetzke@uni-landau.de

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: *22 March 2021*
Accepted: *13 July 2021*
Published: *11 August 2021*

Citation:
Lischetzke T, Schemer L, Glombiewski JA, In-Albon T, Karbach J and Könen T (2021) Negative Emotion Differentiation Attenuates the Within-Person Indirect Effect of Daily Stress on Nightly Sleep Quality Through Calmness. Front. Psychol. 12:684117. doi: 10.3389/fpsyg.2021.684117

INTRODUCTION

Individual differences in emotion differentiation (also called emotional granularity) refer to the degree to which individuals make fine-grained distinctions between similarly valenced emotional states (Barrett et al., 2001; Tugade et al., 2004). Individuals high in emotion differentiation tend to use discrete emotion words (e.g., angry, disappointed, and lonely) in a context-specific way, whereas individuals low in emotion differentiation tend to use same-valenced emotion words interchangeably across different situational contexts. In particular, the ability to differentiate between negative emotional states [negative emotion differentiation (NED)] has been conceptualized as a trait that facilitates effective emotion regulation and thereby promotes well-being (e.g., Kashdan et al., 2015). Two recent meta-analyses demonstrated a significant but small association between NED and psychosocial functioning: The results by O'Toole et al. (2020) indicated a small positive relation between NED and behavioral adaptation in non-clinical populations, and the results by Seah and Coifman (2021) indicated a small negative association between NED and the enactment of maladaptive behaviors, such as aggression or avoidance. The fact that the meta-analytic effect sizes were rather small may call into question the importance of NED as an adaptive skill. However, as O'Toole et al. (2020) and others (e.g., Barrett et al., 2001; Kashdan et al., 2015; Ottenstein and Lischetzke, 2020) have argued, high NED can be assumed to be most helpful under circumstances that evoke intense negative emotions (e.g., stressful events). In the present study, we aimed to shed more light on the assumed adaptive value of NED during times of stress.

Negative emotion differentiation is typically measured indirectly in daily life and operationalized as the degree of covariation between negative emotions over time (Erbas et al., 2014). That is, individuals are requested to repeatedly rate their momentary emotional experience using ambulatory assessment (AA) methodology (also termed experience sampling or ecological momentary assessment; Trull and Ebner-Priemer, 2014). For each individual, the degree of covariation between negative emotions over time is quantified by the intraclass correlation coefficient (ICC) measuring average consistency. A high ICC reflects that individuals frequently report feeling different discrete negative emotions (such as anger, sadness, or fear) at the same time (i.e., low NED). A low ICC reflects that individuals report more divergent patterns of negative emotional experience depending on the circumstances (i.e., high NED).

A large portion of previous research on NED can be classified into two major types of studies: The first major type of study compared NED in healthy controls and clinical populations, including individuals diagnosed with major depressive disorder (Demiralp et al., 2012), social anxiety disorder (Kashdan and Farmer, 2014), borderline personality disorder (Suvak et al., 2011), schizophrenia (Kimhy et al., 2014), and autism spectrum disorder (Erbas et al., 2013). Taken together, the findings from these studies indicated that low NED might represent a transdiagnostic factor that contributes to the development and maintenance of various mental disorders.

In the second type of study, concurrent or predictive associations of NED with other individual difference constructs (e.g., measured via global self-report or estimated via aggregated/mean repeated states) were analyzed. Among the individual differences that have been studied were emotional clarity (Boden et al., 2013), verbal ability (Ottenstein and Lischetzke, 2020), emotion regulation (Barrett et al., 2001; Ottenstein, 2020), emotional intelligence (MacCann et al., 2020), mindfulness (Tong and Keng, 2017), physical health (Oh and Tong, 2020), psychopathological symptoms (Liu et al., 2020; Schreuder et al., 2020), and well-being (Lennarz et al., 2018; Dejonckheere et al., 2019; Ottenstein, 2020). This type of research has helped to map out the nomological net that reflects the potential antecedents and consequences of NED. However, the added value of NED (and other emotional complexity measures) in predicting overall levels of well-being and psychopathology has recently been called into question because the predictive utility of NED disappeared when mean affect was controlled for (Dejonckheere et al., 2019, Schreuder et al., 2020). This allows two conclusions: First, it is important to test whether the predictive utility of NED remains significant after accounting for the mean levels of negative emotions. Second, more research is needed on the role that NED plays in predicting *individual differences in within-person processes* of momentary affect regulation and daily coping with stress. Thereby, process-oriented studies might shed more light on why low NED is related to higher overall levels of negative emotionality and a higher risk of developing psychopathological symptoms.

To date, only relatively few studies have investigated NED as a predictor of individual differences in within-person affect-related processes. In one AA study (Kashdan et al., 2010), NED moderated (buffered) the within-person link between momentary negative affect and alcohol consumption, and in another AA study (Pond et al., 2012), NED buffered the within-person link between momentary anger and aggressive behavior. Recently, Starr et al. (2020) proposed a diathesis-stress model of NED. They hypothesized that individuals with high (vs. low) NED may be "better prepared to manage the emotional and behavioral aftermath of stress exposure" (p. 2), decreasing the likelihood that stressful experiences result in depressive symptoms. In a similar vein, Kashdan et al. (2015) argued that high differentiators may be less likely to be overwhelmed in stressful situations. Consistent with Starr et al.'s diathesis-stress model, NED moderated the within-person relation between daily hassles and daily depressed mood in a community sample of adolescents: For low differentiators, daily hassles were more strongly associated with higher daily depressed mood than for high differentiators (Starr et al., 2020). Starr et al. (2017) also found that NED moderated the within-person relation between daily hassles and daily depressed mood in a sample of help-seeking veterans. However, this moderator effect did not generalize to a sample of college students—which suggests that further replication of the proposed stress-buffering effect of NED is warranted. In the present research, we sought to conceptually replicate Starr et al. (2017, 2020) findings in the context of coping with stressors during times of crisis by testing whether NED would be found to buffer the link between daily stress and calm-tense mood in the evening.

Moreover, we aimed to extend the within-person process under scrutiny by additionally analyzing the potential detrimental consequences of tense mood on sleep quality. We expected an indirect within-person effect of perceived daily stress on subjective sleep quality through calmness in the evening (see the Level 1 part of **Figure 1**). Within-person fluctuations in daily stress have been shown to be associated with fluctuations in nightly sleep quality: In healthy adults (Morin et al., 2003; Garde et al., 2011; Åkerstedt et al., 2012; Tousignant et al., 2019) and in

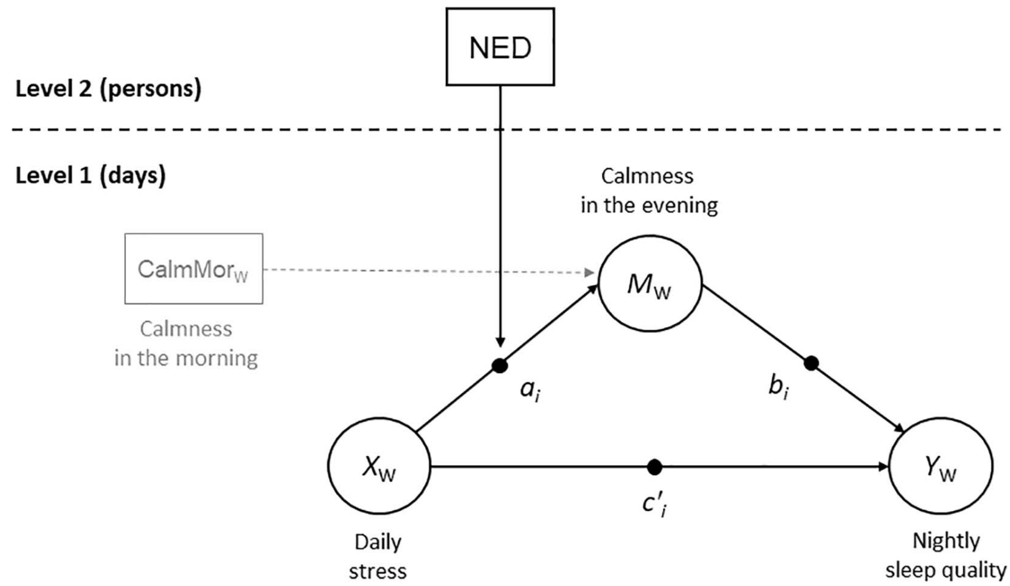

FIGURE 1 | Moderated multilevel (1-1-1) mediation model (First-Stage Multilevel Conditional Process Model). Index W indicates the within-person part of the time-varying variables. Time was included as a control variable at Level 1 (predicting M_W and Y_W), but for simplicity, time is not depicted. NED, negative emotion differentiation.

individuals with insomnia (Morin et al., 2003), subjective sleep quality was lower on the days on which individuals experienced more stress than usual. Heightened cognitive and somatic arousal before bedtime have been proposed as mediators of the link between daily stress and sleep quality (Morin et al., 2003; Winzeler et al., 2014; Tousignant et al., 2019). Consistent with this view, a recent review that summarized findings of AA studies on the within-person link between day-to-day fluctuations in sleep and mood (Konjarski et al., 2018) suggested that feelings of serenity and calmness (i.e., low tense arousal) are the most beneficial feelings for a good night's sleep. In the present research, we aimed to test whether daily stress has an indirect effect on sleep quality through calmness in the evening. On the basis of the diathesis-stress model of NED by Starr et al. (2017, 2020), we expected that NED would moderate this within-person indirect effect by buffering the link between daily stress and calmness in the evening (see **Figure 1**).

What might be the mechanisms by which higher NED ameliorates the adverse impact of daily stress on mood? Drawing on theoretical accounts of NED and stress management, Starr et al. (2020) proposed that high (vs. low) differentiators should be better able to identify the cause of their experienced emotions in response to stressors, and hence, to generate an adaptive response. Similarly, Kashdan et al. (2015) speculated that high NED should make it easier for individuals to shift their attentional focus and adopt a more self-distanced perspective on their feelings, thereby enhancing the opportunity for goal-directed regulatory behavior. On the basis of these (yet untested) ideas, we additionally aimed to explore whether daily rumination about emotions would increase daily stress reactivity and whether low NED would predict more daily rumination. In one of two studies, Kalokerinos et al. (2019) found empirical support that lower NED predicted more rumination in daily life. However, given that rumination was operationalized as referring to a single specific event in this study (first-year students receiving grades) and that the evidence was inconsistent, more research is warranted.

THE PRESENT RESEARCH

With the present research, we aimed to conceptually replicate and extend Starr et al.'s (2017, 2020) findings on the stress-buffering effect of NED. We conducted a 3-week AA study during times of stress (the first pandemic lockdown in 2020) to investigate the indirect within-person effect of perceived daily stress on nightly subjective sleep quality through calmness in the evening. We selected tense vs. calm mood as mood dimension of interest because it has been conceptualized as an indicator of psychological stress reactivity (e.g., Klaperski et al., 2013) and was positively related to nightly sleep quality (Konjarski et al., 2018) and negatively related to depressive symptoms (e.g., Huffziger et al., 2013; Timm et al., 2017). We tested the following hypotheses:

Hypothesis 1: Daily stress will have an indirect effect on poorer subjective sleep quality through calmness in the evening.

Hypothesis 2: The within-person indirect effect of daily stress on nightly sleep quality through calmness in the evening will vary on the basis of NED. Specifically, NED will moderate the within-person relation between daily stress and calmness in the evening such that at higher (vs. lower) levels of NED, higher daily stress will be less strongly associated with a more tense mood in the evening.

In statistical terms, these hypotheses translate into a first-stage multilevel conditional process model (Hayes and Rockwood, 2020)—that is, a moderated multilevel (1-1-1) mediation model in which the predictor *X* (daily stress), the mediator *M* (calmness in the evening), and the dependent variable *Y* (that night's sleep quality) are measured at Level 1 (i.e., the day level), and NED is included as a Level 2 (i.e., person-level) moderator of the Level 1 association between *X* and *M* (cross-level interaction).

To control for potential effects of day-to-day fluctuations in mood on the perception of daily stress, we assessed calmness in the morning and included it as an additional Level 1 predictor of calmness in the evening in the multilevel mediation model. This allowed us to model within-day change in calmness from morning to evening, and hence, path a_i in the multilevel (1-1-1) mediation model (see **Figure 1**) represented the within-person relation between daily stress and within-day change in calmness (for a similar strategy, in which lagged affect is included as a Level 1 predictor, see, e.g., Kalokerinos et al., 2019). To test whether the hypothesized moderating effect of NED would hold when controlling for mean negative affect (Dejonckheere et al., 2019; Schreuder et al., 2020), we added individuals' mean level of negative emotions across the AA study phase and their level of depressive symptoms (assessed shortly before the start of the AA study phase) as Level 2 predictors in the model. We controlled for both mean negative emotions and depressive symptoms to align our analyses with Starr et al.'s (2020) analyses.

Making use of a recently proposed framework to study momentary emotion differentiation at the level of measurement occasions (Erbas et al., 2021), we additionally set out to explore within-person (i.e., in our case, daily) fluctuations in NED. More specifically, we calculated Erbas et al.'s (2021) novel momentary index of NED and analyzed whether the stress buffering effect of person-level NED translates to day-level NED (i.e., whether stress reactivity would be lower on days on which an individual's NED is higher than usual). Moreover, as a first step toward elucidating a potential mechanism through which NED might exert a stress-buffering function, we additionally explored whether rumination about emotions would enhance negative responses to daily stress (i.e., whether daily rumination would act as a Level 1 moderator of the within-person link between daily stress and calmness in the evening) and whether lower daily NED would be associated with more daily rumination about emotions.

MATERIALS AND METHODS

We present the methodological details of our AA study by following the guidelines by Trull and Ebner-Priemer (2020).

Study Design

The study consisted of an initial online survey and an AA phase across 21 days with two interval-based assessments per day (one morning survey and one evening survey). Participants chose a specific time schedule that best fit their waking hours (6 am/6 pm, 8 am/8 pm, or 10 am/10 pm). Data were collected using the software SoSci Survey (Leiner, 2020). Links to the daily surveys were sent via SMS, allowing participants to complete the surveys online using their own smartphone. Each link was valid for a certain time period (3 h for the morning survey, 6 h for the evening survey). During an initial online survey, participants completed a demographic questionnaire, COVID-19-related questions, and trait self-report measures. In the daily evening survey, participants rated their momentary mood and their experiences during the day (stress, positive and negative emotions, emotion regulation, worrying, and coping). In the morning survey, participants rated their momentary mood, the quality of their sleep from the previous night, and their expectations for the day. We selected a daily sampling schedule for experiences such as stress or emotions and a twice-per-day sampling schedule for momentary mood to fit the expected temporal variability of the constructs without overburdening participants.

Procedure

Participants were recruited via mailing lists and social media platforms (Facebook, Twitter, and Instagram) and encouraged to inform family members, friends, and colleagues about the study. To be eligible, participants needed to be 15 years of age or older, to have access to a laptop, computer, or tablet in order to take part in the initial online survey, and to have access to a smartphone in order to participate in the AA phase. The AA phase spanned the same time period for each participant (April 13, 2020 through May 3, 2020). It began during the first complete pandemic lockdown due to COVID-19 in Germany (which had been established approximately 4 weeks prior to our assessment) when contact restrictions were implemented by the government. Toward the end of the AA phase, some protective measures were slowly lifted (e.g., the re-opening of small shops), and face mask policies were implemented.

All participants were informed about the study procedure via an information sheet on the registration webpage. They gave active consent to take part in the study via mouse click. Participants were reimbursed up to 60 EUR, partially contingent upon their compliance during the AA phase. The study procedure was approved by the institutional ethics committee of the psychology department at the University of Koblenz-Landau (258_2020).

Participants

Seven hundred seventy-two individuals signed up to participate in the study. To achieve a more age-heterogeneous sample while at the same time complying with budgetary constraints on the total sample size of compensated participants, 311 individuals who had signed up and were between the ages of 20 and 29 (selected randomly) were not invited to participate. Four hundred sixty individuals (out of the 461 who were invited) began answering the initial online survey, of which 381 completed the entire initial online survey. Again, in the interest of achieving a more age-heterogeneous sample for the subsequent AA phase, out of the individuals between the ages of 20 and 25 who had filled out the online survey, 20 individuals per birth year (randomly selected from each birth year) were invited to participate in the AA phase of the study. This resulted in 52 participants aged 20–25 who were not invited to continue with the study and 329 participants who were invited to take part in the AA phase. Of these, 327 participants provided daily reports. Participants' data were included in the statistical analyses if at least seven morning and seven evening surveys were available after checks for technical problems and careless responding (see the Compliance and section "Data Cleaning"). Data from five participants who did not fulfill this criterion were excluded. For the present analyses, the data of nine individuals with a negative ICC score (see section "Measures") were excluded, leaving a final sample of 313 participants (74.1% women) between the ages of 15 and 82 (M = 30.1, SD = 14.9).

None of these 313 participants knowingly suffered from COVID-19 at the time of the initial online survey, but 55 participants (17.6%) reported cases of COVID-19 among their relatives or in their social environment. The prevalence of risk factors for severe COVID-19 in our sample was similar to estimates from a modeling study for Europe (Clark et al., 2020): 63.9% of participants indicated that they had no increased risk, 24% reported having one risk factor, and 12.1% reported having two or more risk factors. When asked for their level of concern regarding COVID-19 (ranging from 1 = *not at all* to 7 = *very much*), participants reported relatively low concerns about potential job loss (M = 2.72, SD = 1.87) and their individual financial situation (M = 3.10; SD = 1.88), moderate concerns about their own health (M = 3.45; SD = 1.68), and relatively high concerns about the health of their relatives (M = 5.44; SD = 1.51). These psychological reactions to the pandemic mirrored observations from representative surveys that were conducted during the same time period (Betsch et al., 2020).

Measures

Within-Person (Daily) Measures

Daily stress

We measured daily subjective stress in the evening surveys with the item "How stressed did you feel today?" (Erbas et al., 2018). The response format was a visual slider that showed verbal anchors at each end (ranging from *not at all* to *very much*). The slider position selected by the participant was captured on a 101-point scale, which could be scaled as ranging, for instance, from 0 to 100. To avoid convergence issues in multilevel modeling due to the scaling of variables, we decided to scale the slider values as ranging from 0 to 1 in steps of 0.01.

Daily rumination about emotions

We measured daily rumination about emotions in the evening surveys with the item "I thought over and over again about my emotions" (Grommisch et al., 2020). Individuals indicated whether they had ruminated about their emotions during the day (0/*no*, 1/*yes*).

Momentary calmness

In both morning and evening surveys, we assessed momentary mood with an adapted short version of the Multidimensional Mood Questionnaire (Eid et al., 1999), which has previously been used in AA studies (e.g., Lischetzke et al., 2012). Two items tapped calmness [tense-relaxed, calm-uneasy (reverse-scored)]. Participants indicated how they felt at the moment using a bipolar visual slider scale that showed verbal anchors at each end (e.g., ranging from *tense* to *relaxed*). The slider position selected by the participant was captured on a 101-point scale, which was scaled as ranging from 0 to 1 in steps of 0.01. We calculated a mean score across the two items so that a higher score indicated a calmer mood. The reliability of the scale was estimated separately for the day level (within-person reliability) and the person level (between-person reliability) in accordance with Geldhof et al. (2014). Given that the scale consisted of two items, we calculated two-level alpha (because omega can only be calculated for at least three items). For evening (morning) assessments, within-person alpha was 0.77 (0.75), and between-person alpha was 0.96 (0.97).

Nightly sleep quality

We assessed subjective sleep quality in the morning surveys with three items ["How well did you sleep last night?" "How restlessly did you sleep last night?" (reverse-coded), "How easily did you fall asleep yesterday evening?"] that have been used in previous research (Åkerstedt et al., 2012; Könen et al., 2015). The response format was a 5-point Likert scale, ranging from 1 (e.g., *very poorly*) to 5 (e.g., *very well*). We calculated a mean score across the items so that a higher score indicated better sleep quality. To estimate the scale's reliability, we calculated two-level omega (Geldhof et al., 2014). Within-person omega was 0.76, and between-person omega was 0.84.

Daily negative emotion differentiation

Each evening, participants indicated the intensity with which they had experienced eight negative emotions (anger, fear, disappointment, sadness, embarrassment/shame, regret, boredom, and loneliness) during the day. On the basis of an appraisal account of the affective space of discrete emotions (Scherer, 2005), we selected the items to represent negative emotions that differed on the appraisal dimension of coping potential/control (low: sadness, loneliness, fear; moderate: embarrassment/shame, disappointment, regret; high: boredom, anger). Participants rated the emotions on a visual slider scale ranging from not at all to very intense. The slider position selected by the participant was captured on a 101-point scale, which was scaled as ranging from 0 to 1 in steps of 0.01. If an emotion was not experienced at all during the day, participants were asked to set the slider to the far left. Because it may have been difficult for participants to indicate a value of exactly 0 on their smartphone touchscreen, we recoded all ratings $\leq$ 0.05 to 0 (cf. Koval et al., 2015). As an index of daily NED, we used the momentary index of emotion differentiation proposed by Erbas et al. (2021). More specifically, we applied the function calculate_ed from the R package emodiff described in Erbas et al. (2021) to calculate daily NED scores for each measurement occasion and each person. Resulting daily NED scores are more strongly negative when the level of momentary differentiation is low, and they approach zero when the level of differentiation is high (for details on the derivation of the momentary index from the classical between-person ICC index, see Erbas et al., 2021).

Daily mean of negative emotions

The daily negative emotion ratings were also used to compute an index of daily mean negative emotionality (by calculating the mean of all negative emotion items).

Between-Person (Trait) Measures

Depressive symptoms

To measure depressive symptoms, we used the nine-item depression module from the Patient Health Questionnaire (Spitzer et al., 1999; Gräfe et al., 2004), which is an instrument that is widely used to screen for mental disorders. In the initial online survey, participants rated the frequency of nine depressive symptoms during the past 2 weeks on a 4-point Likert scale ranging from 0 (*not at all*) to 3 (*almost every day*). We calculated a sum score across all the items, with higher scores indicating more depressive symptoms. Omega was 0.83.

Negative emotion differentiation

For each participant, we computed the ICC(3, k) measuring average consistency between negative emotions across measurement occasions (e.g., Erbas et al., 2014). Following previous recommendations (e.g., Kalokerinos et al., 2019; Erbas et al., 2021), negative ICC values were excluded from the analyses. This was the case for nine participants. Subsequently, ICC values were Fisher Z-transformed and reversed (multiplied by -1) so that higher values represented higher NED.

Mean level of negative emotions

The daily negative emotion ratings were also used to compute an index of mean negative emotionality experienced across the AA phase. For each participant, we calculated the mean of all negative emotion items across all measurement occasions.

Data Cleaning

The 327 participants who completed the AA phase provided a total of 6,399 morning surveys and 6,519 evening surveys. Due to technical problems, for some of the assessments, the time window during which the surveys could be completed was longer than intended. Three morning surveys that had been completed after 1 p.m. as well as 34 evening surveys that had been completed after 4 a.m. were excluded from the analyses. One morning survey, which had erroneously been completed twice, was excluded from the analyses. Moreover, 11 morning and two evening surveys for which participants terminated their responding before they completed the first set of items (corresponding to sleep items in the morning and momentary mood items in the evening) were excluded from the analyses. To screen for careless responding, inconsistent responding across reverse-poled (momentary mood) items and response times were analyzed (Meade and Craig, 2012). Eighty-one morning and 100 evening surveys were excluded due to inconsistent responding, and three morning and 282 evening surveys were excluded due to extremely short response times[1]. Subsequently, we excluded data from five participants who completed fewer than seven morning and seven evening surveys, leaving a sample of 6,084 evening surveys and 6,263 morning surveys nested in 322 participants.

Final Sample and Compliance

For the present analyses, the data of nine participants whose ICC values were negative were excluded (see section "Measures"). This resulted in a sample of 5,912 evening surveys and 6,095 morning surveys nested in 313 participants. On average, participants provided 18.89 (out of 21 possible) evening surveys (SD = 2.83, Min = 7, Max = 21) and 19.47 (out of 21 possible) morning surveys (SD = 1.96, Min = 11, Max = 21). For the mediation analyses in the present paper, we included evening surveys from Day 1 through Day 20 (n = 5,645 surveys) and merged them with the morning mood ratings from the same day (i.e., from Day 1 to Day 20; n = 5,303 surveys) as well as with the sleep quality ratings collected the next morning (i.e., from Day 2 to Day 21; n = 5,302 surveys). The reason for excluding the data from Day 21 was that the sleep-quality ratings referring to this day were missing by design. Hence, the analyses in the present paper were based on a total of 5,645 days nested in 313 individuals.

Sample Size Considerations

According to a simulation study on the power to detect a cross-level interaction in multilevel modeling (Mathieu et al., 2012), a combination of 115 Level 2 units and 18 Level 1 units per Level 2 unit yielded a power of larger than 0.80 to detect a medium-sized cross-level interaction effect. Given that the size of our sample (313 persons and 18.89 evening assessments per person, on average) met or exceeded these sample sizes, we deemed our data set large enough to test our central hypothesis that NED would be found to moderate the within-person indirect effect of daily stress on daily sleep quality using a moderated multilevel (1-1-1) mediation model.

Analytic Strategy

We applied a multilevel structural equation modeling (MSEM) approach using Bayesian estimation (Asparouhov and Muthén, 2019) with default uninformative priors in Mplus Version 8.5 (Muthén and Muthén, 1998-2020). The advantages of using Bayesian estimation (as a pragmatic approach) for multilevel mediation models with multiple random effects are that latent centering of observed time-varying variables can be applied (Asparouhov and Muthén, 2019), standardized parameter estimates (and estimates of level-specific R^2) can be obtained, and a non-symmetric Bayesian credibility interval, which does not assume normality, can be used to evaluate the significance of the estimated within-person indirect effect (Muthén, 2010). To evaluate convergence, we inspected whether the parameter estimates and the potential scale reduction (PSR) values (obtained via the Mplus TECH8 output) changed when we increased the number of iterations to 10,000 (e.g., Zyphur and Oswald, 2015). With the latent centering method in MSEM, the observed daily variables X_{ti}, M_{ti}, and Y_{ti} (where t represents days and i represents persons) are decomposed into a within-person part (X_{W}, M_{W}, and Y_{W}) and a between-person part (X_{B}, M_{B}, and Y_{B}).

[1]The response time cutoff values were determined by conducting a pilot AA study (that contained the same items) in which research assistants were instructed to complete the morning and evening surveys as quickly as possible without switching to careless responding. In this pilot study, the fastest response time for a morning survey was 1.17 s/item, and the fastest response time for an evening survey was 1.56 s/item (We attributed the shorter response time for the morning survey to the fact that items in the evening survey included more text, on average, than items in the morning survey). In the main study, surveys with a response time below these cutoff values were excluded from the analyses.

To test the within-person effects of daily stress (X_W) on calmness in the evening (M_W) and that night's sleep quality (Y_W), we specified a lower level (1-1-1) mediation model (Model 1; see the Level 1 part of **Figure 1**) with random slopes for all Level 1 path coefficients (Preacher et al., 2010). Two additional Level 1 variables were included as control variables: To rule out the possibility that within-person relationships between X_W, M_W, and Y_W were simply due to shared time trends in these variables across the study period, time (centered at Day 11 and coded so that the total study time represented a time unit of 1) was included as a predictor of M_W and Y_W (Note that for simplicity, time is not depicted as a predictor in **Figure 1**). Calmness in the morning was included as a Level 1 (person-mean-centered) predictor of calmness in the evening so that path a_i represented the within-person relation between daily stress and within-day change in mood. At the between-person level (Level 2), we allowed the between-person slopes a_i, b_i, and c_i' and the between-person intercepts to correlate freely (Preacher et al., 2016). The average within-person indirect effect is defined as $E(a_ib_i) = ab + \sigma_{a_i,b_i}$, where a is the mean of the random slopes a_i, b is the mean of the random slopes b_i, and σ_{a_i,b_i} is the covariance between the random slopes a_i and b_i (Bauer et al., 2006). We expressed the average within-person indirect effect as a model constraint in Mplus and evaluated it on the basis of the estimated (non-symmetric) 95% Bayesian credibility interval (which uses the 2.5th and 97.5th percentiles of the posterior distribution, thus allowing for skewness). Note that establishing mediation does not require the total effect of X_W on Y_W to be significant (MacKinnon et al., 2000). One reason for this is that the statistical test of the total effect can have less power than the test of the indirect effect (Hayes, 2009; MacKinnon and Fairchild, 2009).

In the next step, to test whether the within-person relation between daily stress (X_W) and evening mood (M_W) varied as a function of NED, we extended the model to a first-stage multilevel conditional process model (Hayes and Rockwood, 2020). That is, NED was added as a Level 2 predictor of the random slope term a_i (Model 2; see **Figure 1**). Note that NED was also added as a predictor of the random intercept term for calmness in the evening because main effects always have to be included when testing for a moderator effect. To enhance the interpretation of the model estimates, NED was grand-mean centered. To probe the cross-level interaction, we estimated the conditional effect of X_W on M_W at high ($M + 1$ SD) and low (M – 1 SD) values of NED as well as the conditional indirect effect of X_W on Y_W through M_W at those values of NED.

To test whether the hypothesized moderator effect of NED held when we controlled for between-person differences in mean negative emotions and depressive symptoms, these variables were added as grand-mean-centered predictors of the random slope term a_i (and as predictors of the random intercept term for calmness in the evening) at Level 2 (Model 3).

In our supplementary analyses, we explored (a) whether evidence for a stress buffering of NED could be found when daily NED (instead of person-level NED) was analyzed (i.e., whether daily NED would moderate the within-person link between daily stress and calmness in the evening), and (b) whether this effect held when daily mean negative emotions were controlled. To analyze (a), we specified a two-level model in which daily stress, daily NED, and their interaction predicted calmness in the evening at Level 1. Following Enders and Tofighi's (2007) recommendations, we centered both the continuous variable (daily NED) and the dichotomous variable (rumination) at the person mean and subsequently computed the interaction term. Again, calmness in the morning and time were included as Level 1 control variables. To analyze (b), we added person-mean centered daily mean negative emotions as a Level 1 predictor. Moreover, to examine a potential mechanism through which NED might exert a stress buffering effect, we explored (c) whether daily rumination about emotions would moderate the within-person link between daily stress and calmness in the evening. We computed the Level 1 interaction term between daily stress and daily rumination about emotions and set up the model in the same way as described for the model involving the interaction between daily stress and daily NED. Finally, we explored (d) whether lower daily NED would predict a higher probability of ruminating about emotions, and (e) whether this relation would hold when daily mean negative emotions were controlled. To do so, we added daily NED and daily mean negative emotions as Level 1 predictors of daily rumination to model (c).

RESULTS

Descriptive Statistics

Correlations and descriptive statistics for the day-level and person-level variables are provided in **Tables 1**, **2**.

Multilevel (1-1-1) Mediation Model

The fixed effects of the multilevel (1-1-1) mediation model (including time and calmness in the morning as Level 1 control variables) are displayed in **Table 3** (Model 1). The fixed effects of time represent the average within-person trajectories in evening mood and sleep quality across the study phase. On average, sleep quality significantly increased by 0.111 points (on a 1–5 scale) across the total duration of the study of 3 weeks, which might be indicative of a small overall effect of participants' adaptation to the (first-ever) pandemic lockdown in Germany.

The results supported Hypothesis 1 on the within-person indirect effect of daily stress (X_W) on daily sleep quality (Y_W) through calmness in the evening (M_W), $E(a_ib_i) = -0.063$ (see Model 1, **Table 3**). As expected, higher daily stress was related to less calmness in the evening within persons ($a = -0.222$), and this effect was moderate in size. Less calmness in the evening in turn was related to worse sleep quality within persons ($b = 0.412$), and this effect was small in size.

Of note, individuals differed significantly in the within-person relations (as indicated by variance estimates for the random slope terms whose 95% credibility intervals did not include 0). To examine the patterns of individual differences in within-person relations in more detail, we calculated the percentage of slopes < 0 and the 95% predictive interval for paths a_i and b_i (Hox et al., 2018). Assuming a normal distribution of random slopes, the percentage of slopes < 0 indicates the proportion of regression slopes that is estimated to be negative, and the

TABLE 1 | Within- and between-person correlations and descriptive statistics for daily variables.

Variable	1	2	3	4	5	6
1. Calmness in the morning	–	−0.61***	0.87***	0.53***	−0.22***	−0.53***
2. Daily stress	−0.17***	–	−0.62***	−0.44***	0.27***	0.57***
3. Calmness in the evening	0.13***	−0.32***	–	0.52***	−0.25***	−0.63***
4. Nightly sleep quality	−0.01	−0.02	0.08***	–	−0.19**	−0.42***
5. Daily rumination[1]	−0.05**	0.12***	−0.13***	0.02	–	0.41***
6. Daily mean neg. emotions	−0.11***	0.35***	−0.36***	−0.04**	0.22***	–
7. Daily NED[2]	0.02	−0.15***	0.17***	0.03*	−0.13***	−0.46***
M	0.67	0.41	0.70	3.75	0.38	0.22
SD_{within}	0.15	0.23	0.16	0.74	–	0.12
SD_{between}	0.16	0.14	0.14	0.47	–	0.12
ICC	0.53	0.28	0.43	0.29	0.49	0.52
Range	0–1	0–1	0–1	1–5	0–1	0–1

N_{Level1} = 5,645 days, N_{Level2} = 313 persons. Within-person correlations are presented below the diagonal, and between-person correlations are presented above the diagonal. M, grand mean (i.e., the mean across days and persons); SD_{within}, within-person standard deviation; $SD_{between}$, between-person standard deviation; ICC, intraclass correlation coefficient.

[1]For the binary variable daily rumination (0/no, 1/yes), the mean represents the average proportion of days on which individuals ruminated about their emotions, and the intraclass correlation was estimated using Goldstein et al.'s (2002) method D.

*[2]By definition, daily NED (i.e., the momentary differentiation index by Erbas et al., 2021) is a within-person variable. Therefore, the ICC is 0, and only within-person correlations are depicted. For information on the person-level index of NED, see **Table 2**. Descriptive statistics for daily NED were M = −2.43, SD = 4.27, Range: −58.29–0.*

**p < 0.05; **p < 0.01; ***p < 0.001.*

95% predictive interval indicates the range of values between which 95% of the person-specific regression slopes are estimated to lie. For path a_i, the percentage of slopes < 0 was 92%, and the 95% predictive interval was (−0.526, 0.082) [corresponding to standardized estimates of (−0.734, 0.114)]. For path b_i, the percentage of slopes < 0 was 28%, and the 95% predictive interval was (−1.008, 1.832) [corresponding to standardized estimates of (−0.223, 0.407)]. That is, for our focal path a_i, whose random slopes represent individual differences in stress reactivity, this means that a negative link between daily stress and calmness in the evening was estimated for the large majority of individuals—however, the size of this relationship differed greatly across individuals.

TABLE 2 | Between-person correlations and descriptive statistics for person-level variables.

Variable	1	2
Trait variables		
1. NED	–	
2. Depressive symptoms	−0.09	–
Daily variables (between-person part)		
3. Calmness in the morning	0.13*	−0.45***
4. Daily stress	−0.11	0.39***
5. Calmness in the evening	0.16**	−0.49***
6. Nightly sleep quality	0.09	−0.51***
7. Daily rumination	−0.08	0.34***
8. Daily mean negative emotions	−0.20***	0.58***
M	0.36	7.57
SD	0.19	4.85
Range	0.08–1	0–27

N = 313 persons. To aid in interpretability of the mean for NED, we report the descriptive statistics for the raw scores (i.e., prior to Fisher's Z-transformation), reverse scored.

**p < 0.05; **p < 0.01; *** p < 0.001.*

Moderated Multilevel (1-1-1) Mediation Models (First-Stage Conditional Process Models)

Next, we entered NED as a Level 2 predictor to the model. The fixed effects of the moderated multilevel (1-1-1) mediation model are displayed in **Table 3** (Model 2). NED predicted higher calmness in the evening (main effect of NED on the varying intercepts), and this corresponded to a small effect size (see row NED → M_B in **Table 3**). Supporting Hypothesis 2, NED positively predicted the varying random slopes for the effect of daily stress on calmness in the evening (see row NED → a_i). The within-person relation between daily stress and less calmness in the evening was stronger at low (*M* – 1 *SD*) NED, simple slope estimate = −0.261, 95% CI (−0.297, −0.224), than at high (*M* + 1 *SD*) NED, simple slope estimate = −0.189, 95% CI (−0.226, −0.151). **Figure 2** illustrates this cross-level interaction. Additionally, we estimated the conditional within-person indirect effect of X_W on Y_W through M_W at low (*M* – 1 *SD*) and high (*M* + 1 *SD*) values of NED. This was done by centering NED at these values of interest and re-running the model (Hayes and Rockwood, 2020). The estimated indirect effect then represented the conditional indirect effect when NED was equal to that specific value of interest. For individuals with low NED, the estimated within-person indirect effect was significant, $E(a_ib_i)$ = −0.061, 95% CI (−0.116, −0.014). For individuals with high NED, the estimated within-person indirect effect was non-significant, $E(a_ib_i)$ = −0.037, 95% CI (−0.082, 0.007).

Finally, we controlled for mean negative emotions and depressive symptoms at Level 2 (Model 3). The fixed effects results for this model can be found in **Table 4**. Both mean negative

TABLE 3 | Estimates for (moderated) multilevel (1-1-1) mediation models.

	Model 1					Model 2				
Coefficients	**Est.**	**Post. *SD***	**One-tailed *p***	**95% CI**	**Stand. est.**	**Est.**	**Post. *SD***	**One-tailed *p***	**95% CI**	**Stand. est.**
Fixed effects										
Time → M_W	0.015	0.008	0.029	(−0.001, 0.032)	0.026	0.015	0.009	0.048	(−0.003, 0.033)	0.026
Time → Y_W	0.111	0.043	0.005	(0.021, 0.194)	0.042	0.111	0.042	0.006	(0.025, 0.194)	0.041
CalmMor_W → M_W	0.067	0.017	<0.001	(0.035, 0.103)	0.061	0.070	0.018	<0.001	(0.033, 0.106)	0.062
X_W → M_W (*a*)	**−0.222**	**0.014**	**<0.001**	**(−0.250, −0.195)**	**−0.301**	**−0.225**	**0.013**	**<0.001**	**(−0.251, −0.197)**	**−0.303**
M_W → Y_W (*b*)	**0.412**	**0.081**	**<0.001**	**(0.254, 0.577)**	**0.086**	**0.372**	**0.085**	**<0.001**	**(0.215, 0.546)**	**0.078**
X_W → Y_W (c')	0.011	0.051	0.427	(−0.100, 0.095)	0.002	−0.011	0.058	0.417	(−0.142, 0.091)	−0.004
NED → a_i						**0.107**	**0.041**	**0.007**	**(0.021, 0.183)**	**0.161**
NED → M_B						0.039	0.019	0.022	(0.001, 0.077)	0.063
Indirect effect [$E(a_i b_i)$]	**−0.063**			**(−0.109, −0.014)**		**−0.050**			**(−0.097, −0.004)**	
Total effect [$E(a_i b_i) + c'$]	−0.054			(−0.155, 0.033)		−0.063			(−0.179, 0.036)	
R^2 at Level 1										
R^2 (M_W)	0.172					0.173				
R^2 (Y_W)	0.055					0.056				
R^2 at Level 2										
R^2 (a_i)						0.026				
R^2 (M_B)						0.004				

Focal effects of the (moderated) mediation model are bolded. Index W (B) indicates the within- (between-) person part of time-varying variables. The covariance (correlation) between the random slopes a_i and b_i was 0.029 (0.269) in Model 1 and 0.033 (0.303) in Model 2. X, Daily stress; M, calmness in the evening; Y, nightly sleep quality; CalmMor, calmness in the morning; Est., estimate; Stand. Est., standardized estimate; Post. SD, posterior standard deviation; One-tailed p, Bayesian one-tailed p-value; CI, Bayesian credibility interval.

emotions and depressive symptoms predicted the intercept for calmness in the evening (see rows NegEmo → M_B and Depr → M_B in **Table 4**), whereas the main effect of NED on calmness in the evening (row NED → M_B) was no longer different from zero. The cross-level interaction of NED and daily stress on calmness in the evening was retained (see row NED → a_i). Neither mean negative emotions nor depressive symptoms moderated the within-person relation between daily stress and calmness in the evening (see rows NegEmo → a_i and Depr → a_i)[2].

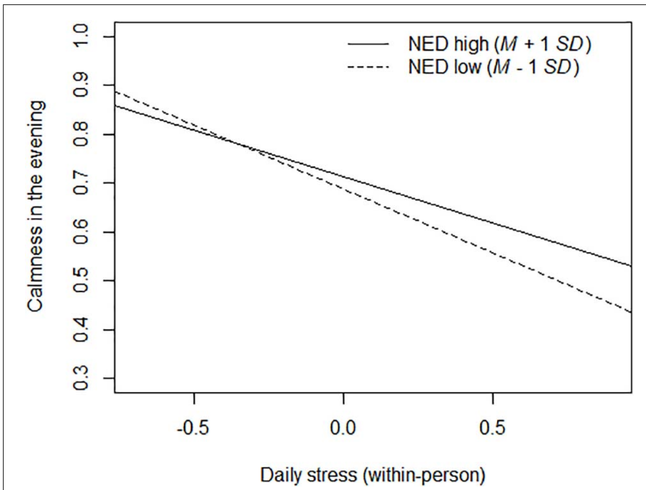

FIGURE 2 | Simple slopes for the moderator effect of NED on the within-person relation between daily stress and calmness in the evening.

Supplementary Analyses

In our supplementary analyses, we first explored (a) whether the stress buffering effect that we found for person-level NED translates to day-level NED (i.e., whether stress reactivity would be lower on days on which an individual's momentary differentiation is higher than usual). In a two-level model predicting calmness in the evening by daily stress and daily NED and their interaction (controlling for calmness in the morning and time), the Level 1 interaction term was significant [estimate = 0.013, 95% CI (−0.007, 0.022)]. As expected, on days with higher NED, the stress-calmness link was less negative [simple slope estimate = −0.143, 95% CI (−0.181, −0.109)] than on days with lower NED [simple slope estimate = −0.258, 95% CI (−0.301, −0.220)]. However, when (b) daily negative mean emotions was added to the model as a Level 1 predictor, the Level 1 interaction term was no longer significant [estimate = 0.002, 95% CI (−0.004, 0.008)].

Additionally, we explored daily rumination as a potential mechanism through which NED might exert its stress-buffering effect. In model (c), we analyzed whether daily rumination about

[2]To explore whether the within-person relation between calmness in the evening and sleep quality (path b_i) varied as a function of NED, we additionally ran a first- and second-stage multilevel conditional process model in which NED predicted the random slope terms a_i and b_i (and the two random intercept terms for evening mood and sleep quality). NED did not moderate the random slope term b_i (estimate = −0.267, posterior *SD* = 0.247, one-tailed Bayesian p = 0.138, 95% CI (−0.752, 0.210)], nor did NED predict the intercept term for sleep quality (estimate = 0.067, posterior *SD* = 0.080, one-tailed Bayesian p = 0.200, 95% CI (−0.090, 0.223)].

emotions moderated the within-person relation between daily stress and calmness in the evening (controlling for calmness in the morning and time). A two-level model revealed a significant Level 1 interaction between daily stress and daily rumination [estimate = −0.052, 95% CI (−0.109, −0.003)]. On the days on which individuals ruminated, the negative stress-calmness link was stronger [estimate = −0.242, 95% CI (−0.277, −0.200)] than on days on which individuals did not ruminate about their emotions [estimate = −0.191, 95% CI (−0.225, −0.160)]. In the next step (model d), we added daily NED to the model as a Level 1 predictor of daily rumination. The regression coefficient for daily NED was significant [estimate = −0.008, 95% CI (−0.012, −0.004)]. That is, on days with lower NED, the probability to ruminate was higher. However, when we added daily mean negative emotions as an additional Level 1 predictor of daily rumination (model e), this effect vanished [estimate = −0.002, 95% CI (−0.005, −0.002)].

DISCUSSION

With the current AA study, we aimed to investigate the indirect within-person effect of perceived daily stress on subjective sleep quality through calmness in the evening in a community sample of adults during times of stress (the first pandemic lockdown in 2020). Our main moderator hypothesis represented a conceptual replication and extension of Starr et al.'s (2017, 2020) findings on the role of NED in buffering daily stress reactivity. As expected, higher daily stress was related to within-day change in calmness from morning to evening, resulting in less calmness in the evening within persons. Less calmness in the evening, in turn, was related to poorer nightly sleep quality within persons. Supporting our main hypothesis, NED moderated the within-person relation between daily stress and calmness in the evening, with lower NED predicting a stronger negative link between daily stress and calmness in the evening. This also meant that the indirect within-person effect of daily stress on sleep quality through calmness in the evening was found to be conditional on an individual's standing on NED. For low differentiators, daily stress was negatively linked to sleep quality through calmness in the evening, whereas for high differentiators, this within-person indirect effect was non-significant.

Ambulatory assessment studies on within-person processes linking day-to-day fluctuations in stress to affective states prior to sleep and to sleep quality that night are still scarce (cf. Tousignant et al., 2019). Our result that the within-person indirect effect of daily stress on sleep quality through calmness in the evening was, on average, negative is consistent with previous research that found that cognitive and somatic arousal at bedtime mediated the link between daily stress and subjective sleep quality (Morin et al., 2003; Winzeler et al., 2014; Tousignant et al., 2019). Despite variation with respect to the concrete operationalization of calmness/tense arousal (ratings of mood adjectives in our study vs. ratings of statements describing cognitive processes and felt somatic states in the cited studies), the time point that was referred to (evening vs. bedtime), and the type of assessment that

TABLE 4 | Estimates for moderated multilevel (1-1-1) mediation model including level 2 control variables (Model 3).

Coefficients	Estimate	Post. *SD*	One-tailed *p*	95% CI	Stand. estimate
Fixed effects					
Time → M_W	0.015	0.008	0.034	(−0.002, 0.032)	0.027
Time → Y_W	0.117	0.040	0.002	(0.045, 0.197)	0.043
CalmMor_W → M_W	0.072	0.018	<0.001	(0.038, 0.113)	0.063
$X_W \rightarrow M_W$ (*a*)	**−0.221**	**0.014**	**<0.001**	**(−0.251, −0.194)**	**−0.299**
$M_W \rightarrow Y_W$ (*b*)	**0.402**	**0.085**	**<0.001**	**(0.223, 0.558)**	**0.082**
$X_W \rightarrow Y_W$ (c')	0.006	0.056	0.470	(−0.096, 0.114)	−0.004
NED → a_i	**0.109**	**0.042**	**0.002**	**(0.028, 0.189)**	**0.160**
NegEmo → a_i	0.077	0.143	0.286	(−0.170, 0.411)	0.045
Depr → a_i	−0.005	0.004	0.120	(−0.012, 0.002)	−0.107
NED → M_B	0.019	0.018	0.130	(−0.015, 0.054)	0.037
NegEmo → M_B	−0.363	0.061	<0.001	(−0.487, −0.246)	−0.266
Depr → M_B	−0.003	0.001	0.014	(−0.006, 0.000)	−0.089
Indirect effect [$E(a_ib_i)$]	**−0.065**			**(−0.114, −0.007)**	
Total effect [$E(a_ib_i) + c'$]	−0.056			(−0.164, 0.041)	
R^2 at Level 1					
R^2 (M_W)	0.172				
R^2 (Y_W)	0.060				
R^2 at Level 2					
R^2 (a_i)	0.049				
R^2 (M_B)	0.083				

Focal effects of the moderated mediation model are bolded. Index W (B) indicates the within- (between-) person part of time-varying variables. The covariance (correlation) between the random slopes a_i and b_i was 0.024 (0.215). X, daily stress; M, calmness in the evening; Y, nightly sleep quality; CalmMor, calmness in the morning; NegEmo, mean negative emotions; Depr, depressive symptoms; Post. SD, posterior standard deviation; One-tailed p, Bayesian one-tailed p-value; CI, Bayesian credibility interval.

was used (e.g., momentary mood ratings collected in the evening or before going to sleep vs. retrospective judgments collected in the morning in Tousignant et al.'s study), the results converged in showing that more negative affective reactions to daily stress predicted impaired sleep quality within persons. Calmness in the evening could be important because falling asleep requires the inhibition of multiple arousal systems (Szymusiak and McGinty, 2008), and the ease with which a person falls asleep is a crucial aspect of sleep quality (Åkerstedt et al., 1994, 2012). There is some empirical evidence suggesting that the relation between nightly sleep and daily affect may be bidirectional (Konjarski et al., 2018), potentially resulting in a vicious circle of tense arousal and disturbed sleep (Garde et al., 2011). In our study, we decided to analyze nightly sleep quality as an outcome variable because our focus was on (individual differences in) daily stress reactivity and its consequences. However, we controlled for daily "baseline levels" of calmness in our models (by entering calmness in the morning as an additional predictor of calmness in the evening) to reduce the possibility that inverse effects of sleep quality on the next day's tense arousal would bias our models' within-person estimates.

At the person level, we found that NED had a small association with higher calmness across the study period of 3 weeks. When we controlled for mean negative emotions (and depressive symptoms), this "main effect" of NED on average calmness vanished. This finding is in line with results from Dejonckheere et al. (2019), who showed that small relations between NED and well-being indicators became non-significant when mean affect was controlled for. Unique explanatory power of NED over and above reliable trait-like measures of affective functioning would be expected for outcome variables in which a considerable amount of variance is due to more complex temporal dynamics (e.g., Dejonckheere et al., 2019). Thus, the disappearing predictive utility of NED when mean negative emotions were controlled might be particularly informative about the outcome measure: Average calmness across 3 weeks during an uncertain time (a pandemic lockdown) can be considered as an indicator of individuals' dispositional affective functioning. Moreover, we found that NED was unrelated to depressive symptoms and average sleep quality. Previous research has revealed small to moderate negative correlations between NED and depressive symptoms in healthy populations (Erbas et al., 2014; Starr et al., 2017, 2020; Dejonckheere et al., 2019). However, this link may also be mainly due to the variance that both NED and depressive symptoms share with mean negative emotions (Dejonckheere et al., 2019). Taken together, our non-significant "main effects" of NED at the person level underscore the need to scrutinize within-person regulatory processes more closely because "it is possible that unique associations between affect dynamics and psychological well-being exist, but that current research practices leave it undisclosed" (Dejonckheere et al., 2019, p. 486).

The results of our moderated multilevel (1-1-1) mediation analysis conceptually replicated and extended Starr et al.'s (2017, 2020) findings on the stress-buffering effect of NED. In a community sample of adults, and using calm mood (instead of depressive mood) as an indicator of stress reactivity, we found evidence for the expected moderating effect of NED on the within-person relation between daily stress and calmness. Importantly, the stress buffering effect of NED was not accounted for by individual differences in mean negative emotions and depressive symptoms. That is, our results provide additional support for Starr et al.'s (2020) diathesis-stress model of NED, and hence, for NED as a protective factor that helps to explain why some individuals remain more resilient during times of stress than others. Moreover, our finding that the indirect within-person effect of daily stress on nightly sleep quality via calmness in the evening was negative for low differentiators and not significantly different from zero for high differentiators hints at within-person processes through which NED might confer health-related benefits during times of stress. Finally, it is important to note that the cross-level interaction between NED and daily stress could also be interpreted to demonstrate that the predictive power of NED is limited to specific situational conditions: In line with theoretical reasoning (Kashdan et al., 2015; O'Toole et al., 2020) and previous empirical evidence (Ottenstein and Lischetzke, 2020), high (vs. low) NED was most beneficial on stressful days that presented a challenge to a person's well-being—that is, when the need for regulation was greatest.

In our supplemental analyses, we additionally scrutinized whether the stress buffering effect of person-level NED could also be found for within-person fluctuations in NED. When applying the recently proposed momentary index of emotion differentiation (Erbas et al., 2021) to our data, we found that daily NED moderated the within-person stress-calmness link, and the form of this Level 1 interaction was similar to the form of the cross-level interaction. However, in contrast to the person level, where the stress buffering effect of NED held beyond mean negative emotions (and depressive symptoms), the moderator effect of daily NED was not significant after controlling for daily mean negative emotions. One reason for this might be that the shared variance between NED and mean negative emotions was smaller at the between-person level ($r = -0.20$) than at the within-person level ($r = -0.46$). A moderate to high negative correlation between the momentary index of NED and the mean negative emotion scores at each occasion is expected to occur if the mean emotion scores are right-skewed (see Erbas et al., 2021), which is typical for negative emotions and was also the case in our study. Another aim of our supplementary analyses was to explore whether a reduced tendency to ruminate about emotions might represent a potential mechanism through which NED exerts its stress-buffering effect. In line with previous findings on the deleterious effect of daily rumination on affect (e.g., Puterman et al., 2010; Catalino et al., 2017), the within-person link between daily stress and calmness in the evening was more negative on days on which individuals ruminated about their emotions. Lower daily NED predicted a higher tendency to ruminate about emotions, thus providing support for a strategy selection effect of NED (Kalokerinos et al., 2019). However, the association with daily rumination was not unique for daily NED because the predictive power of NED disappeared when we controlled for daily mean negative emotions. Given the novelty of the momentary index of emotion differentiation, more research is needed on the conditions under which it shows predictive utility beyond mean affect. This might include assessment-related aspects such as the selection of emotions (which differ in the frequency and intensity with which they are experienced in daily life), design-related aspects such as the degree of variability in situational context individuals are in during the study phase, or substantive aspects such as outcome variables that refer to different points in the affect regulation process.

Limitations

Our measure of daily stress was a retrospective measure collected in the evening. Retrospective end-of-day measures have been shown to converge strongly with aggregated momentary ratings within persons (Neubauer et al., 2020). Nonetheless, participants' daily stress ratings might have been affected by their momentary mood when completing the end-of-day assessment. To control for potential effects of day-to-day fluctuations in mood on the perception of daily stress, we assessed calmness in the morning and included it as a control variable in our analyses. Still, we cannot fully rule out an effect of momentary mood in the evening on the daily stress rating. Therefore, more research is needed to scrutinize whether an alternative way to measure daily stress (for instance, by assessing momentary stress multiple times during the day instead of retrospectively in the evening) would yield similar findings.

Although our study is one of only a few studies to date that have examined the predictive utility of NED with respect to individual differences in within-person regulatory processes, it remains unclear whether the stress-buffering effect of NED translates into longer term resilience against adversity. Future research could use multiple intensive assessment phases separated by longer time intervals (i.e., measurement burst designs) to study both short- and longer-term outcomes.

Despite rates of individual COVID-19-related risk factors that were comparable to those in the general population in Europe (Clark et al., 2020) and psychological reactions to the pandemic that were similar to those in the general German population during the first lockdown in 2020 (Betsch et al., 2020), our community sample was not representative in other respects: women between the ages of 20 and 29 were overrepresented. Therefore, the results might not be generalizable beyond a female, young adult population.

Conclusion

The present study adds to the growing literature on the role of individual differences in NED in within-person affect regulation processes. Our findings support the notion that higher NED buffers daily stress reactivity and thereby attenuates the negative indirect effect of daily stress on nightly sleep quality. The unique predictive utility of NED (beyond mean negative emotions and depression) was found for the prediction of individual differences in these within-person regulatory processes but not for the prediction of individual differences in mean levels of well-being indicators (e.g., average calm mood or average sleep quality). This discrepancy underscores the need for more process-oriented research to investigate the specific benefits that the ability to differentiate discrete negative emotions might confer.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Institutional Ethics Committee of the Psychology Department at the University of Koblenz-Landau. Written informed consent from the participants' legal guardian/next of kin was not required to participate in this study in accordance with the National Legislation and the Institutional Requirements.

AUTHOR CONTRIBUTIONS

LS and TL organized the database. TL performed the statistical analyses and wrote the first draft of the manuscript. All authors contributed to conception and design of the study, manuscript revision, read, and approved the submitted version.

FUNDING

This research was supported by the Research Initiative of Rhineland-Palatinate, Germany (Forschungsinitiative Rheinland-Pfalz).

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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frontiers in Psychology

ORIGINAL RESEARCH
published: 01 September 2021
doi: 10.3389/fpsyg.2021.685851

Emotion Differentiation in Current and Remitted Major Depressive Disorder

Renee J. Thompson[1]*, Daphne Y. Liu[1], Ella Sudit[1] and Matt Boden[2]

[1] Emotion and Mental Health Lab, Department of Psychological & Brain Sciences, Washington University in St. Louis, St. Louis, MO, United States, [2] VA Palo Alto Health Care System, Palo Alto, CA, United States

People with current major depressive disorder (MDD) experience diminished emotion differentiation. We tested the hypothesis that this emotional disturbance is chronic and also characterizes those whose MDD has remitted. As our main aim, we examined emotion differentiation in conjunction with elevated negative and diminished positive emotional intensity, which are both cardinal symptoms of MDD. As an exploratory aim, we examined the predominant theoretical conceptualization that people low in emotion differentiation use more general state terms (e.g., bad) and fewer emotion terms (e.g., anger) to describe their emotional experience. Participants (assessed via diagnostic interview) included individuals who had current MDD (current depressed; n = 48), individuals whose MDD was in full remission (remitted depressed; n = 80), and healthy controls (n = 87). Participants also completed two self-report measures of depressive symptoms and reported momentary emotion repeatedly for 14 days via experience sampling, from which we computed emotion differentiation (i.e., intraclass correlation coefficient) and emotional intensity (i.e., average of the mean emotion ratings across surveys). Finally, participants described a momentary emotional experience via an open-response format, which was coded for the use of general state and emotion terms. Compared to the healthy control group, the current and remitted depressed groups showed similarly low levels of negative and positive emotion differentiation. These findings suggest that diminished emotion differentiation may be a stable characteristic of depressive disorders and a possible target for future prevention efforts. Diminished negative emotion differentiation was significantly associated with higher depressive symptoms as assessed by only one of the depression measures, though this finding did not hold after adjusting for negative emotional intensity. Finally, participants' emotion differentiation was not associated with use of general state and emotion terms, and groups did not use general state and emotion terms in ways that were consistent with the predominant theoretical conceptualization of emotion differentiation, suggesting the need for clarification in this research domain.

Keywords: emotion differentiation, major depressive disorder, emotional granularity, remitted depression, experience sampling

OPEN ACCESS

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Alexandra E. Kelly,
Drexel University Philadelphia, United States, in collaboration with reviewer EGC

****Correspondence:***
Renee J. Thompson
renee.thompson@wustl.edu

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: *25 March 2021*
Accepted: *11 August 2021*
Published: *01 September 2021*

Citation:
Thompson RJ, Liu DY, Sudit E and Boden M (2021) Emotion Differentiation in Current and Remitted Major Depressive Disorder. Front. Psychol. 12:685851. doi: 10.3389/fpsyg.2021.685851

INTRODUCTION

Major depressive disorder (MDD) is among the most prevalent and debilitating mental disorders (Eaton et al., 2012), and the already high prevalence rate is increasing (Weinberger et al., 2018). It is a highly recurrent disorder (Bockting et al., 2015), with more people experiencing recurrent episodes than single episodes (e.g., Andrade et al., 2003). These prevalence rates highlight the need to improve prevention efforts, including identifying possible risk factors. Depressive episodes are characterized by various disturbances in emotion (e.g., Houben et al., 2015; Liu and Thompson, 2017). Examining these emotional disturbances that characterize depressive episodes that are in remission could help identify risk factors associated with the onset and recurrence of MDD, informing primary and secondary prevention efforts.

One emotional disturbance that may confer risk for MDD is low emotion differentiation (hereafter differentiation; Barrett et al., 2001; Demiralp et al., 2012). Individuals with low differentiation are theorized to use general state terms (e.g., good, bad) to describe their feeling states and not to discern nuances between distinct emotions, whereas individuals with high differentiation are theorized to use emotion terms to describe how they feel and to discern the nuances between distinct emotions (e.g., sad versus angry; e.g., Boden et al., 2013; Dixon-Gordon et al., 2014; Erbas et al., 2014; Kashdan et al., 2015). Researchers most commonly measure differentiation using repeated measurements of precise emotion terms and compute a statistic, such as an intraclass correlation coefficient (ICC) (Thompson et al., 2021b). In this case, individuals with low differentiation are theorized to use similar terms over time to describe their feeling states, whereas those with high differentiation report varying combinations of emotions over time to describe their feeling states.

Differentiation of negative emotions (NED) and positive emotions (PED) have often been examined separately. Higher differentiation, particularly NED, has been shown to be adaptive, and it is associated with greater psychological well-being and reduced engagement with maladaptive behaviors (Erbas et al., 2014; Seah and Coifman, 2021). Researchers have proposed that low differentiation could lead to increases in depressive psychopathology via difficulty with emotion regulation, which characterizes MDD (e.g., Ottenstein, 2020). For example, people with low differentiation may have difficulty utilizing the nuanced information provided by emotions to effectively engage in emotion regulation, such as selecting the appropriate emotion regulation strategies (Barrett et al., 2001; Kashdan et al., 2015). Difficulties with emotion regulation have been theorized to lead to increased depressive psychopathology (e.g., Gross and Muñoz, 1995; Ottenstein, 2020). Consistent with this, evidence has linked low differentiation with increases in depressive symptoms over time (Rieffe and De Rooij, 2012; Liu et al., 2020). This led us to theorize that low differentiation may play a role in the etiology of depressive psychopathology and may exist outside of active depressive episodes. Therefore, we posit that low differentiation is a chronic feature of MDD and expect that diminished differentiation will characterize those whose MDD is in remission.

Most existing research on differentiation and depression among adults has focused on NED. Most studies have found that higher NED was associated with lower depressive symptoms (Erbas et al., 2014, Studies 2 and 3; Plonsker et al., 2017; Starr et al., 2017; Liu et al., 2020). Grühn et al. (2013) and Matt et al. (2016) did not find a significant association between NED and depressive symptoms, with Matt et al. (2016) speculating that the null finding may be due to their sample having low levels and a restricted range of current depressive symptoms. Consistent with this speculation, lower NED was significantly associated with higher depressive symptoms in adults with MDD (Goldston et al., 1992), as well as samples with elevated depressive symptoms or a sizable portion reporting clinically significant depressive symptoms (Starr et al., 2017; Liu et al., 2020; Ottenstein, 2020). Further, adults with current MDD had lower NED compared to healthy controls (Demiralp et al., 2012). Taken together, it appears that lower NED was more consistently associated with higher depressive symptoms when the samples had elevated and/or a wide range of depressive symptomatology. However, a significant inverse association between NED and depressive symptoms has been found in relatively healthy samples (e.g., Willroth et al., 2020), suggesting that factors other than the range of depressive symptoms may explain the mixed results, such as the use of different depression measures. Given the heterogeneity of the samples and designs of existing research, it is challenging to detect any pattern related to depression measure type, however.

In contrast to NED, there has been less research on depression and PED in adult samples (O'Toole et al., 2019; Liu et al., 2020; Thompson et al., 2021b), although the findings have been more consistent. PED has not been significantly related to depressive symptoms (Grühn et al., 2013; Matt et al., 2016; Starr et al., 2017; Liu et al., 2020). Similarly, adults with current MDD did not differ from healthy controls in PED (Demiralp et al., 2012). However, given that only one study has examined PED in those with MDD, it is critical to examine whether findings replicate. The role of PED versus NED in psychopathology is much less clear, though there are reasons to believe that PED is indeed related to adaptive emotion responding (e.g., Fredrickson, 2001; Shiota et al., 2014). Thus, more research on PED and psychopathology, more generally, is needed (Thompson et al., 2021b).

The central aim of the study was to examine differentiation in current and remitted MDD. We assessed differentiation via experience sampling, a method with good ecological validity. Experience sampling also minimizes retrospective recall bias (Schwarz, 2012), which is critical in depressed samples who are characterized by several negative cognitive biases (e.g., Gotlib and Joormann, 2010). Although most research on differentiation and depression has focused on depressive symptoms among relatively healthy samples (e.g., Liu et al., 2020), we recruited participants representing a wide range of depressive psychopathology: current MDD, remitted MDD (i.e., experienced a depressive disorder in the past but not currently), and a healthy control group. Groups were identified via diagnostic interviewing, the gold standard method of assessing depressive disorders instead of only assessing depressive symptoms using self-report measures, which tend to have low specificity and assess constructs that are not unique to depression (e.g., general distress; Bredemeier et al., 2010).

By recruiting individuals at different stages of MDD (in and outside of depressive episodes), we included participants who represent much of the spectrum of the disorder and vary in their levels of current depressive symptoms, which we assessed using two self-report measures. In addition, examining differentiation among those whose MDD is in remission will inform whether diminished NED is a chronic feature of MDD, which could provide more insight into the role of NED in the etiology of MDD.

We examined differentiation in conjunction with emotional intensity, as high negative and low positive emotional intensity are primary symptoms of MDD (American Psychiatric Association, 2013). Replicating existing work on negative emotional intensity in MDD (e.g., Watson et al., 1988) and NED (Demiralp et al., 2012), we expected that the current depressed group would have higher negative emotional intensity and lower NED than the healthy control group. In terms of remitted MDD, research has found that people whose MDD is in remission experience higher negative emotional intensity than healthy controls (e.g., Wichers et al., 2012), and lower negative emotional intensity than those with current depressive disorders (Schoevers et al., 2020). Because we expected that diminished NED is relatively chronic and not only a state effect of being in a depressive episode, we hypothesized that the current and remitted depressed group would both have diminished NED relative to the healthy control group. This investigation will be the first to examine NED in remitted MDD, which could help inform whether NED may be a risk factor for MDD.

Based on the diagnostic criteria of MDD (American Psychiatric Association, 2013) and research on positive emotional intensity and PED, we expected that the current depressed group would have significantly lower positive emotional intensity (e.g., Watson et al., 1988) but similar levels of PED (Demiralp et al., 2012) relative to the healthy control group. Most evidence suggests that those with remitted MDD do not differ from healthy controls in positive emotional intensity (e.g., Wichers et al., 2012). Furthermore, those with remitted MDD have been found to have higher positive emotional intensity than those with current MDD (Schoevers et al., 2020). Regarding PED, we did not expect that the remitted depressed group would differ from the healthy control group or current depressed group based on existing literature investigating depressive psychopathology and PED. Although we did not expect group differences in PED, this study nevertheless contributes to the literature by examining PED in remitted depression for the first time.

The present study is also novel because of its exploratory aim focused on testing one tenet of the predominant theoretical conceptualization of differentiation–the use of general state and emotion terms. As in the present study, most researchers have measured differentiation using experience sampling (Thompson et al., 2021b), where participants are repeatedly prompted to rate the extent to which they feel a given list of emotion terms for a number of days or weeks. Researchers often compute ICCs between emotion terms to index trait differentiation (Thompson et al., 2021b), with high intercorrelation indicating low differentiation. However, this method does not allow researchers to test an important tenet of the predominant differentiation theory–whether low differentiation is characterized by a greater likelihood of using general state terms and a lower likelihood of using emotion terms (Thompson et al., 2021b). To address this limitation, we administered an online survey that assessed participants' momentary emotional experiences using a free-response format. Assessing how these open-ended responses are correlated with differentiation using ICCs derived from experience sampling data allowed us to explicitly examine whether differentiation corresponds with how it is predominantly conceptualized (i.e., use of general state and emotion terms). Additionally, we examined whether the current depressed group, who has been shown to have diminished NED relative to a healthy control group (Demiralp et al., 2012), would be more likely to use general state terms and less likely to use emotion terms when describing their momentary emotional experiences–a pattern that would be consistent with the predominant theoretical conceptualization of differentiation. If the remitted depressed group reflects the current depressed group in terms of diminished NED, we would also expect them to show the same pattern in their use of general state and emotion terms relative to the healthy control group.

Finally, one might reasonably argue that a higher verbal ability would be associated with higher differentiation. However, Ottenstein and Lischetzke (2020) found that NED (assessed using ICCs) was associated with verbal ability to a small and non-significant degree. Further, Ottenstein and Lischetzke (2020) did not find a significant association between verbal ability and their open-ended measure of NED (i.e., specificity index) either. It is important to see if this pattern of findings replicate and examine the associations between verbal ability and PED. Consequently, we administered the vocabulary subtest of the Wechsler Adult Intelligence Scale–Third Edition (WAIS-III; Weschler, 1997) as a proxy for verbal ability to examine its associations with differentiation and with the use of general state and emotion terms.

MATERIALS AND METHODS

Participants

The sample included 215 participants recruited for a study on everyday emotions and decision making. Participants were recruited from participant registries, ads (e.g., Craigslist), and fliers posted at local businesses and clinics. The sample was composed of 66.0% women and 34.0% men, with an average age of 44.3 years (SD = 16.1). Racial/ethnic composition included 69.8% White, 19.5% Black, 2.8% Asian, 0.5% Native American, and 7.0% other or multiracial (0.5% did not report). In addition, 1.4% reported that they were Latinx/a/o. Participants were generally highly educated with the following levels of education: bachelor's degree (32.6%), a graduate or professional degree (32.1%), some college (24.2%), some high school or high school diploma (9.8%), and unknown (1.4%). In terms of employment status, 19.1% were employed part-time, 40.9% were employed full-time, 14.4% were retired, and 10.7% were unemployed; others were on disability, stay-at-home parents, and so forth.

Eligibility criteria for the study included speaking English as a primary language and not having severe visual or hearing impairments. In addition, individuals needed to meet criteria for one of three groups as defined by the Diagnostic and Statistical Manual of Mental Disorders (5th ed.; DSM-5; American Psychiatric Association, 2013). For the current depressed group (n = 48), individuals needed to meet criteria for a current major depressive episode in the context of MDD or persistent depressive disorder (regardless of the number of previous major depressive episodes). For the remitted depressed group (n = 80), individuals needed to meet criteria for at least two fully remitted depressive episodes in the context of MDD or persistent depressive disorder. For the healthy control group (n = 87), individuals were required to have no current or past mood or anxiety disorders. Inter-rater reliability scores showed that raters demonstrated perfect agreement in assessing the presence of current MDD, current persistent depressive disorder, past MDD, and past persistent depressive disorder (k = 1.0 for each) in a random subset of interviews (n = 48). Exclusionary criteria included current or past diagnoses of bipolar I, bipolar II, cyclothymic disorder, and current or past psychotic symptoms. Due to the high rate of comorbidity between depressive and anxiety disorders (Kessler et al., 2003), individuals with comorbid anxiety disorders were eligible for the two depressed groups, resulting in 70.8% of the participants in the current depressed group and 18.8% in the remitted depressed group meeting criteria for at least one comorbid anxiety disorder.

Procedures

Interested individuals completed an initial telephone screen conducted by a post-baccalaureate project manager or an undergraduate research assistant, who briefly assessed participants' experiences with the two cardinal symptoms of MDD (i.e., depressed mood and anhedonia, American Psychiatric Association, 2013). Individuals who were deemed as likely to be eligible for the study completed a series of self-report measures administered online (i.e., home survey) before attending a laboratory session, during which their eligibility would be more thoroughly assessed. In the laboratory session, participants completed Modules B/C (Psychotic Screening), D (Mood Disorders), and F (Anxiety Disorders) of the Structured Clinical Interview for DSM-5.0 (SCID-5-RV; First et al., 2015). Interviews were conducted by clinical psychology graduate students who had completed a graduate-level assessment course in which they learned to administer the SCID-5-RV. Interviewers obtained telephone supervision from the first author, a licensed psychologist, as needed. Participants completed two self-report measures of depressive symptoms–the anhedonic depression scale of the Mood and Anxiety Symptom Questionnaire (MASQ) (Watson et al., 1995) and the Center for Epidemiologic Studies Depression Scale (CES-D) (Radloff, 1977) before the SCID-5-RV interview.

Participants who met criteria for any of the three groups also completed additional self-report measures, cognitive tasks, including the WAIS-III vocabulary subtest (Weschler, 1997), and a 30-min individual experience sampling tutorial during the laboratory session. For the tutorial, undergraduate experimenters helped participants install the experience sampling software on their own iPhones or provided participants with a 4th-generation iPod Touch. We used the Status/Post iOS app developed by Christopher Metts, M.D., which collects data offline, obviating the need for Wi-Fi or a smartphone. The tutorial also included a presentation with slides and a full practice survey. Throughout the tutorial, experimenters assessed whether the participant understood the procedure and provided standardized examples. At the end of the session, participants were financially compensated for the home survey ($6) and for the laboratory session ($12/h). Participants who attended the laboratory session via public transportation received additional compensation for associated costs ($4 if traveled by bus or $5 if traveled by rail).

During the 14-day sampling period, which started the day after the laboratory session, participants were randomly prompted to complete five surveys a day for a total of 70 surveys. Participants chose the 15-h window during which they would complete surveys, and prompts occurred at random times within five 3-h windows per day. Participants had up to 15 min to start the survey before the survey closed, in which case data were marked as missing. Surveys occurred at an average of 3 h, 0 min, and 18 s apart (SD = 1 h, 1 min, 35 s). The mean percentage of surveys completed was 74.8% (SD = 18.3%, range = 20.0–99.0%). Groups did not differ in the time between surveys, $F(2) = 0.20$, $p = 0.82$, or the percentage of surveys completed, $F(2) = 0.30$, $p = 0.74$. The sample of 215 did not include 22 participants who experienced app problems (n = 7), withdrew (n = 7), had completed less than 20.0% of the surveys (n = 7), or whose behavior evoked concern about the validity of the data (n = 1). To encourage compliance, participants were called a few days into the sampling period to trouble-shoot problems. After the sampling period, participants were debriefed via email and financially compensated for the experience sampling portion ($40), with an additional bonus of $10 for completing at least 80.0% of surveys.

Target sample sizes were pre-determined to ensure sufficient power to examine hypotheses using multilevel modeling analyses for other study hypotheses. For the current study, *post hoc* power analyses of our central hypotheses tested using a multivariate analysis of variance (MANOVA). Follow-up analyses of variance (ANOVA) revealed adequate power given observed sample and effect sizes (Range = 0.78–0.99; Faul et al., 2007).

Measures

Emotional Intensity

At each experience sampling survey, participants rated their momentary levels of emotion. Using a five-point scale ranging from 0 (*not at all*) to 4 (*extremely*), participants indicated the extent to which they were currently feeling a series of emotions using the following format: "I felt [EMOTION] at the time of the beep." Emotions included low, moderate, and high arousal emotions from the affective circumplex (Barrett and Russell, 1999). Mean levels of negative emotion (i.e., bored, sluggish, sad, frustrated, nervous, and angry) and positive emotion (i.e., relaxed, content, calm, happy, excited, and enthusiastic) were computed for each survey, and these scores were averaged, creating an overall mean for negative emotion and for positive emotion. Importantly, research has shown that aggregating state measurements of a construct (e.g., emotional intensity) is often superior to assessing global measures of the same construct (Augustine and Larsen, 2012). As recommended by Nezlek (2017), we computed the mixed modeling functional equivalent to Cronbach's α for negative and positive emotional intensity, which were 0.65 and 0.74, respectively. The ICC for negative emotional intensity was 0.42, meaning that 42 and 58% of the variance was at the between- and within-person-levels, respectively. The ICC for positive emotional intensity was 0.43.

Emotion Differentiation

We assessed differentiation using experience sampling data and computed differentiation following past research (e.g., Erbas et al., 2014). First, we computed the average ICC measuring consistency (Shrout and Fleiss, 1979) between negative emotions (i.e., bored, sluggish, sad, frustrated, nervous, and angry) and between positive emotions (i.e., relaxed, content, calm, happy, excited, and enthusiastic) across the experience sampling surveys, resulting in NED and PED, respectively. Based on 2 considerations, 14 participants (11 healthy controls, 3 current depressed) with negative ICC values obtained from ratings of negative emotions were re-coded as having a value of zero rather than excluding them from analyses. First, theorists have stated that negative ICC values can be interpreted as representing low agreement between ratings (Giraudeau, 1996; Taylor, 2010). Second, in our data set, participants with negative ICC values and with lower ICC values (0–0.50) were similar in (a) the average number and percent of zero responses per prompt, and (b) average levels of negative affect intensity and variance per prompt. Negative ICC values may have resulted in part from participants responding to fewer prompts (relative to participants with positive, high and low ICC values). Thus, like participants with low ICC values, we considered participants with negative ICC values as having high emotion differentiation. Then we transformed the ICC values using a Fisher's r-to-z transformation (Pond et al., 2012). Finally, because higher ICC values reflect greater similarity in ratings of different emotions across occasions (i.e., lower differentiation), we subtracted the transformed scores from one, so that higher scores reflected greater differentiation to ease interpretation.

Depressive Symptoms

Mood and anxiety symptom questionnaire (MASQ)–anhedonic depression

Depressive symptoms were measured using the anhedonic depression subscale (22 items) of the MASQ (Watson et al., 1995). The MASQ anhedonic depression scale focuses on aspects of depressive psychopathology that uniquely characterize depression–anhedonia (e.g., "felt like nothing was enjoyable") and low positive affect (e.g., "felt cheerful;" reverse-coded). It has been found to be psychometrically distinct from anxiety symptoms (Watson et al., 1995; Nitschke et al., 2001). Participants reported the extent to which they experienced depressive symptoms over the preceding week using a five-point Likert scale ranging from 1 (*not at all*) to 5 (*extremely*). A composite anhedonic depression scale score was computed for each participant by summing the 22 individual item scores, with the 14 items focusing on positive affect reverse-scored to reflect low positive affect. Higher scores indicate greater severity of depressive symptoms. The MASQ anhedonic depression scale has strong psychometric properties in community (Watson et al., 1995; Nitschke et al., 2001) and clinical samples (e.g., Watson et al., 1995). Internal reliability of the MASQ anhedonic depression subscale was excellent ($\alpha = 0.96$).

Center for epidemiological studies depression scale (CES-D)

Depressive symptoms were also assessed using the 20-item CES-D (Radloff, 1977). The CES-D covers a wide range of depressive symptoms, including depressed affect (e.g., "I feel depressed"), lack of positive affect (e.g., "I feel hopeful about the future;" reverse-coded), somatic complaints (e.g., "I did not feel like eating; my appetite was poor"), and interpersonal concerns (e.g., "I felt that people dislike me"). Participants rated the frequency at which they had experienced each symptom over the preceding week using a four-point Likert scale ranging from 0 (*rarely or none of the time*) to 3 (*most or all of the time*). A composite CES-D score was computed for each participant by summing their scores of the 20 individual items, four of which were reverse-coded. Higher CES-D scores indicate greater severity, with scores equal or greater than 16 suggesting symptom severity of clinical significance (Radloff, 1977). The CES-D was developed to assess depressive symptoms of community samples, demonstrating adequate reliability and validity (Eaton et al., 2004), and has been validated in clinical samples (Weissman et al., 1977; Morin et al., 2011). Internal reliability of the CES-D was excellent ($\alpha = 0.94$).

General State and Emotion Terms

As part of the home survey, participants completed an open-ended measure assessing momentary emotional experience. They were presented with the instructions, "Please answer with as much detail as you need to describe your feelings," before being asked to "Describe how you feel right now" by typing their responses in a textbox. For each response, we identified terms describing general states (i.e., vague, general, diffuse, or generic feeling states) and emotions (multifaceted, embodied phenomena that involve loosely coupled changes in subjective experience, behavior, and peripheral physiology; Barrett et al., 2007). We coded these terms into eight categories: (1) positive general states (e.g., good, wonderful), (2) negative general states (e.g., bad, awful), (3) mixed general states (e.g., mixed, ambivalent), (4) neutral general states (e.g., fine, ok, so-so), (5) positive emotions (e.g., happy, excited), (6) negative emotions (e.g., sad, angry), (7) mixed emotions (e.g., bittersweet), and (8) neutral emotions (e.g., surprise). All eight categories were binary coded (e.g., someone who used one or more positive emotions would be coded as having a "one" for the positive emotion category). No participants used mixed general state or emotion terms, so these were dropped from further analyses. Two advanced undergraduate research assistants, both of whom were blind to participants' group status, independently scored each response with disagreements in ratings resolved through discussion with the first author. Consensus ratings were used. Interrater reliability, as measured by percent agreement between raters (McHugh, 2012), was excellent for the eight term categories (Range = 97.0–100.0%).

Verbal Ability

We administered the WAIS-III vocabulary subtest (Weschler, 1997) as a proxy for verbal ability or verbal intelligence quotient (IQ) as in Muhtadie et al. (2015). The subtest was administered via MediaLab software on a desktop computer, with the experimenter reading the instructions that were visible to the participant. Participants were asked to define each word, which were presented one at a time. The experimenter left the room while the participant was given 4 min to define as many of the 26 words as possible. Then undergraduate research assistants scored each definition as a 0, 1, or 2, for a total composite score with a range of 0–52. After practicing on data from ten participants, the research assistants individually coded data from 85 participants. Then they met with a graduate student who had experience coding this task to arrive at consensus ratings for any disagreements; kappas (one per vocabulary word, total of 26 words) ranged from 0.81 to 1.00 (M = 0.92; SD = 0.05). After high reliability was established, the remaining data were coded by one of the undergraduate research assistants. Internal consistency of the items was also good ($\alpha = 0.81$).

RESULTS

Demographic Data by Group

First, we examined whether demographic and clinical characteristics differed by group, using ANOVA and chi-squared tests. There were no group differences in age, $F(2, 212) = 0.72$, $p = 0.49$, gender, $\chi^2(2, N = 215) = 4.83$, $p = 0.09$, distribution by race/ethnicity, $\chi^2(8, N = 214) = 6.04$, $p = 0.64$, or distribution by Latino/a/x, $\chi^2(2, N = 215) = 1.43$, $p = 0.43$. The three groups did not differ in the highest level of education completed, $\chi^2(6, N = 212) = 7.96$, $p = 0.24$, or employment status, $\chi^2(16, N = 212) = 23.26$, $p = 0.11$. The three groups significantly differed in levels of depressive symptoms as assessed by the MASQ anhedonic depression scale, $F(2, 210) = 63.87$, $p < 0.001$ (current depressed: M = 78.5, SD = 15.5; remitted depressed: M = 56.5, SD = 16.0; healthy control: M = 48.0, SD = 13.5), which is consistent with previous work (e.g., Figueroa et al., 2018). Importantly, the mean of the healthy control group was similar to levels reported in community samples (e.g., Bredemeier et al., 2010), and the means of the remitted depressed and healthy control groups were well below an established clinical cutoff of 76 (Buckby et al., 2007). We see a similar pattern of depressive symptoms by group for the CES-D measure too: The groups significantly differed in CES-D scores, $F(2, 210) = 147.0$, $p < 0.001$ (current depressed: M = 33.40, SD = 10.05; remitted depressed: M = 13.33, SD = 9.64; healthy control: M = 7.34, SD = 6.27). The groups also significantly differed in verbal ability, $F(2, 208) = 3.69$, $p = 0.027$, $\eta_p^2 = 0.034$; a *post hoc* Tukey test showed that the remitted depressed group (M = 27.90, SD = 8.84) scored significantly higher than the healthy control group (M = 24.96, SD = 9.73), $p = 0.042$, as well as than the current depressed group (M = 23.68, SD = 8.71), $p = 0.013$; the healthy control group and the current depressed group did not differ from each other in verbal ability, $p = 0.444$.

Measure Descriptives and Correlations

Across the entire sample, NED ranged from −0.65 to 1.00 (M = 0.50, SD = 0.27), and PED ranged from −1.70 to 0.83 (M = −0.09, SD = 0.31). The low and negative values of differentiation scores were consistent with previous work (e.g., Dixon-Gordon et al., 2014; Lennarz et al., 2018; Widdershoven et al., 2019). Negative emotional intensity ranged from 0 to 2.04 (M = 0.47, SD = 0.37), and positive emotional intensity ranged from 0.06 to 3.01 (M = 1.51, SD = 0.62). Before testing our main hypotheses, we examined Spearman's correlations between differentiation and emotional intensity (see **Table 1**). Negative emotional intensity and NED were significantly inversely associated, as were positive emotional intensity and PED. The small-to-moderate size of these correlations indicate that emotional intensity and differentiation have substantial unshared variance and are thus distinct constructs.

To test whether differentiation was associated with depressive symptoms in our sample, we computed the correlations of differentiation with the CES-D and with the MASQ anhedonic depression scale (see **Table 1**). Lower NED was significantly associated with higher depressive symptoms as measured by the CES-D, but not the MASQ anhedonic depression scale. PED showed a more consistent pattern in that it was not associated with either depressive symptom measure. Given that both NED and CES-D were significantly correlated with negative emotional intensity (**Table 1**) and based on existing concerns about the unique explanatory power of differentiation beyond emotional intensity (i.e., mean affect) in predicting well-being indices (Dejonckheere et al., 2019), we further examined the association between NED and CES-D scores controlling for negative emotional intensity. Results showed that the NED was no longer significantly associated with CES-D scores after accounting for negative emotional intensity, $b = -3.19$, $p = 0.28$.

Verbal ability was associated with NED and PED to a small and non-significant degree. Regarding the open-ended responses, verbal ability was significantly negatively correlated with positive general state terms, $r = -0.15$, $p = 0.04$, but it was uncorrelated with negative, $r = -0.02$, $p = 0.81$, neutral, $r = 0.004$, $p = 0.95$, or overall (across valence) general state terms, $r = -0.09$, $p = 0.21$. Additionally, verbal ability was significantly positively correlated with negative emotion terms, $r = 0.16$, $p = 0.03$, and overall (across valence) emotion terms, $r = 0.19$, $p = 0.007$, but it was uncorrelated with positive, $r = 0.09$, $p = 0.20$, or neutral emotion terms, $r = 0.06$, $p = 0.39$.

Experience Sampling Data

Testing Group Differences in Differentiation and Emotional Intensity (Aim 1)

To assess group differences in differentiation and emotional intensity, we used a MANOVA. In terms of Pillai's trace, there

TABLE 1 | Spearman's correlations between emotion differentiation, emotional intensity, depressive symptoms, and verbal ability.

	NED	Negative emotional intensity	PED	Positive emotional intensity	Depressive symptoms: MASQ	Depressive symptoms: CES-D
NED	–					
Negative emotional intensity	−0.38**	–				
PED	0.17*	−0.04	–			
Positive emotional intensity	0.05	−0.22*	−0.15*	–		
Depressive symptoms: MASQ	−0.07	0.45**	0.09	−0.52**	–	
Depressive symptoms: CES-D	−0.23**	0.54**	0.07	−0.47**	0.83**	–
Verbal ability	0.06	0.16*	−0.10	−0.06	−0.05	−0.08

*CES-D = the Center for Epidemiological Studies Depression Scale; MASQ = the anhedonic depression subscale of the Mood and Anxiety Symptom Questionnaire; NED = negative emotion differentiation; PED = positive emotion differentiation. *p < 0.05 (two-tailed), **p < 0.01 (two-tailed).*

was a significant effect of group on NED, negative emotional intensity, PED, and positive emotional intensity, $V = 0.275$, $F(8, 418) = 8.327$, $p < 0.001$, $\eta_p^2 = 0.137$. We conducted separate univariate ANOVAs on the outcome variables, which revealed significant effects on NED, negative emotional intensity, PED, and positive emotional intensity. See **Table 2** for means, SDs, and difference tests. For NED, *post hoc* tests using *Hochberg's GT2* showed that the two depressed groups had significantly lower NED than the healthy control group, ps < 0.05, but they did not differ from each other, $p = 0.60$. For negative emotional intensity, the three groups significantly varied from each other: The current depressed group had the highest levels, followed by the remitted group, with the healthy control group having the lowest levels, ps < 0.05. For PED, a pattern similar to NED emerged: The two depressed groups had significantly lower levels than the healthy control group, ps < 0.05, but the two depressed groups did not differ from each other, $p = 0.95$. In terms of positive emotional intensity, the current depressed group had significantly lower levels than the other two groups, ps < 0.01, who did not vary from each other, $p = 0.85$. Lastly, an analysis of covariance (ANCOVA), including verbal ability as a covariate, showed that the group effect was significant for NED, $F(2, 206) = 4.596$, $p = 0.011$, $\eta_p^2 = 0.043$, and PED, $F(2, 207) = 4.496$, $p = 0.012$, $\eta_p^2 = 0.042$.

Open-Ended Emotional Responses

Likelihood of Term Use Across the Full Sample

To inform tests of Aim 2, we examined participants' open-ended responses that described their momentary emotional experiences. Given that participants' use of general state and emotion terms are paired categorical data, we conducted an exact McNemar's test to examine participants' relative use of emotion versus general state terms. Results suggested that, across valence, participants on average were significantly more likely to use emotion terms than general state terms to describe their momentary emotional experiences, $p < 0.001$. This pattern was true for experiences of negative valence and positive valence, ps < 0.001. However, participants were more likely to use general state terms than emotion terms to describe neutral experience, $p < 0.001$. Additionally, although participants infrequently used general state terms to describe their momentary emotional experiences overall, they were significantly more likely to use positive than negative general state terms, $p < 0.001$, but they were equally likely to use negative and positive emotion terms, $p = 0.93$.

Empirically Examining Theoretical Conceptualizations of Differentiation (Aim 2)

Association between differentiation and term use

To examine the association between differentiation and use of general state and emotion terms, we computed eight point-biserial correlations between NED and use of general state terms or emotion terms (i.e., negative, positive, neutral, and overall general state terms, as well as negative, positive, neutral, and overall emotion terms); we computed eight correlations for PED in a similar way. All correlation coefficients were small in magnitude and non-significant, ranging from −0.11 to 0.09 for NED and −0.13 to 0.04 for PED. This pattern of findings suggests a lack of correspondence between differentiation and use of general state or emotion terms.

Group differences in general state and emotion term use

We used Fisher's exact tests to assess group differences in the likelihood of using general state and emotion terms overall (i.e., collapsing terms across positive, negative and neutral valence). This test examines whether the groups differ in the percentage of participants who used, for example, at least one general state term. See **Table 2** for percentages and difference tests. The groups did not significantly differ in overall use of general state terms, $p = 0.30$. Similarly, we found no significant group effect on overall use of emotion terms, $p = 0.46$. We examined group differences in term use across valence because the groups significantly varied in negative and positive emotional intensity. That is, we did not examine whether groups differed in their use of general state terms and emotion terms by valence as this could reflect their different levels of emotional intensity. However, we still describe results of group differences in term use of a specific valence below, which are also summarized in **Table 2**.

Regarding general state terms, very few participants used negative general state terms. Consequently, we examined whether groups differed in the likelihood using positive and neutral general state terms. Results indicate that the three groups did not significantly differ in the likelihood of using positive or neutral general state terms.

Regarding group differences in use of emotion terms, because only one participant used a neutral emotion term, we only

TABLE 2 | Emotion differentiation, emotional intensity, and open-ended responses of emotional experience by group.

	Healthy Control (n = 48)	Remitted Depressed (n = 80)	Current Depressed (n = 87)	
		Experience Sampling Data		
	***M* (*SD*)**	***M* (*SD*)**	***M* (*SD*)**	**Difference Test (ANOVA)**
NED	$0.56\ (0.28)_a$	$0.46\ (0.24)_b$	$0.43\ (0.29)_b$	$F(2, 211) = 4.60$, $p = 0.010$, $\eta_p^2 = 0.042$
Negative emotional intensity	$0.34\ (0.35)_a$	$0.44\ (0.29)_b$	$0.73\ (0.41)_c$	$F(2, 212) = 20.61$, $p = 0.001$, $\eta_p^2 = 0.163$
PED	$-0.01\ (0.33)_a$	$-0.14\ (0.24)_b$	$-0.14\ (0.35)_b$	$F(2, 212) = 4.71$, $p = 0.010$, $\eta_p^2 = 0.043$
Positive emotional intensity	$1.61\ (0.60)_a$	$1.60\ (0.56)_a$	$1.16\ (0.62)_b$	$F(2, 212) = 10.68$, $p < 0.001$, $\eta_p^2 = 0.092$
		Open-Ended Responses		
	Percentage[d]	**Percentage**	**Percentage**	**Difference Test (Fisher's Exact Test)**
Emotion Terms				
Negative	26.8_a	39.7_a	66.0_b	Cramér's $V = 0.30$, $p < 0.001$, 95% CI [0.20, 0.43]
Positive	59.8_a	33.8_b	14.9_c	Cramér's $V = 0.36$, $p < 0.001$, 95% CI [0.24, 0.47]
Neutral[e]	1.2	0	0	–
Overall (across valence)	73.2_a	66.7_a	76.6_a	Cramér's $V = 0.09$, $p = 0.46$, 95% CI [0.01, 0.24]
General State Terms				
Negative[e]	0	1.3	2.1	–
Positive	7.3_a	9.0_a	2.2_a	Cramér's $V = 0.10$, $p = 0.34$, 95% CI [0.04, 0.23]
Neutral	6.1_a	14.1_a	8.5_a	Cramér's $V = 0.12$, $p = 0.23$, 95% CI [0.03, 0.28]
Overall (across valence)	13.4_a	21.8_a	12.8_a	Cramér's $V = 0.11$, $p = 0.30$, 95% CI [0.01, 0.25]

NED = negative emotion differentiation, PED = positive emotion differentiation.
Means and percentages with different subscripts within a row indicate significant pairwise comparison, $p < 0.05$.
[d]These are percentages of participants who responded to the open-ended question with a particular type of general state or emotion term in each diagnostic group; for example, 26.8% of the participants in the healthy control group responded with negative emotion term(s). [e]We did not examine group differences in the use of neutral emotion terms or negative general state terms due to their low frequencies.

assessed group differences in the use of negative and positive emotion terms. There was a significant group difference in the likelihood of using negative emotion terms, $p < 0.001$. The current depressed group was more likely to use negative emotion terms than the remitted depressed group and healthy control group, who did not differ from each other ($p = 0.095$). For positive emotion terms, the three groups significantly differed from each other, $p < 0.001$. The current depressed group was the least likely to use positive emotion terms, followed by the remitted group, with the healthy control group most likely to use positive emotion terms. Given that Fisher's exact test does not permit including covariates, we did not examine whether these group differences would hold after accounting for verbal ability.

DISCUSSION

A rich history documents the ways in which emotional functioning of people with current MDD varies from that of healthy controls (e.g., Houben et al., 2015), and many successful MDD treatments target these emotional disturbances (e.g., Greenberg and Watson, 2006). Despite advances in psychological and psychopharmacological treatments, the prevalence of MDD has not decreased in the last two decades (e.g., Jorm et al., 2017). One effective way to reduce the individual and societal burden of MDD is by decreasing its recurrence rates. Elucidating emotional disturbances that characterize those whose MDD is in remission may identify viable targets for primary and secondary prevention efforts. We focused on differentiation as one such target by investigating it in individuals whose MDD was in full remission, comparing them to a group with current depression and a healthy control group.

In terms of negative emotion, we found that compared to the healthy control group, the *current depressed group* had higher negative emotional intensity and lower NED. The negative emotional intensity findings are consistent with the diagnostic criteria of MDD (American Psychiatric Association, 2013) and many other studies (e.g., Watson et al., 1988; also see Thompson et al., 2021a). The current depressed group having lower NED than the healthy control group replicates Demiralp et al. (2012) and may help clarify associations between NED and depression, which have not been entirely consistent. NED may only be associated with depressive psychopathology when examining a wide range of current depressive symptoms, such as in the present study (also see Demiralp et al., 2012).

This is the first investigation to examine NED in a sample whose MDD was in full remission. We found that the levels of NED in the *remitted depressed group* are diminished compared to the healthy control group, which is consistent with our hypothesis. In addition, the two depressed groups had similarly diminished NED, providing evidence that low NED is not a state effect of being in a depressive episode. Diminished NED could represent a more chronic feature of MDD, which may be a risk factor for MDD that exists outside depressive episodes or something that emerges during an episode and lasts even after the episode remits (i.e., a scar; Burcasa and Iacono, 2007). Prospective longitudinal research could track people who are at elevated risk for depression to see if NED predicts the onset of MDD. Preliminary evidence on depressive symptoms suggests that this might be the case (Rieffe and De Rooij, 2012; Liu et al., 2020), and if so, NED could represent a risk or vulnerability factor for the onset of MDD and be a viable target for prevention efforts. Another interpretation of these findings is that NED is only diminished in samples whose current depressive symptoms are above a certain threshold. Based on the current findings, that threshold may be the depressive symptom level that divides the healthy control and remitted depressed groups, the latter of which showed elevated current depressive symptoms than healthy controls. In contrast, at lower levels of severity, there may not be a straightforward association between NED and depressive symptoms. Accumulating research points to an interaction between NED and various risk factors in predicting a host of negative psychological outcomes (Seah and Coifman, 2021). For example, diminished NED predicted increases in depressive symptoms only in combination with high levels of brooding (Starr et al., 2017).

In terms of positive emotion, the current depressed group had significantly lower positive emotional intensity than the remitted and control groups, who did not vary from each other. These findings are consistent with the diagnostic criteria of MDD (American Psychiatric Association, 2013) and long history of research on positive emotional intensity and MDD status (e.g., Watson et al., 1988). PED was lower in the current depressed group than in the healthy control group, which is inconsistent with research findings indicating that depressive symptoms are unrelated to PED (e.g., Starr et al., 2017) and that those with current MDD do not vary in PED from healthy controls (Demiralp et al., 2012). Notably, NED and PED were positively correlated in the current study, but they were uncorrelated in Demiralp et al. (2012). This may be attributed to different positive emotions being assessed in these two studies. The present study included six positive emotions that represent a variety of arousal levels; in contrast, Demiralp et al. (2012) sampled four positive emotions that represent moderate to high levels of arousal (i.e., happy, excited, alert, and active). Future research should investigate if differentiation among high arousal positive emotions is not diminished in those with MDD. Another explanation could involve the age of the samples. The present sample included adults who were between 18 and 77 years old with an average age of 44.3 years, which is older than the sample in Demiralp et al. (2012) that averaged 27.8 years and did not include participants over 40 years old. Relatedly, research has found that age is positively associated with NED (Mankus et al., 2016), as well as many other putatively adaptive dimensions of emotion (e.g., emotional stability; Carstensen et al., 2011). Of course, although these ideas are speculative, they highlight the importance of research continuing to elucidate PED in clinical samples, consistent with recommendations by Thompson et al. (2021b).

We also examined emotional intensity in the remitted depressed group, and the findings largely serve as a replication of the extant literature. The remitted depressed group experienced levels of negative emotional intensity that were lower than the current depressed group but higher than the healthy control group. This pattern of findings is consistent with research comparing those with remitted MDD versus healthy controls (e.g., Wichers et al., 2012) as well as research comparing those with remitted versus current depressive disorders (Schoevers et al., 2020). In terms of positive emotional intensity, the remitted depressed group did not differ from the healthy control group, consistent with the majority of the extant literature (e.g., Wichers et al., 2012). Also replicating past work (Schoevers et al., 2020), those with remitted MDD had higher positive emotional intensity than those with current MDD. Because the intensity findings followed an expected pattern, they suggest that our sample is comparable to other samples, lending more confidence in the novel findings from this study.

In addition to conducting diagnostic interviews to assess depressive disorders, we assessed depressive symptoms using two measures–the MASQ anhedonic depression scale and the CES-D. Consistent with prior evidence (e.g., Starr et al., 2017), PED was not associated with depressive symptoms (as assessed by either measure). Interestingly, lower NED was significantly associated with higher CES-D, but it was not significantly associated with MASQ anhedonic depression, indicating that the link between NED and depressive symptoms may vary based on the depression measure. The current findings could help elucidate the role of depressive symptom measures in explaining the mixed findings on the association between NED and depressive symptoms.

One possible explanation for the discrepant findings across the two depressive symptoms measures is that they tap different aspects of depressive psychopathology (Nitschke et al., 2001; Bredemeier et al., 2010). Whereas the MASQ anhedonic depression scale focuses on symptoms unique to depression (i.e., anhedonia and low positive affect), the CES-D covers a wider range of symptomatology, including those that are non-specific to depression and anxiety, such as high negative emotional intensity (Clark and Watson, 1991; Buckby et al., 2007). It may be that the depressive symptomatology captured by the CES-D but not MASQ anhedonic depression, such as high negative emotional intensity, is driving its associations with NED. In fact, NED was no longer associated with CES-D when negative emotional intensity was taken into account, which is in line with Dejonckheere et al. (2019) argument that differentiation lacks explanatory power in predicting psychological well-being beyond negative emotional intensity (i.e., negative affect). As such, inconsistency in controlling for emotional intensity in past research, along with other reasons such as the range of depressive symptoms in the sample and the choice of depression measures, could explain some of the mixed findings. It is important to note, however, that NED has been significantly associated with depressive symptoms even after accounting for negative emotional intensity (e.g., Starr et al., 2017). These complex patterns speak of the need for future research to further clarify how NED is associated with depression, anxiety, and their overlapping features.

Our exploratory aim was to test predominant theoretical conceptualization of differentiation–whether individuals with lower differentiation use more general state terms and fewer emotion terms. Specifically, we examined (a) the correspondence between differentiation and participants' use of general state and emotion terms, and (b) whether the depressed groups, who have lower differentiation relative to the healthy control group, would be more likely to use general state and less likely to use emotion terms. Our experience sampling protocol, like almost all others, used a list of emotion terms to assess momentary experience (Thompson et al., 2021b). The list did not include general state terms, the use of which would characterize low differentiation according to multiple conceptualizations (Kashdan et al., 2015). Therefore, we had participants generate their own descriptions of a momentary experience using an open-response format, which we coded for the presence of general state and emotion terms.

Regarding the correlations between differentiation and term use, neither NED nor PED were significantly associated with the use of any general state or emotion terms. Moreover, because both depressed groups had diminished NED and PED, according to predominant differentiation theory, they should show higher overall use of general state terms and lower overall use of emotion terms when describing their momentary emotional experience compared to a healthy control group. Inconsistent with this prediction, no group differences emerged for the overall use of general state and emotion terms (across valence). Therefore, these patterns of findings reflect a lack of correspondence between differentiation (as assessed via repeated measurements and computed using ICCs) and how the predominant theorizing of differentiation describes the use of general state and emotion terms.

This lack of correspondence between theoretical conceptualization and measurement of differentiation may be partly due to our assessment of general state and emotion terms at one point of time, which assessed momentary emotional experience. In contrast, computing ICCs across a series of momentary emotion ratings more likely reflects trait or global differentiation. Others have examined momentary and trait differentiation and found that they do not always align in their associations with well-being measures, suggesting the importance of considering the time frame within which differentiation is measured (Tomko et al., 2015; Erbas et al., 2021). However, it is also likely that the theoretical conceptualization of differentiation and its common measure tap distinct constructs. In fact, Ottenstein and Lischetzke (2020) measured trait differentiation by computing ICC as well as by aggregating a series of open-responses (i.e., proportion of specific affective state out of specific plus general affective states) and found that these two measures were unrelated (Study 2). Similarly, Williams and Uliaszek (2021) also measured NED via ICC and coding of open-ended descriptions of emotional experience, finding that these two measures were not significantly related. Thus, more research, especially using repeated open-ended measures to assess the use of general state and emotions terms, is needed in this area.

We also examined group differences in the use of general state and emotion terms by valence. Regarding general state terms, no group differences emerged for the use of positive or neutral general state terms (Group differences in negative general state terms were not examined due to their low frequency). Regarding emotion terms, the current depressed group was more likely to use negative emotion terms than the other two groups. The healthy control group was most likely to use positive emotion terms, followed by the remitted depressed group, with the current depressed group being the least likely to use positive emotion terms (Group differences in neutral emotion terms were not examined due to their low frequency). Readers should keep in mind that the open-ended responses assessed momentary emotion, not differentiation *per se*, and that there were some group differences in negative and positive emotional intensity. Consequently, interpreting these findings in the context of differentiation theory is complicated. For example, the current depressed group used the fewest positive emotion terms, but we cannot tease apart whether this is driven by the current depressed group's diminished *positive* emotional intensity or low tendency to use positive *emotion* terms. To compare group difference patterns in differentiation and term use within a particular valence (e.g., between PED and positive emotion terms), future researchers could explicitly ask participants to report on their positive and negative emotion or restrict participants' free response to a valence of interest.

The current research also informs how verbal ability is implicated in differentiation. Replicating Ottenstein and Lischetzke (2020), verbal ability was not significantly associated with NED in the present study. Verbal ability was also not significantly associated with PED either, extending this literature to examine PED. Although Ottenstein and Lischetzke did not find significant relations between verbal ability and their open-ended assessment of differentiation (i.e., specificity index), we found significant associations between verbal ability and the use of certain categories of general state and emotion terms. We find these significant findings particularly surprising because our open-ended measure of momentary emotion was not designed to assess differentiation *per se*, and we coded responses in a straightforward way–whether participants' descriptions contained general state terms and emotion terms. That is, our coding scheme did not take into account the specificity, nuance, or complexity of terms. For example, the emotion terms sad and bittersweet were coded similarly. We also did not compute any sort of ratio of these two categories; that is, scores for general state and emotion terms were considered independently. Despite this, findings suggest that verbal ability is more strongly implicated when participants provide open-ended responses (versus making Likert type ratings of emotions). It will be useful for future research to further explore the relation between verbal ability and differentiation given the proliferation of studies examining differentiation using open-ended responses (e.g., Williams and Uliaszek, 2021) and implication for the conceptualization of differentiation (Thompson et al., 2021b).

Though the present study was novel in many ways and extends the literature on differentiation and depression, we want to note a few additional limitations. First, given that the present study consisted of one wave of data collection, we cannot rule out that NED and PED were diminished before the onset of MDD. Consequently, the temporal nature of the association between NED and MDD is unclear and requires further investigation. Second, although the study's hypotheses are couched in theory and existing research, we did not pre-register their hypotheses. Third, the open-ended format we used to assess participants' momentary emotional experience was administered as part of an online survey participants completed outside the laboratory. Because participants may have completed the survey when they are in certain emotional states (e.g., neutral, calm), this study design may have resulted in sampling a narrower range of emotional experiences than had we utilized repeated sampling (e.g., Ottenstein and Lischetzke, 2020) or a mood induction (Williams and Uliaszek, 2021). In addition, because this measure was only administered once, we could not assess certain psychometric properties (e.g., reliability).

In conclusion, the present study contributes to the literature on differentiation by including participants with remitted MDD. Further, by also including those with current depression, our sample represented a wide range of depressive psychopathology assessed via diagnostic interviewing, addressing limitations in many differentiation and depression studies (i.e., assessing depression using self-report measures, using relatively healthy samples; Matt et al., 2016). Finding that both current and remitted depressed groups have diminished NED and PED suggests that low differentiation may be a vulnerability factor for MDD or a lasting consequence of the disorder itself (i.e., a scar). Future research using longitudinal designs to elucidate the temporal associations between diminished differentiation with the onset and recurrence of MDD will inform whether interventions targeting differentiation may be useful in reducing the risk for the onset or recurrence of MDD. Finally, our exploratory data provides further evidence (see Ottenstein and Lischetzke, 2020) of a lack of correspondence between the predominant theoretical conceptualization and its common measurement. Considering the mounting evidence that differentiation is linked to well-being, including depression, it is critical for future research to clarify the concept of differentiation and its appropriate measurements.

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://osf.io/6hb9f/?view_only=efec095bf84c44dfa1b30403fe0b8bb0.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Institutional Review Board at Washington University in St. Louis. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

RT and MB developed the study concept. RT supervised the performance of data collection. RT, DL, and MB performed the data analysis. RT, DL, and ES drafted the manuscript. MB provided critical revisions. All authors contributed to the study design and approved the final version of the manuscript for submission.

FUNDING

This research was supported by the Spencer T. and Ann W. Olin Fellowship, Washington University in St. Louis, to DL.

ACKNOWLEDGMENTS

We thank Hee Yeon Hwang for managing data collection, Allison Rossel for coding the open-ended responses, and Haijing Wu Hallenbeck, Mert Taskiran, and Sarah Horwitz for coding the verbal ability data.

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frontiers in Psychology

ORIGINAL RESEARCH
published: 18 November 2021
doi: 10.3389/fpsyg.2021.712418

The Role of Interoceptive Sensibility and Emotional Conceptualization for the Experience of Emotions

Carlos Ventura-Bort[1], Julia Wendt[1] and Mathias Weymar[1,2]*

[1] Department of Biological Psychology and Affective Science, Faculty of Human Sciences, University of Potsdam, Potsdam, Germany, [2] Faculty of Health Sciences, Brandenburg Medical School, University of Potsdam, Potsdam, Germany

The theory of constructed emotions suggests that different psychological components, including core affect (mental and neural representations of bodily changes), and conceptualization (meaning-making based on prior experiences and semantic knowledge), are involved in the formation of emotions. However, little is known about their role in experiencing emotions. In the current study, we investigated how individual differences in interoceptive sensibility and emotional conceptualization (as potential correlates of these components) interact to moderate three important aspects of emotional experiences: emotional intensity (strength of emotion felt), arousal (degree of activation), and granularity (ability to differentiate emotions with precision). To this end, participants completed a series of questionnaires assessing interoceptive sensibility and emotional conceptualization and underwent two emotion experience tasks, which included standardized material (emotion differentiation task; ED task) and self-experienced episodes (day reconstruction method; DRM). Correlational analysis showed that individual differences in interoceptive sensibility and emotional conceptualization were related to each other. Principal Component Analysis (PCA) revealed two independent factors that were referred to as sensibility and monitoring. The Sensibility factor, interpreted as beliefs about the accuracy of an individual in detecting internal physiological and emotional states, predicted higher granularity for negative words. The Monitoring factor, interpreted as the tendency to focus on the internal states of an individual, was negatively related to emotional granularity and intensity. Additionally, Sensibility scores were more strongly associated with greater well-being and adaptability measures than Monitoring scores. Our results indicate that independent processes underlying individual differences in interoceptive sensibility and emotional conceptualization contribute to emotion experiencing.

Keywords: emotion, granularity, emotional intensity, well-being, adaptability, interoceptive sensibility, interoception

OPEN ACCESS

Edited by:
Jennifer Marie Binzak Fugate, University of Massachusetts Dartmouth, United States

Reviewed by:
Jennifer K. MacCormack, University of Pittsburgh, United States
Erik M. Benau, State University of New York at Old Westbury, United States

****Correspondence:***
Carlos Ventura-Bort
ventura@uni-potsdam.de

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: *20 May 2021*
Accepted: *06 October 2021*
Published: *18 November 2021*

Citation:
Ventura-Bort C, Wendt J and Weymar M (2021) The Role of Interoceptive Sensibility and Emotional Conceptualization for the Experience of Emotions. Front. Psychol. 12:712418. doi: 10.3389/fpsyg.2021.712418

INTRODUCTION

Traditional theoretical approaches posit that the perception and experience of a particular emotion depend on neural circuitries specialized in generating discrete affective responses (Adolphs and Anderson, 2018; Dolcos et al., 2020b). However, more recent perspectives, such as the theory of constructed emotions (TCE; Barrett and Lisa Feldman, 2006, Barrett, 2017a,b; Lindquist et al., 2012;

MacCormack and Lindquist, 2017), suggest that the experience of an emotion results from the interaction of more general components that are not specific to emotion generation and whose final goal is to maintain the homeostasis of the organism (Barrett, 2017a,b). This view resembles neuroscientific models in suggesting that psychological events are the product of the interaction of large-scale networks (Deco et al., 2011; Lindquist et al., 2012; Barrett and Satpute, 2013; Wilson-Mendenhall et al., 2013; Kleckner et al., 2017). In the TCE, Barrett and colleagues assume that at least four components may be involved in the construction and experience of emotions, namely, core affect, conceptualization, attention, and the verbalization of emotions (Barrett and Lisa Feldman, 2006, Barrett, 2017a,b; Lindquist et al., 2012; MacCormack and Lindquist, 2017). In the current study, we focused on how potential correlates of core affect and conceptualization moderate the experience of emotions (for detailed reviews on attention and emotional verbalization see Barrett et al., 2004; Lindquist, 2017; Hoemann et al., 2019; Satpute and Lindquist, 2021).

Core affect refers to the mental representation of bodily changes that are sometimes, but not always, associated with pleasure or displeasure and arousal (Barrett and Russell, 1999; Lindquist et al., 2012; Barrett and Simmons, 2015; Barrett, 2017a; MacCornmack and Lindquist, 2017). Bodily changes are crucial to regulating energy expenditure and maintaining physiological, immunological, and hormonal equilibrium. As an active entity, our brain generates models that predict what the upcoming optimal bodily state should be in order to efficiently distribute and organize energy (Seth, 2013; Barrett and Simmons, 2015; Ainley et al., 2016). When afferent signals do not match with the expected optimal internal state, signals from the body are fed back to the brain as prediction errors to adapt to the current circumstances by reducing this mismatch (Barrett and Simmons, 2015). Core affect is, thus, directly influenced by interoceptive signals that are sent from the body to the brain.

Of note, it has been suggested that interoception comprises three distinct facets depending on the nature of the measurement: accuracy, sensibility, and awareness (Garfinkel et al., 2015; Critchley and Garfinkel, 2017). Interoceptive accuracy is understood as the objective accuracy in detecting internal bodily sensations (e.g., heart rate, respiration rate, stomach dilatation) and is typically measured using standard and objective behavioral tasks such as Heartbeat counting task or Whitehead heartbeat detection task (Critchley and Garfinkel, 2017; Smith et al., 2020; Legrand et al., 2021). Interoceptive sensibility refers to the subjective perception and beliefs about the internal focus and/or accuracy of an individual in perceiving interoceptive signals. Interoceptive sensibility is commonly assessed *via* self-report measures asking participants to make explicit propositional statements about how (in)accurately they perceive their bodily sensations, or how attentive they are to them (Brewer et al., 2016; Cabrera et al., 2018; Murphy et al., 2020; Gabriele et al., 2020). Interoceptive awareness, as the third interoceptive facet, reflects the meta-cognitive awareness of interoceptive accuracy, which is the degree of convergence between interoceptive accuracy and sensibility (Critchley and Garfinkel, 2017). Given the tight link between interoception and core affect, individual differences in interoceptive processing, especially interoceptive accuracy, could be considered a reliable index of core affect (Kleckner et al., 2017).

Interoceptive sensations and core affect *per se* do not construct an instance of emotion. They need to be categorized and made meaningful. This conceptualization process, the second component of emotion construction, occurs when the brain uses prior knowledge and experiences to give meaning to the bodily sensations felt in a particular moment within a particular context (Wilson-Mendenhall et al., 2011; Barrett, 2017a,b). Categorizing internal and/or external inputs thus allows to identify bodily sensations as meaningful entities and assign them causation. For instance, a pounding heart could be categorized as happiness in the context of meeting a romantic interest, or as exhaustion in the context of a race. Some common measures used to evaluate conceptualization are based on self-report. These questionnaires assess the beliefs of participants regarding their ability to mentally represent emotions (also known as emotional intelligence, awareness, or expertise) by asking them to evaluate how accurately they experience their emotions, or how attentive they are to them (Bagby et al., 1994; Swinkels and Giuliano, 1995; Kang and Shaver, 2004; see also Lindquist and Barrett, 2008; MacCormack and Lindquist, 2019; MacCormack et al., 2020, for a detailed review see Hoemann et al., 2020, for experimental manipulations of emotional conceptualization). Self-report measures of alexithymia, a sub-clinical condition characterized by a poor ability to identify and describe one's own emotions, have also often been used to assess individual differences in emotional conceptualization (Lindquist and Barrett, 2008). Recent evidence further suggests that the integrity of the default mode network (DMN), as the potential primary network involved in conceptualization (Lindquist et al., 2012; Satpute and Lindquist, 2019), may constitute a neural correlate of this component (Liemburg et al., 2012; Imperatori et al., 2016; Takeuchi et al., 2016).

Previous studies investigating how individual differences in interoception and emotional conceptualization may relate to emotional experience focused on three main aspects: emotional intensity, activation or arousal, and granularity. Emotional intensity is defined as the strength with which a particular emotion is felt, ranging from high (e.g., "extremely happy") to low (e.g., "not happy at all"). Emotional activation or arousal is a more general term encompassing the degree of activation in a specific situation and typically ranges from calm to active or excited (e.g., Lang et al., 1990; Cacioppo and Berntson, 1994; Reisenzein, 1994; Barrett and Russell, 1999; Kuppens et al., 2013). Although emotional intensity and arousal may overlap, emotional arousal is not always associated with high intensity, for instance, emotions such as satisfaction or sadness can be experienced with high intensity under low arousal states (Kuppens et al., 2013). Emotional granularity is defined as the ability to precisely differentiate emotions. People with high emotional granularity are able to label their emotional experience in precise terms (i.e., distinguishing between experiencing "sadness" and "compassion") whereas those with low emotional granularity tend to use the same terms to describe different experiences (i.e., differentiating only between feeling "good" or "bad"; Lindquist and Barrett, 2008).

In one of the first studies investigating the relationship between interoceptive accuracy and emotional experience, Pollatos et al. (2007) observed that participants with high relative to low interoceptive accuracy experienced the viewing of unpleasant and pleasant scenes as more arousing, as indicated by higher subjective arousal ratings (see also, Wiens et al., 2000; Barrett et al., 2004; Critchley et al., 2004; Pollatos et al., 2005; Herbert et al., 2007, 2010; Pollatos and Schandry, 2008). Importantly, not only interoceptive processing but also individual differences in emotional conceptualization, seem to play a role in the intensity and activation of experienced emotions. For instance, Mantani et al. (2005) observed that imagined past emotional events were experienced with lesser intensity by participants with high, compared to low, alexithymia scores (see also, Stone and Nielson, 2001; Luminet et al., 2004). Similarly, Pollatos and Schandry (2008) observed that participants with high alexithymia scores rated emotional pictures as less arousing than those scoring low on this scale. Despite previous evidence linking interoceptive processing and emotional conceptualization to emotional intensity and arousal, little is known about how these constructs relate to emotional granularity. Although a positive association between individual differences in emotional conceptualization and emotional granularity has been theorized (Lindquist and Barrett, 2014; Smith et al., 2019), this question remains under-examined (Lindquist, 2013; Lindquist and Barrett, 2014; Erbas et al., 2016).

To shed more light on the role of interoception and emotional conceptualization in emotion experience, the current study aimed to investigate how individual differences in these constructs interact to moderate emotional intensity, arousal, and granularity. Unlike previous studies in which interoceptive processing was operationalized using objective measures (i.e., interoceptive accuracy), here, we used self-report measures of interoception, particularly focusing on interoceptive sensibility. Similarly, emotional conceptualization was evaluated using self-report measures. Emotional intensity, arousal, and granularity were extracted from two emotion experience tasks that involved standardized material (emotion differentiation task; ED, e.g., Nook et al., 2018) and self-experienced episodes (DRM; Barrett et al., 2001; Lee et al., 2017).

Based on previous literature, we expected that measures of interoception would show a positive relationship with emotional intensity and arousal, whereas measures of emotional conceptualization would show a positive association with emotional intensity, arousal, and granularity (Pollatos et al., 2007; Lindquist and Barrett, 2014).

Finally, higher interoceptive sensibility and emotional conceptualization scores are considered to reflect a more efficient functioning of the underlying components, leading to a better adaptation to the environment, and in turn, higher well-being (Ainley et al., 2016; Barrett et al., 2016; Khalsa et al., 2018; Hoemann et al., 2020). To test for that, we further examined the association between individual differences in interoceptive sensibility and emotional conceptualization and subjective reports of adaptability and well-being.

MATERIALS AND METHODS

Participants

A total of 157 participants (135 women, 22 men; *M* age = 25.92; *SD* age = 8.39) took part in the two-session, online study in exchange for course credits. Each individual provided informed consent in accordance with the data protection laws of the University of Potsdam. Twenty-three participants were excluded from analysis because they reported one or more of the following excluding criteria: German proficiency level lower than C1 (i.e., advanced level), history of neurological disorder, undergoing psychological treatment at the moment of the study or having suffered any psychological disorder during the last year, and undergoing acute or long-term psychiatric treatment. In addition, participants were excluded based on their speed of completion as the online platform *soscisurvey.de* (Leiner, 2019a) calculates two indices of suspicious survey completion (Leiner, 2019b). The index *DEG_TIME* marks those participants who complete the survey exceptionally quickly relative to the rest of the sample. It is recommended to exclude individuals with scores larger than 100. The index *TIME_RSI* corresponds to the relative speed index and calculates the relative time to complete the questionnaire in comparison to the median of the overall sample (Leiner, 2019b). It is recommended that individuals with scores larger than 2, indicating that the questionnaire was completed in less than half the time required by the typical responder, are excluded. The final sample consisted of 131 participants (112 women, 19 men; mean age = 26.18).

Questionnaires[1]

A series of questionnaires were selected to measure individual differences in interoception and conceptualization along with psychological well-being and adaptability.

Interoception Scales

Although there are different questionnaires available that measure individual differences in interoceptive sensibility, they tend to focus on different aspects of interoception (e.g., physiological sensibility vs. self-regulation). Indeed, these questionnaires correlate weakly, suggesting they might be measuring different sub-constructs of interoceptive sensibility (see Desmedt et al., 2021). To address this heterogeneity, new questionnaires providing a clearer differentiation of facets of interoception have recently been developed (Brewer et al., 2016; Gabriele et al., 2020; Murphy et al., 2020). Because core affect relies on the ability to accurately perceive interoceptive signals, we chose to focus on questionnaires measuring physiological sensibility. We used recently developed questionnaires that assess this facet (i.e., beliefs of an individual concerning the (in)ability to

[1]The authors will make all questionnaires that have been used in this study available upon request.

perceive or differentiate physiological changes) along with scales that evaluate other facets of interoception.

Interoceptive Confusion Questionnaire (ICQ)

The Interoceptive Confusion Questionnaire (ICQ; Brewer et al., 2016) is a 20-item scale that evaluates the degree to which individuals have difficulties interpreting their own non-affective interoceptive states, such as hunger, muscle pain, or arousal (e.g., *I often find that I'm suddenly very thirsty; I only realize I am stressed when others tell me*). Responses are given on a 5-point Likert scale ranging from 1 (does not describe me) to 5 (describes me very well). The final score of the ICQ is the sum of all the items.

In the current study, we used a German version of the ICQ that is used for validation of other interoceptive questionnaires[2]. Similar to the original validation sample (Brewer et al., 2016), in the current study, the consistency of the ICQ was rather poor (Cronbach's $\alpha = 0.55$), however, we decided to use this scale because of its established construct validity (Brewer et al., 2016).

Interoceptive Accuracy Scale (IAS)

The interoceptive accuracy scale (IAS; Murphy et al., 2020) is a 21-item questionnaire that assesses the global beliefs concerning the ability of an individual to accurately perceive interoceptive signals (e.g., *I can always accurately perceive when my heart is beating fast; I can always accurately perceive when I am thirsty*). The items are answered using a 5-point Likert scale ranging from 1 (Disagree Strongly) to 5 (Agree Strongly). Total score of the IAS is calculated by summing all the items. In contrast to the ICQ, the IAS has shown good psychometric properties (Murphy et al., 2020). The IAS has been validated in an English-speaking sample, providing good construct and external validity, along with notable test-retest reliability and consistency (Murphy et al., 2020). Although the German validation is still in progress, our unpublished findings replicate the results from the original English version (see text footnote 2). In the current sample, the IAS showed good consistency (Cronbach's $\alpha = 0.84$).

Multidimensional Assessment of Interoceptive Awareness Version-2

The Multidimensional Assessment of Interoceptive Awareness Version-2 (MAIA-2; Mehling et al., 2018) consists of 37 items divided into 8 scales, and measuring multiple dimensions of interoception, including Noticing (4 items; e.g., *I notice when I am uncomfortable in my body*), Not-Distracting (6 items; *I distract myself from sensations of discomfort*), Not-Worrying (5 items; e.g., *When I am in discomfort or pain I can't get it out of my mind*), Attention Regulation (7 items; e.g., *I can return awareness to my body if I am distracted*), Emotional Awareness (5 items; e.g., *I notice that my breathing becomes free and easy when I feel comfortable)*, Self-Regulation (4 items; e.g., *I can use my breath to reduce tension*), Body Listening (3 items; e.g., *I listen to my body to inform me about what to do*), and Trust (3 items; e.g., *I trust my body sensations*). The MAIA-2 aims to differentiate between adaptive and maladaptive styles of interoception, related to resilience and anxiety, respectively (Mehling et al., 2018; Reis, 2019). Each item is rated on a 6-point Likert-scale, ranging from 0 (never) to 5 (always). Scores for each scale are calculated by performing the average of the corresponding items. In the current sample, the Cronbach's α indices of the MAIA-2 subscales range from 0.5 to 0.87.

Conceptualization Scales

Because the conceptualization component is involved in the categorization of emotions during a particular event, it is expected that a more efficient conceptualization is reflected by higher accuracy in perceiving and understanding emotions. To evaluate individual differences in conceptualization, we selected a series of questionnaires that assess how (in)accurately one perceives their own emotions (Bagby et al., 1994; Swinkels and Giuliano, 1995; Kang and Shaver, 2004).

Toronto Alexithymia Scale (TAS-20)

The Toronto Alexithymia Scale (TAS-20; Bagby et al., 1994) consists of 20 items grouped in three subscales: Difficulties Identifying Feelings (7 items; e.g., *I am confused about what emotion I am feeling)*, Difficulties Describing Feelings (5 items; e.g., *It is difficult for me to find the right words for my feelings*), and Externally Oriented Thinking (8 items; e.g., *I prefer talking to people about their daily activities rather than their feelings)*. Items are rated on a five-point Likert scale, ranging from 1 (does not describe me) to 5 (describes me). Previous studies showed that the TAS-20 has a good consistency and construct validity (Bagby et al., 1994). The total score of the TAS-20 is the sum of all the items. In the current sample, good consistency of the TAS-20 was observed (Cronbach's $\alpha = 0.83$).

Mood Awareness Scale (MAS)

The Mood Awareness Scale (MAS; Swinkels and Giuliano, 1995) consists of 10 items that evaluate the attention toward one's mood states. The MAS is subdivided into two subscales: the mood labeling subscale (5 items; e.g., *Right now I know what kind of mood I'm in*) evaluates the ability to identify, categorize or give a name to feelings (Swinkels and Giuliano, 1995); the mood monitoring subscale (5 items; e.g., *I find myself thinking about my mood during the day*) assesses the degree of focus or vigilance on the affective states of an individual. Items are rated on a 6-point Likert-scale, ranging from 1 (disagree very much) to 6 (agree very much). The scores for each scale are calculated by summing the corresponding items, and the total score is calculated by summing over all the items. In the current sample, the MAS showed good consistency (Cronbach's α : 0.70–0.79).

Range and Differentiation of Emotional Experience Scale (RDEES)

The Range and Differentiation of Emotional Experience Scale (RDEES; Kang and Shaver, 2004) consists of 14 items and two subscales, the Differentiation scale (7 items; e.g., *I am*

[2]https://aspredicted.org/e6tr3.pdf

aware of the subtle differences between the feelings I have), and the Range scale (7 items; e.g., *I experience a wide range of emotion*). The ratings are given using a 5-point Likert-scale ranging from 1 (it does not describe me very well) to 5 (describes me very well). The score for each scale is calculated by summing the corresponding items. The sum of all items forms the total RDEES score. In the current sample, the RDEES showed good consistency (Cronbach's α: Range = 0.75, Differentiation = 0.8, Total = 0.81).

Trait Meta-Mood Scale (TMMS)

The Trait Meta-Mood Scale (TMMS; Salovey et al., 1995) is a 30-item questionnaire that evaluates one's abilities to manage and reflect upon emotions. The TMMS is divided into three subscales, the attention subscale (13 items; e.g., *I pay a lot of attention to how I feel*) which measures the attention devoted to the feelings of an individual, the clarity subscale (11 items; e.g., *I usually know my feelings about a matter*) which assesses the clarity of the experienced feelings, and the repair subscale (6 items; e.g., *When I become upset, I remind myself of all the pleasures in life*) which evaluates the beliefs about ending negative mood states or prolonging positive ones. The items are rated on a 5-point Likert-scale ranging from 1 (strongly disagree) to 5 (strongly agree). The Cronbach's α denoted good consistency (Cronbach's α :0.8–0.87).

Well-Being Scale

Well-Being Questionnaire (W-BQ12)

The Well-Being Questionnaire (W-BQ12; Mitchell and Bradley, 2001) consists of 12 items, evaluating psychological well-being by asking about the frequency of experiencing different feelings over the past few weeks. Each item is scored using a 4-point Likert-scale, ranging from 0 (not at all) to 3 (all the time). The W-BQ12 is divided into three 4-item subscales: Negative Well-Being (NWB; e.g., *I have crying spells or feel like it*), Positive Well-Being (PWB; e.g., *I have lived the kind of life I wanted to*) and Energy (e.g., *I feel energetic, active, or vigorous*). The scores for each subscale are calculated by summing the scores of each item. The general well-being score is calculated using the following formula: 12-NWB + Energy + PWB. In our sample, the W-BQ12 showed poor consistency (Cronbach's α = 0.5). However, we decided to use this scale due to its established construct validity.

Tasks

Emotional experience was induced by way of two different tasks, allowing us to measure emotional intensity, arousal, and granularity scores (see Analysis section).

Emotion Differentiation Task

The Emotion Differentiation (ED) task is an online adaptation of previous laboratory-based protocols (Nook et al., 2018; Israelashvili et al., 2019). This task is designed to assess how participants identify the experienced emotions which are evoked by a series of scenes. A total of 40 pictures (20 negative and 20 positive) extracted from the *International Affective Picture System* (IAPS; Lang et al., 2008) were used to evoke emotions. Images were chosen to represent a heterogeneous pool of scenes with different content, valence, and arousal levels. The normative valence and arousal ratings of the selected images were as follows: valence = 7.04, arousal = 4.86, for pleasant images, and valence = 3.02, arousal = 5.59, for unpleasant images. Each image was presented twice consecutively (see **Figure 1**). In the first presentation, participants were asked to rate their experienced level of valence and arousal in response to the picture, using a sliding bar superimposed over a miniature representation of the Self-Assessment Manikin Scale (SAM; Lang et al., 2008). The position of the sliding bar was then quantified as a percentage of the scale (i.e., distance between the left-most point and the rating of the scale). In the second presentation, participants were instructed to indicate to what extent they felt each of the following eight emotions: amusement, happiness, satisfaction, sympathy, fear, anger, disgust, and sadness. To give their ratings, participants could move a sliding bar along the scale that ranged from 0 (not at all) to 100 (very much). The initial position of the sliding bar was always in the middle (50). The presentation of each of the 40 images was fully randomized. Although there was no time limit for rating each picture, participants were instructed not to overthink their responses.

Day Reconstruction Method

As the second emotional task, we used an online-adapted version of the DRM (Barrett et al., 2001; Lee et al., 2017). The DRM was conducted two times on two different days. On each day, participants were asked to recall up to 15 episodes that happened to them the previous day (5 from the previous morning, 5 from the afternoon, and 5 from the evening), leading to up to 30 episodes. For each episode, participants were asked to report when it occurred, what they were doing, where and with whom they were, and the level to which they experienced the following positive and negative emotions: amusement, awe, contentment, excitement, gratitude, happiness, love, pleasure, pride, serenity, anger, boredom, disgust, dissatisfaction, downheartedness, embarrassment, fear, sadness, and fatigue. The responses here were given on a 7-point Likert-scale, ranging from 0 (not at all) to 6 (very much).

Procedure

Each of the two sessions of the study lasted for about 45 min. In the first session, participants first completed a demographic questionnaire. Thereafter, the description of the ED task was provided. After being informed that the ED task contained very explicit scenes (e.g., mutilations or sex-related contents), participants could choose whether to perform the ED task or not. If they did decide to perform the ED task, the instructions for the task were presented and, after two practice trials, the main task was conducted. Thereafter, the instructions for the DRM were presented followed by the task. If participants decided not to take part in the ED task, they were immediately directed to the DRM task.

Between 2 and 7 days after the first session, participants were invited to take part in the second session. This session began with the DRM followed by the self-report questionnaires. The questionnaires were administered in two fixed orders which were counterbalanced across participants. No questionnaires or tasks other than those reported in this section were administered.

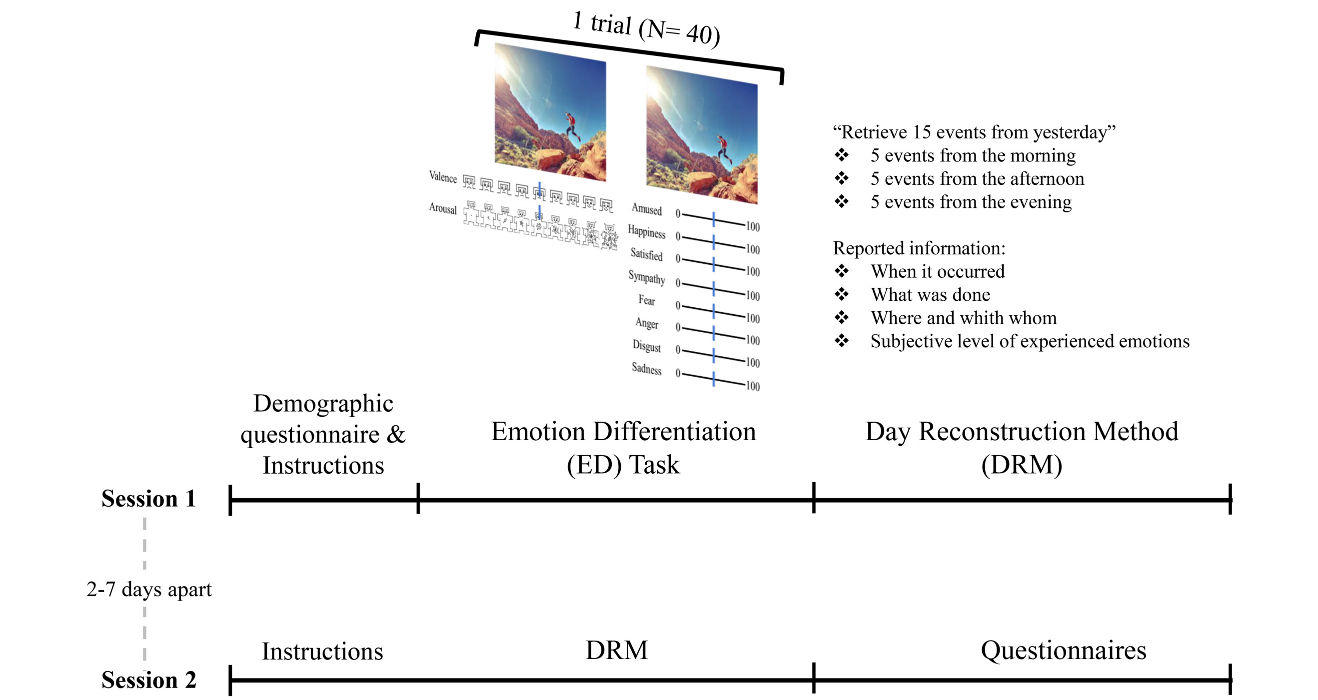

FIGURE 1 | Visual representation of the procedure. In the first of the two-session study, participants performed the Emotion Differentiation (ED) task (if they chose to) and the first part of the Day Reconstruction Method (DRM). In session 2, which took place 2 to 7 days after session 1, participants completed the second part of the DRM and the questionnaires. Picture source: https://pxhere.com/.

Analysis

Association Between Interoceptive Sensibility and Conceptualization Scores

To investigate the relationship between interoception and emotional conceptualization questionnaires, Pearson's correlation analyses were performed. Thereafter, Principal Component Analysis (PCA) was performed to extract the factors underlying the questionnaire scores. Initially, a PCA with varimax rotation (i.e., to maximize simple structure) was performed to identify the number of relevant underlying factors.

Of note, The MAIA-2 is a heterogeneous questionnaire that not only assesses the ability to perceive and "listen to" the physiological changes of an individual (i.e., Noticing, Emotional Awareness, Trusting, Body Listening, Attention Regulation scales), but also adaptive regulatory strategies when dealing with interoceptive changes (i.e., Non-Distracting, Not-Worrying, Self-Regulation scales). Reflecting this heterogeneity, scores of the MAIA-2 have been considered as an indicator of interoceptive sensibility along with a correlate for maladaptive or beneficial interoceptive strategies (Mehling et al., 2018). Similarly, scores of the MAIA-2 have been shown to predict psychological improvement trajectories, and are negatively related to several mental health symptoms and emotion regulation difficulties (Barker, 2019; Eggart and Valdés-Stauber, 2021; Millon and Shors, 2021). Considering the different constructs that the MAIA-2 comprises with each subscale, we decided to include the subscales related to physiological sensibility, namely, the Noticing, Emotional Awareness, Trusting, Body Listening, and Attention Regulation subscales, in the PCA. The subscales that assess the usage of maladaptive or beneficial interoceptive strategies, namely, the Non-Distracting, Not-Worrying, and Self-Regulation subscales, were used as indices of adaptability.

Extraction of Emotional Intensity, Arousal and Granularity Indexes

Emotional intensity was taken as the intensity of the emotional word with the highest rating for each trial, which was averaged across trials. Emotional arousal was extracted by averaging the experienced arousal across trials in the ED task. Because intensity and arousal scores were negatively skewed ($skewness > -0.79$), they were normalized using the following formula: $sqrt(max(S + 1) - S)$, where S refers to the mean intensity/arousal scores. Normal distribution was achieved after applying this transformation ($0.06 < skewness < 0.09$).

Emotional granularity was extracted from the ED and DRM tasks by computing the intra-class correlation index (ICC; Kalokerinos et al., 2019) for positive and negative emotional adjectives or nouns separately, resulting in two ICC indices per participant, one ICC for positive and one for negative emotions. The ICC was computed using the package *irr*[3]. Both participants and emotion words were considered as random effects (i.e., two-way model) and the unit was set to average (see also Kalokerinos et al., 2019). Higher ICC scores indicate that the ratings for different emotion types are highly correlated. On the

[3]https://rdocumentation.org/packages/irr/versions/0.84.1

other hand, a lower ICC is indicative of a lower correlation between emotion ratings. It is assumed that participants with higher ICC experience emotions in a similar fashion across trials, whereas participants with lower ICC experience each emotion independently, and thus, are able to distinguish emotions in a detailed manner. As reliable ICC scores range between 0 and 1, participants with negative, uninterpretable ICCs were excluded (12 participants for negative and 1 for positive adjectives in the DRM, and 1 participant for negative adjectives in the ED task; Kalokerinos et al., 2019). We normalized the ICC scores using Fischer's transformation (Kalokerinos et al., 2019). The ICC scores were reversed ($-1 \times$ ICC) to make higher values correspond to higher granularity. The relation between emotional intensity, arousal, and granularity was tested using Pearson's correlations.

Association Between Principal Component Analysis Components and Emotional Experience

We used multiple regression analyses to investigate the relationship between the factor scores extracted from the interoception and emotional conceptualization questionnaires and emotional intensity, arousal, and granularity extracted from the ED and DRM tasks. For this purpose, we used the factor variables as predictors and the emotional experience scores as predicted variables. For the scores from the DRM task, we also added the number of retrieved episodes as a predictor to control for differences in the number of retrieved episodes.

Association Between Principal Component Analysis Factors and Well-Being and Adaptability

Finally, we used correlational analysis to investigate the relationship between the factor scores and indices of adaptability and well-being. Correlations between the factor scores and well-being and adaptability indices were compared with the Pearson and Filon's Z, using the *cocor* package in R (Diedenhofen and Musch, 2015).

RESULTS

Correlation Analysis

Table 1 contains the correlational analysis between all questionnaire scales from a total of 109 (83% of the included sample) participants.

Principal Component Analysis (PCA)

An initial PCA with rotation varimax revealed that four factors with eigenvalues larger than 1 explained a total of the 65.1% of the variance (Factor 1: eigenvalue = 6.60, percentage of variance explained: 38.9; Factor 2, eigenvalue = 1.71, percentage of variance explained: 10; Factor 3, eigenvalue = 1.54, percentage of variance explained: 7.54; Factor 4, eigenvalue = 1.21, percentage of variance explained: 7.1; See **Table 2**). However, some of the factors were mostly loaded by subscales from the same questionnaire (e.g., Factor 1 by subscales of the TAS-20; Factor 2 by subscales of the MAIA-2). To ensure that the extracted components reflected general constructs underlying all the variables, we decided to force the PCA to two factors (see **Table 2**). In factor 1, ICQ and the subscales from TAS-20 loaded negatively, whereas IAS, the subscales Attention Regulation and Trusting of the MAIA-2, MAS Labeling, RDEES Differentiation, TMMS Clarity, and TMMS Repair loaded positively. In factor 2, the subscales Noticing and Emotional Awareness of the MAIA-2, MAS Monitoring, RDEES Range, and TMMS Attention loaded positively. The subscale Body Listening loaded in both factors equally.

The factor scores did not differentiate between interoceptive sensibility and emotional conceptualization scales. Instead, they revealed overlapping variance between measures of both components. Factor 1 mostly comprised scales measuring sensibility toward perceiving physiological changes and emotion and was named "*Sensibility.*" Factor 2 consisted of scales that are related to perceptions about attentional resources devoted to physiological and emotional aspects and was labeled "*Monitoring*." **Table 2** shows the loading scores from each of the scales.

Relation Between Principal Component Analysis Factors and Emotional Intensity and Granularity

Emotion Differentiation (ED) Task

A total of 127 participants (96% of the included sample) performed the ED task (**Table 3**). Correlational analysis between emotional intensity, arousal, and granularity scores showed that emotional intensity correlated positively with arousal, $r(126) = 0.25$, $p = 0.006$, and with emotional granularity for negative words, $r(125) = 0.28$, $p < 0.001$. However, no significant association was found with emotional granularity for positive words, $r(126) = 0.06$, $p = 0.45$. Arousal scores showed no significant association with emotional granularity for positive [$r(126) = -0.01$, $p < 0.89$] or negative words [$r(125) = 0.084$, $p = 35$], whereas emotional granularity for positive words correlated positively with emotional granularity for negative words, $r(125) = 0.25$, $p = 0.004$.

Sensibility and Monitoring did not predict either emotional intensity, arousal, or granularity

Multiple regression analysis revealed no association between the factor scores and emotional intensity: Monitoring: $t(84) = 0.70$, $p = 0.48$, $\beta = 0.076$; Sensibility: $t(84) = 0.83$, $p = 0.41$, $\beta = 0.091$; Monitoring $\times$ Sensibility: $t(84) = 0.1$, $p = 0.91$, $\beta = -0.07$. Similarly, no association was observed between the factor scores and mean arousal scores: Monitoring: $t(84) = 0.21$, $p = 0.84$, $\beta = 0.02$; Sensibility: $t(84) = 0.13$, $p = 0.89$, $\beta = 0.012$; Monitoring $\times$ Sensibility: $t(84) = 0.44$, $p = 0.66$, $\beta = 0.048$.

Neither granularity scores for positive nor negative emotions showed a significant association with the factor scores. For positive emotions: Monitoring: $t(84) = -1.0$, $p = 0.31$, $\beta = -0.109$; Sensibility: $t(84) = -0.50$, $p = 0.61$, $\beta = -0.056$; Monitoring $\times$ Sensibility: $t(84) = -0.05$, $p = 0.96$, $\beta = -0.01$. For negative emotions: Monitoring: $t(84) = -0.5$, $p = 0.61$, $\beta = -0.054$; Sensibility: $t(84) = 0.45$, $p = 0.65$, $\beta = 0.05$; Monitoring $\times$ Sensibility: $t(84) = 0.89$, $p = 0.39$, $\beta = 0.09$.

TABLE 1 | Pearson's correlation matrix for interoception and conceptualization scales.

Questionnaires	Variable	ICQ	IAS	Noticing	Attn Reg	Emo Awr	Body list	Trust	Desc feel	Id feel	Extern think	Labeling	Monitoring	Range	Diff	Clarity	Attention
IAS	IAS	−0.52 ***	–														
MAIA-2	Noticing	−0.44***	0.44***	–													
	Attn Reg	−0.43***	0.34***	0.49***	–												
	Emo Awr	−0.39***	0.30**	0.56***	0.41***	–											
	Body List	−0.37 ***	0.21*	0.31***	0.43***	0.52***	–										
	Trust	−0.46***	0.26**	0.33***	0.55***	0.41***	0.48***	–									
TAS-20	Desc Feel	0.31**	−0.22*	−0.15	−0.40***	−0.29**	−0.37***	−0.31**	–								
	Id Feel	0.55***	−0.55***	−0.41***	−0.49***	−0.27**	−0.41***	−0.53***	0.52***	–							
	Ext Think	0.17	−0.27**	−0.07	−0.26**	−0.25**	−0.30***	−0.28**	0.37***	0.37***	–						
MAS	Labeling	−0.44***	0.43***	0.36***	0.50***	0.26**	0.43***	0.37***	−0.71***	−0.78***	−0.42***	–					
	Monitoring	−0.16	0.16	0.21*	0.48**	0.34***	0.34***	0.13	−0.14	−0.16	−0.20*	0.15	–				
RDEES	Range	−0.20*	0.19**	0.02	0.18	0.12	0.12	0.03	−0.24*	−0.16	−0.26**	0.28**	0.31**	–			
	Diff	−0.32***	0.43***	0.28**	0.29**	0.27**	0.27**	0.15	−0.39***	−0.44***	−0.32***	0.49***	0.31**	0.38***	–		
TMMS	Clarity	−0.51***	0.49***	0.34***	0.50***	0.27**	0.53***	0.44***	−0.53***	−0.77***	−0.27***	0.77***	0.20*	0.25**	0.49***	–	
	Attention	−0.20*	0.18	0.26**	0.27**	0.37***	0.39***	0.20*	−0.23*	−0.17	−0.37***	0.29**	0.52***	0.28**	0.28**	0.32***	–
	Repair	−0.29**	0.18	0.36***	0.37***	0.38***	0.29**	0.53***	−0.28**	−0.43***	−0.18	0.35***	0.15	0.08	0.20*	0.38***	0.28**

*p < 0.05, **p < 0.01, ***p < 0.001. Attn. Reg.: Attention Regulation; Emo Awr: Emotion Awareness; Body List: Body Listening; Desc Feel: Describing Feelings; Id Feel: Identifying Feelings; Ext Think: Externalizing Thinking; Diff: Differentiation.

TABLE 2 | Principal Component Analysis (PCA) on interoception and emotional conceptualization scales.

		PCA with factors eigenvalue > 1				PCA forced to 2 Factors	
Questionnaires		**F1**	**F2**	**F3**	**F4**	**F1: *Sensibility***	**F2: *Monitoring***
ICQ	*ICQ*		−0.375	**−0.654**		**−0.631**	
IAS	*IAS*			**0.786**		**0.581**	
MAIA-2	*Noticing*			**0.651**	0.375	0.379	**0.547**
	Attn Reg		**0.649**	0.314		**0.632**	
	Emo Awr		0.520		**0.587**		**0.718**
	Body List	0.328	**0.575**		0.360	*0.473*	*0.473*
	Trust		**0.790**			**0.613**	
TAS-20	*Decs Feel*	**−0.752**				**−0.669**	
	Id Feel	**−0.585**	−0.412	**−0.539**		**−0.892**	
	Ext Think	**−0.622**		0.388		**−0.386**	−0.312
MAS	*Labeling*	**0.771**				**0.854**	
	Monitoring				**0.822**		**0.839**
RDDES	*Range*	0.397	−0.321		**0.492**		**0.431**
	Diff	0.455		**0.523**	0.343	**0.474**	0.380
TMMS	*Clarity*	**0.627**	0.355	0.475		**0.836**	
	Attention				**0.713**		**0.721**
	Repair		**0.639**		−0.319	**0.471**	

Attn. Reg.: Attention Regulation; Emo Awr: Emotion Awareness; Body List: Body Listening; Desc Feel: Describing Feelings; Id Feel: Identifying Feelings; Ext Think: Externalizing Thinking; Diff: Differentiation.

TABLE 3 | The descriptive statistics for the Emotion Differentiation (ED) task and the Day Reconstruction Method (DRM) for emotional arousal, intensity, and granularity scores.

	Emotion differentiation (ED) task				Day reconstruction method (DRM)		
	Granularity pleasant	***Granularity unpleasant***	***Emotional intensity***	***Emotional arousal***	***Granularity pleasant***	***Granularity unpleasant***	***Emotional intensity***
Valid	127	126	127	127	129	118	130
Missing	0	1	0	0	1	12	0
Mean	−1.975	−1.005	4.183	4.263	0.193	0.462	1.440
Std. Deviation	0.386	0.272	1.115	1.286	0.125	0.218	0.200
Skewness	−0.297	−0.017	−0.058	0.067	1.618	0.442	0.085
Std. Error of Skewness	0.215	0.216	0.215	0.215	0.213	0.223	0.212
Minimum	−3.042	−1.645	1.000	1.000	0.026	0.090	1.000
Maximum	−1.003	−0.293	7.180	7.458	0.798	0.974	1.959

Day Reconstruction Method (DRM)

A total of 130 participants (99% of the included sample) performed the DRM (**Table 3**). Correlational analysis between emotional intensity and granularity scores showed that emotional intensity did not correlate with emotional granularity for positive [$r(128) = 0.13$, $p = 0.13$] or negative words [$r(117) = -0.03$, $p = 0.74$]. Additionally, no association was observed between emotional granularity for positive and negative words, $r(116) = 0.13$, $p = 0.17$.

Sensibility and Monitoring predict lower emotional intensity

Multiple regressions indicated that Monitoring significantly predicted lower emotional intensity $t(86) = 3.056$, $p = 0.003$, $\beta = -0.31$. Sensibility was associated with emotional intensity at a trend level, $t(86) = -1.98$, $p = 0.05$, $\beta = -0.20$. No significant interaction between factor scores was observed, $t(86) = -1.54$, $p = 0.12$, $\beta = 0.15$. The number of events reported was also related to emotional intensity at a trend level $t(86) = 1.75$, $p = 0.082$, $\beta = -0.17$ (**Figure 2**).

Differential effects of sensibility and monitoring on emotional granularity

Granularity scores for positive emotions were negatively associated with Monitoring, $t(86) = -1.99$, $p = 0.049$, $\beta = -0.21$ but not with Sensibility, $t(86) = -1.17$, $p = 0.24$, $\beta = -0.120$. No significant interaction effects were observed, $t(86) = -1.07$, $p = 0.28$, $\beta = -0.11$ (**Figure 2**).

Granularity scores for negative emotions were differently moderated by Monitoring and Sensibility. Whereas Monitoring predicted lower granularity scores, $t(78) = -2.96$, $p = 0.004$, $\beta = -0.31$, Sensibility was associated with

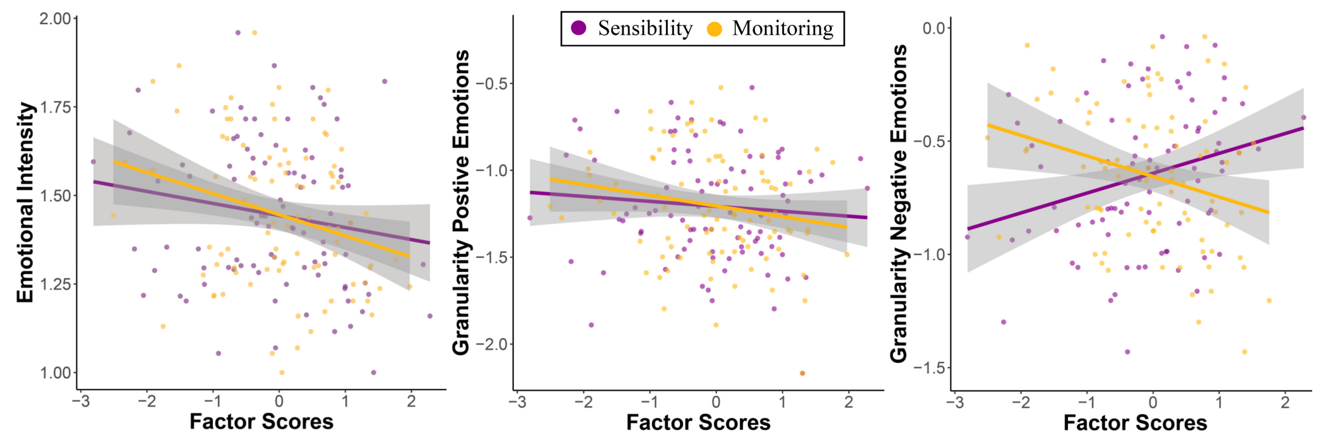

FIGURE 2 | Association between emotional intensity and granularity scores and Sensibility and Monitoring factor scores in the DRM.

higher granularity, $t(78) = 2.59$, $p = 0.011$, $\beta = 0.27$. No interaction effects were observed, $t(78) = 0.07$, $p = 0.94$, $\beta = 0.001$ (**Figure 2**).

Association Between Principal Component Analysis Factors and Adaptability and Well-Being Scales

Table 4 shows the correlation of the Sensibility and Monitoring factors with the adaptability (MAIA-2) and well-being (W-BQ12) scales, and Z scores for the comparison of the correlations.

Although both factors showed significant correlations with the adaptability and well-being scales, in general, Sensibility showed larger correlations than Monitoring, indicating that Sensibility and Monitoring contribute differently to these scales.

DISCUSSION

In the current study, we aimed to investigate how individual differences in interoceptive sensibility and emotional conceptualization interact to moderate different facets of the emotional experience, namely, emotional intensity, arousal, and granularity. We observed that subjective measures of interoceptive sensibility were significantly correlated with measures of emotional conceptualization. PCA analysis revealed two independent factors, labeled Sensibility and Monitoring, in which measures of interoceptive sensibility and emotional conceptualization shared variance. The two factors had somewhat different effects on emotion experience, particularly in the DRM (but not in the ED) task. Sensibility was negatively (albeit non-significantly) related to emotional intensity and granularity for positive words, but positively related to granularity for negative words, whereas Monitoring was negatively related to emotional intensity and granularity for both positive and negative words. Additionally, the two factors showed differential associations with measures of well-being and adaptability: Sensibility scores were more strongly associated with greater well-being and adaptability measures than Monitoring scores.

Association Between Interoceptive Sensibility and Emotional Conceptualization

We observed significant associations between self-report measures of interoceptive sensibility and emotional conceptualization. Specifically, self-report measures of interoceptive (in)accuracy were related to scales measuring (in)accuracy or clarity of detecting emotional states, convening in a common factor labeled Sensibility. Moreover, scales assessing how often attentional resources are deployed to bodily signals were related to a variety of self-report measures that assess the amount of attentional resources devoted to the emotions of an individual, overlapping in a factor labeled Monitoring.

The factor Sensibility reflects self-beliefs on how well one distinguishes, labels, and understands their physiological and emotional state. The convergence between self-beliefs of accuracy and/or confidence of two different entities is in line with recent findings, showing a moderate association between subjective (i.e., confidence ratings), but not objective accuracy scores of interoception and exteroception tasks (Legrand et al., 2021). Confidence about the accuracy of an individual in behavioral performance, and potentially, when detecting bodily changes and emotions, is an important aspect to guide adaptive behavior, particularly in the absence of feedback (Fleming and Daw, 2017). In this line, a positive association has been found between confidence and objective accuracy in various tasks (e.g., Yonelinas, 2002; Martino et al., 2013; Fleming and Daw, 2017; Murphy et al., 2020; Legrand et al., 2021).

The Monitoring factor reflects a general tendency to devote attentional resources to the internal physiological and emotional states of an individual. The role of selective and executive attention is crucial in the construction and experience of

TABLE 4 | Pearson's correlation between factor scores and well-being and adaptability measures.

Factor and questionnaires	Variable	Sensibility	Monitoring	Z scores
	Monitoring	0.00	–	
MAIA-2	*not Distracting*	0.17	0.09	0.64
	not Worrying	***0.40****	*−0.20**	***4.94****
	self-Regulation	***0.54****	***0.38****	1.40
W-BQ12	*Positive*	***0.45****	**0.24****	1.8
	Negative	***−0.54****	0.07	***−5.23****
	Energy	***0.47****	0.11	**2.93****
	Total	***0.58****	0.12	***3.94****

**p < 0.05, **p < 0.01, ***p < 0.001. Correlation indices were compared between factors (Z scores).*

emotions (Barrett, 2017a; Smith et al., 2019). Which aspect of the ongoing processing the attention is deployed to, e.g., either to the bodily changes, or the surrounding environment, may have a strong influence on the interpretation of the current state of an individual (Barrett et al., 2004).

Previous theoretical models and empirical studies suggest that two different but complementary processes influence the disposition to understand and attend to physiological and emotional states (Boden and Thompson, 2017; Murphy et al., 2019). Our results support and extend this distinction by showing that these independent processes similarly relate to both physiological and emotional states. Within the framework of TCE, the Sensibility factor may be associated with individual differences in conceptualization, whereas Monitoring may be associated with individual differences in attentional processes. However, future studies that combine self-report measures with objective and/or physiological correlates are needed to provide more insights into the distinction between these components.

Association Between Sensibility and Emotional Granularity, Well-Being, and Adaptability

Active inference accounts of emotion predict a positive association between the beliefs of an individual in understanding their own emotions and the ability to precisely use emotion concepts and differentiate between them (Lindquist and Barrett, 2014; Smith et al., 2019). In support of this assumption, we observed that Sensibility scores were positively related to emotional granularity for negative words. Thus, these results suggest that individual differences in conceptualization moderate the extent of differentiation between experienced negative emotions[4].

According to the theory of constructed emotions (Barrett, 2017a,b), accurately identifying the actual internal state, either emotional or physiological, may activate more accurate predictions. This, in turn, can lead to better regulation of the available resources and help to prepare more adequate actions that favor the maintenance of homeostasis. For instance, if someone can accurately identify and differentiate between hunger or sadness, a series of more precise predictions may become accessible. These predictions would allow the person to act upon their needs or feelings and produce specific actions that lead to the ceasing of hunger or sadness, like getting some food or calling a close friend in search of support.

Importantly, this adaptive behavior may then result in greater psychological well-being and adaptability (Lindquist and Barrett, 2014). Correspondingly, the higher emotional granularity for negative words has been positively associated with healthy and adaptive behaviors such as the use and efficacy (Barrett et al., 2001; Kalokerinos et al., 2019) of emotional regulation strategies. Also, emotional granularity has been negatively related to depressive and social anxiety symptomatology, and it has been suggested as a correlate of resilience against the development of psychological disorders (Tugade et al., 2004; Kashdan et al., 2010; Demiralp et al., 2012; see also Erbas et al., 2014; Kashdan and Farmer, 2014). Here, we observed a positive association between Sensibility scores and well-being and adaptability scores, thereby providing further evidence for the association between correlates of conceptualization and well-being and adaptability.

Association Between Monitoring and Emotional Intensity and Granularity

In the current study, we observed a negative relationship between Monitoring and granularity for negative and positive words. These findings indicate that participants with a higher tendency to attend to the internal state of an individual (i.e., physiological and/or emotional) showed a higher overlap between representations of emotional categories. Since lower

[4]It must be noted that the positive association between sensibility scores and emotional granularity was exclusively observed for negative words. Although we did not predict a valence-specific effect, this finding converges with previous studies showing stronger associations between the granularity for negative words and external indicators (Barrett et al., 2001; Demiralp et al., 2012; Kashdan and Farmer, 2014; Kalokerinos et al., 2019). One potential reason for the divergence between the granularity for positive and negative words may be related to the fact that, at least in the current sample, granularity for positive words did not reflect the differentiation between emotional experiences to the same extent as granularity for negative words. In this line, we found that the granularity scores for negative words were significantly higher than for their positive counterparts ($t[116] = 13.39$, $p < 0.001$, $d = 1.23$), indicating that, when describing an event, the differentiation between negative words was higher than between positive ones. Additionally, and unlike previous studies (Barrett, 1998), in the current sample, we observed no significant association between both measures of granularity, suggesting that they might not be moderated by the same underlying process. Future studies examining the differences and similarities between granularity indices for positive and negative words could help understand the dissociation between them.

differentiation between emotions implies that heterogeneous experiences are collapsed within the same emotional category, participants with lower granularity may have difficulties identifying the most appropriate set of predictions and actions to deal with different situations that they categorize within the same emotional label. In turn, they may require the engagement of more attentional resources to their current state to make a proper evaluation. However, this interpretation is merely speculative and requires future research, because, in the current study, we did not examine a causal relationship.

Monitoring scores were also negatively related to emotional intensity. This result indicates that a higher tendency to focus on the emotions of an individual was associated with lower experienced emotional intensity. Previous studies found that focusing on emotional aspects during the experience or retrieval of an emotional event increases the experienced emotional intensity and arousal, whereas focusing on non-emotional aspects of the event decreases the emotional intensity and arousal (Denkova et al., 2015; Iordan et al., 2019; Dolcos et al., 2020a,b). Based on that, the current findings suggest that participants with a higher tendency to focus on their emotions during the experience of an emotional episode, may invest their attentional resources in different aspects of the emotional event (i.e., what causes the emotion, what emotion is felt), reducing the experienced emotional intensity.

Limitations and Future Considerations

In the current study, we did not observe any associations between Sensibility and Monitoring scores and the indexes of emotional experience from the ED task, which may be due to several reasons. Unlike the DRM, where participants idiosyncratically indicate how they felt in previously experienced events, the emotional events (i.e., images) in the ED task were pre-selected (standardized emotional pictures). Although these pictures were previously shown to modulate the extent of experienced valence and arousal, they may not evoke specific emotions. Another important aspect is that in the ED task, eight emotional labels (i.e., four positive and four negative) were used, whereas in the DRM, a total of 18 were provided. It could thus be that the eight available emotion labels did not sufficiently represent the evoked emotional state. Of note, in previous studies that successfully used the ED task, either more emotional labels or only single-valence words (i.e., negative) were used as anchors (Nook et al., 2018; Erbas et al., 2019; Israelashvili et al., 2019). This suggests that, when using standardized stimuli, a wider range of emotion labels is needed to ensure that the evoked emotions are represented in the provided labels.

In the current study, we assessed interoceptive processing using self-report measures. To gain more insights into the role of other facets of interoception in the emotional experience, future studies could use measures such as the Heartbeat counting task, the Whitehead heartbeat detection task, or heart-evoked potentials, which are more closely related to interoceptive accuracy (Critchley and Garfinkel, 2017).

Our sample primarily consisted of young adults and mainly featured female participants, which may constrain the generalizability of our results. In particular, considering that interoceptive sensibility scores and different aspects of the emotional experience may differ between genders and change across the life-span, future research is needed to clarify how these relationships are moderated by gender and aging (Grabauskaitė et al., 2017; Nook et al., 2018; MacCormack et al., 2021; Nook, 2021).

In summary, in the current study, we used self-report measures of interoception and emotional conceptualization to investigate how they interact in moderating different aspects of the emotional experience, namely, emotional intensity, arousal, and granularity. The interrelation between interoception and emotional conceptualization scales revealed two latent constructs that differently moderate the emotional experience. The Sensibility factor, which reflects beliefs of the accuracy of an individual in detecting internal (i.e., physiological and emotional) states, predicted higher granularity for negative words. The Monitoring factor, interpreted as the tendency to focus on the internal states of an individual, was negatively related to emotional granularity, intensity, and diminished psychological well-being. Additionally, the two factors showed differential associations with measures of well-being and adaptability. Sensibility scores were more strongly associated with greater well-being and adaptability than Monitoring scores. Thus, within inference accounts of emotion, these two factors could be interpreted as part of the intertwined components that contribute to the construction and experience of emotions.

SIGNIFICANCE STATEMENT

It has been suggested that different psychological processes, including core affect (mental and neural representation of bodily changes) and conceptualization (meaning-making based on prior experiences and semantic knowledge), are involved in the formation of emotions. In the current study, we used self-report measures of interoceptive sensibility and emotional conceptualization (as potential correlates of these components) to investigate how they interact to moderate different aspects of the emotional experience, particularly emotional intensity, arousal, and granularity. The interrelation between interoceptive sensibility and emotional conceptualization scales revealed two latent constructs that differently moderate the emotional experience. The Sensibility factor, interpreted as a construct that reflects beliefs about the accuracy of an individual in detecting internal physiological and emotional states, predicted higher granularity for negative words. The Monitoring factor, interpreted as the tendency to focus on the internal states of an individual, was negatively related to emotional granularity and intensity. Additionally, the two factors showed differential associations with measures of well-being and adaptability. Particularly, Sensibility scores were more strongly associated with greater well-being and adaptability measures than Monitoring scores. These findings emphasize the role of these two constructs within the intertwined components that contribute to the construction and experience of emotions.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

Data from the current study are part of a larger project involving human participants that was reviewed and approved by the Ethics Committee of the University of Potsdam. The participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

CV-B conceived the idea, defined the design, programmed and analyzed the data, and drafted the manuscript. CV-B, JW, and MW reviewed and edited the manuscript.

ACKNOWLEDGMENTS

We are grateful to Nadine von Stockum for her assistance in the preparation of the study and data collection. We are also thankful to Valentina Jelinčić for her valuable feedback on the manuscript.

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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frontiers in Psychology

ORIGINAL RESEARCH
published: 26 November 2021
doi: 10.3389/fpsyg.2021.703757

From Knowledge to Differentiation: Increasing Emotion Knowledge Through an Intervention Increases Negative Emotion Differentiation

Evgeniya Vedernikova[1], Peter Kuppens[1] and Yasemin Erbas[1,2]*

[1]Faculty of Psychology and Educational Sciences, KU Leuven, Leuven, Belgium, [2]Tilburg School of Social and Behavioral Sciences, Tilburg University, Tilburg, Netherlands

Labeling emotions with a high degree of granularity appears to be beneficial for well-being. However, there are individual differences in the level of emotion differentiation, and some individuals do not appear to differentiate much between different emotions. Low differentiation is associated with maladaptive outcomes, therefore such individuals might benefit from interventions that can increase their level of emotion differentiation. To this end, we tested the effects of an emotion knowledge intervention on the level of emotion differentiation. One hundred and twenty participants were assigned to either an experimental or a control condition. Emotion differentiation was assessed with a Scenario Rating Task before and after the intervention, and at follow-up. As predicted, negative emotion differentiation increased significantly after the emotion knowledge intervention, and this increase was not observed in the control group. Positive emotion differentiation also increased slightly; however, it did not reach significance level. This finding suggests that an emotion knowledge intervention might be beneficial for increasing negative emotion differentiation and may have implications for the clinical context.

Keywords: emotion, emotion differentiation, emotional granularity, emotion knowledge, emotion components, emotion intervention

OPEN ACCESS

Edited by:
Heather Lench,
College Station, United States

Reviewed by:
Paul T. P. Wong,
Trent University, Canada
Claudinei Eduardo Biazoli Jr.,
Federal University of ABC, Brazil

****Correspondence:***
Evgeniya Vedernikova
evgeniya.vedernikova2@gmail.com

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: *30 April 2021*
Accepted: *28 October 2021*
Published: *26 November 2021*

Citation:
Vedernikova E, Kuppens P and Erbas Y (2021) From Knowledge to Differentiation: Increasing Emotion Knowledge Through an Intervention Increases Negative Emotion Differentiation. Front. Psychol. 12:703757. doi: 10.3389/fpsyg.2021.703757

INTRODUCTION

Emotions are ubiquitous in our lives. Individuals experience emotions every day, in response to both minor events and to significant moments of their lives. Emotions can make one feel sky-high or, the opposite, extremely low. Emotions experienced in response to events can help to navigate these events by providing information about them, which can in turn help people to deal with the situation. Given this function, emotions are considered necessary for effective adaptation (Smith and Lazarus, 1990), which in turn is essential for mental health (Manwell et al., 2015).

An important process, through which emotions can be used adaptively, is emotion differentiation, also called as emotional granularity. Emotion differentiation is defined as the tendency to distinguish among one's own emotions and to label one's emotions in a discrete way, sensitive to context (Barrett et al., 2001; Quoidbach et al., 2014; Kashdan et al., 2015). For instance, when asked about their feelings in response to different events, a low differentiator might report feeling both sad and anxious across all situations, whereas a high differentiator would report different emotions in different situations, for example, sad and guilty in response to one event, and anxious, overwhelmed and disappointed in response to another one.

Emotion differentiation is found to be related to various indicators of well-being. For instance, negative emotion differentiation was related to lower levels of negative emotion intensity, depression, neuroticism, and to higher levels of self-esteem (Erbas et al., 2014; Willroth et al., 2019). It also weakened the relationship between rumination and depression (Liu et al., 2020; Seah et al., 2020) as well as the relationship between negative emotions and decreased intrinsic motivation (Vandercammen et al., 2014). In adolescence, negative emotion differentiation was related to lower negativity intensity and negativity propensity (Lennarz et al., 2018). Furthermore, emotion differentiation also appeared to facilitate more successful emotion regulation (Barrett et al., 2001; Kalokerinos et al., 2019). For instance, higher levels of emotion differentiation protected individuals from destructive behavior such as excessive alcohol consumption (Kashdan et al., 2010), aggression (Pond et al., 2012), and unhealthy eating behavior (Mikhail et al., 2019). Positive emotion differentiation in turn was associated with more effective coping styles, i.e., less mental self-distraction during stressful times, higher engagement in the coping process, less automatic responding, and greater thinking through behavioral options before acting (Tugade et al., 2004). Higher differentiation also appeared to be beneficial in relationships with others: it was related to more empathic accuracy (Erbas et al., 2016) and better recognition of others' emotional expressions (Israelashvili et al., 2019). Together, these studies suggest that high levels of emotion differentiation have important implications for well-being.

One factor that may underlie between-person differences in the level of emotion differentiation is related to the amount of unique information an individual associates with each emotion construct. It appears that individuals differ in how different emotion labels are associated with different multimodal instances of affect (Gohm and Clore, 2000). High differentiators link very specific information about the situation (e.g., behavior and physiological response) to particular emotion labels, whereas low differentiators, in contrast, link different labels to more similar and overlapping patterns of such elements (e.g., Erbas et al., 2015).

Consequently, a possible reason why emotion differentiation is beneficial for well-being is because a more granular way of labeling emotions may indicate that individuals represent the unique aspects of emotional events in a highly specific way (Erbas et al., 2018). Thus, when individuals can differentiate their emotions (not disgust, not anger, but fear), they access the information those emotions entail regarding the environment and/or circumstances (e.g., the environment is dangerous; Kashdan et al., 2015; Kalokerinos et al., 2019), which is more specific for individuals with more granular emotions. When this information is perceived and processed, individuals can then use this information to regulate their emotions in order to facilitate strivings (e.g., there is no time for extensive fear and panic, an action is needed).

However, in order to be able to represent aspects of the emotional event with a level of specificity that can be used in a context-sensitive way, different characteristics of the emotional environment should be recognized as distinct and important, and categorized. For individuals who are low in emotion differentiation, the characteristics of the events they attend to are not very specific, and therefore not uniquely associated with specific emotion labels. As such, informing individuals about the different characteristics of emotional events that can be considered as important, and showing examples of different ways to categorize these different aspects, can potentially increase individuals' emotion knowledge.

Knowledge about emotion characteristics is referred to as emotion knowledge: the more of this information is available to the individual, the higher their emotion knowledge is. However, there appear to be individual differences in emotion knowledge, meaning that individuals differ in terms of how much or what type of knowledge they have about emotions (e.g., Bennett et al., 2005; Izard et al., 2008; Schlegel and Scherer, 2018). Importantly, an extensive study by Schlegel and Scherer (2018) found that emotion knowledge correlated with emotional understanding, emotion management, emotion recognition both in the self and in others, and cognitive skills, such as problem-solving, memory, and reasoning (Schlegel and Scherer, 2018), while another study showed that emotion knowledge was correlated with academic performance and social competence in young children (Izard et al., 2001, 2008). Together, these studies suggest that emotion knowledge may be important and beneficial for well-being because it can positively influence how individuals experience emotions and adaptively apply their emotion-related abilities.

In line with this past research, it has been theorized that this conceptual information on emotions and their components is constitutive and would end up making multimodal emotional instances more distinctive by adding complexity to their features (Barrett et al., 2001). It forms the base for how individuals process, communicate and deal with their own emotions (Barrett et al., 2001; Izard et al., 2011; Kashdan et al., 2015). Specifically, it has been argued that emotion knowledge is important for emotion differentiation, because conceptually knowing the different characteristics associated with the different emotions might enable individuals to better recognize these characteristics in themselves and will make differences and similarities between emotions more salient. This in turn might result in a more context-sensitive way of labeling emotions, and thus in higher emotion differentiation. However, empirical research on this relationship is lacking.

The current study is part of a larger study pre-registered at https://osf.io/j389k. Existing empirical research on emotion knowledge and theoretical literature on emotion differentiation implies that more conceptual knowledge of emotions should lead to higher levels of emotion differentiation. The previous studies showed that emotion differentiation could be changed. They provide evidence of emotion differentiation being malleable and variable over time rather than being a stable characteristic or personal trait. For instance, stress on 1 day was negatively related to the level of negative emotion differentiation on a next day (Erbas et al., 2018). Moreover, Mindfulness-based intervention (MBI) led to improvement in both positive and negative emotion differentiation (Van der Gucht et al., 2018). In the current study, we examined this causal relationship between emotion knowledge and emotion differentiation empirically. More specifically, we increased emotional knowledge through an emotion knowledge intervention and assessed whether this increases individuals' level of emotion differentiation, compared to a similar control condition that did not involve emotion-relevant knowledge. We had hypothesized that complementary information on emotions might help individuals to better identify their emotional experiences and navigate among them.

In order to examine the effect of emotion knowledge on emotion differentiation, we conducted an experimental study consisting of two conditions: in the experimental condition, participants received information about emotions through an emotion knowledge intervention, while in the control condition, participants received emotion-irrelevant information regarding countries and continents in order to take into account the Hawthorne effect (Phakiti, 2015). Emotion differentiation was assessed at three occasions: pre-intervention (T1), post-intervention (T2), and at follow-up (T3; 1 month after T2). Emotion differentiation was considered separately for positive and negative emotions. We expected the emotion knowledge intervention to lead to an increase in emotion differentiation both at the between-person level and at the within-person level. More specifically, we expected (H1) participants in the experimental condition to have higher levels of emotion differentiation compared to the participants in the control group at T2 (between-participant level); and (H2) participants in the experimental condition to have a larger increase in emotion differentiation from T1 to T2 compared to the participants in the control condition. Finally, exploratively, we examined whether intervention effects were still present at T3.

MATERIALS AND METHODS

Participants

Participants were recruited *via* the online participant platform Prolific (Palan and Schitter, 2018). A prescreening criterion on Prolific was set to show the study only to individuals whose first language is English. The number of participants was based on an *a priori* conducted power analysis with the software program G*Power (Faul et al., 2007) and on the recommendation to use at least 50 participants per group (Simmons et al., 2013). Power is smaller for interactions, so a power analysis was calculated for an interaction effect. The power analysis (ANOVA: Repeated measures, within-between interaction effect) to detect small effect size ($f = 0.15$, $\alpha = 0.05$, with power 0.9, number of groups = 2, number of measurements = 3) indicated that at least 96 participants were needed. Due to the expected dropout between post-assessment and follow-up, the final sample (for pre- and post-assessment) consisted of 120 English-speaking participants (62 men and 58 women). We randomly assigned 60 individuals per condition with 31 men and 29 women in the control condition and 31 men and 29 women in the experimental condition. Participants were aged between 18 and 74 years old ($M = 35.67$, $SD = 13.43$). Among them, 86.67% were White, 8.33% were Asian, 4.17% were Black, and 0.83% reported having a different ethnicity. English was the first language for 98.33% of participants with one participant having Lithuanian as their first language. With regard to marital status, 37.5% of the participants reported being single (never married), 33.33% were married, 18.33% were living together with a partner, and 10.84% had a different marital status. In terms of residency, 75.83% were residing in the United Kingdom, 10.83% were residing in the United States, and 13.34% elsewhere. Regarding the highest level of education completed, 33.33% of participants had a Bachelor's degree, 30.83% completed some college but did not have a degree, 15.83% held a high school degree or equivalent, and 20.01% had other types of education. In addition, at the beginning of the study, 39.17% were employed full-time, 15.83% were employed part-time, 11.67% were students, and 33.33% had a different employment status.

Participants received a reward of £15 if they completed all parts of the study. The reward consisted of two payments and one bonus. Participants could only receive the first payment if they had completed the first 7 days of the study. They received the second payment and the bonus when they completed the follow-up questionnaires. This study was approved by the Social and Societal Ethics Committee of University of Leuven, KU Leuven, Belgium (G-2017 12 1040).

Materials

Emotion Differentiation

Emotion differentiation was measured with the Scenario Rating Task (SRT; Reisenzein and Hofmann, 1993; Schimmack and Diener, 1997) modified for Dizén and Berenbaum (Dizén and Berenbaum, 2011; Boden et al., 2013). The SRT measures participants' emotional reactions in response to emotional scenarios, which depict real life events. Those scenarios were chosen as a standardized and previously used approach to model a situation, in which an emotion is likely to be experienced. The SRT comprised 20 scenarios (10 positive and 10 negative) depicting everyday life events, and each scenario is approximately 50–90 words long.

Participants rated the intensity of emotions they could feel in response to each scenario on a 7-point Likert scale ranging from 0 ("not at all") to 6 ("extremely strongly"). There were 12 emotions to match the scenarios, mostly based on the six emotion categories (LOVE: love; JOY: joy; ANGER: anger, disgust; SADNESS: sadness, loneliness; FEAR: fear, anxiety; SHAME: shame, guilt) by Diener et al. (1995). Two emotions (relief and satisfaction) were added to the list: relief – to match the scenarios from the SRT, and satisfaction, as an alternative to contentment in Diener et al. (1995), as contentment was absent in an emotion database used to create the emotion knowledge intervention (described below). An emotion differentiation index was computed for each participant by calculating the average intra-class-correlation coefficient (ICC) measuring consistency separately among eight negative (negative emotion differentiation) and four positive (positive emotion differentiation) emotions across 20 different scenarios (Shrout and Fleiss, 1979). Since reliable ICCs lie between 0 and 1, we excluded one negative value (Giraudeau, 1996). Similar to the previous research (Kalokerinos et al., 2019), we normalized ICCs by applying a Fisher's r to z transformation. In order to have more intuitive output, we reverse-scored normalized ICCs ($-1 \times$ ICC), so that higher scores indicated higher differentiation.

Emotion Knowledge Intervention

Participants were randomly assigned to two conditions: the experimental condition in which participants received information about emotions in order to increase their conceptual emotion knowledge, and the control condition in which participants received information about an unrelated topic (i.e., continents and countries). The intervention lasted for 5 consecutive days and took place between days 2 and 6 of the study (see **Figure 1**): On the first 4 days of the intervention (days 2–5 of the study) participants received the information regarding emotions or countries/continents concept by concept (three per day) and on the 5th day (day 6 of the study), they received information on those concepts in comparison to one another. The order of the emotion concepts of days 3–5 was randomized (day 2, the first day of the intervention, was not part of the randomization, meaning that everyone received the same information on that day, because it also contained general information about the study, and therefore it was logistically not possible to make it part of the randomization). In the experimental condition, participants were instructed to study information on 12 different emotions. The list of these 12 emotions is the same as in the SRT and is mainly based on Diener et al. (1995): love, joy, satisfaction, relief, anger, disgust, sadness, loneliness, fear, anxiety, shame, and guilt. For each emotion, participant received a text description and visual stimuli (the materials can be shared upon request to the corresponding author). Text description of emotions included a "definition" of a certain emotion as well as circumstances and situations in which individuals might experience this emotion (Delft Institute of Positive Design, n.d., 2017; Desmet, 2012; Yoon et al., 2015). The materials that we used were retrieved from the Delft Institute of Positive Design database.

Participants were also presented with three visual stimuli for each emotion. These stimuli were retrieved from the tool and methods database of the Delft Institute of Positive Design (Delft Institute of Positive Design, n.d., 2017; Yoon et al., 2015; Kurdi et al., 2017). For each emotion, the stimuli consisted of one drawing and two photos, and each stimulus had a different function. Either it was aimed at eliciting a certain emotion (a photo), or it depicted a person who was experiencing this emotion (a drawing and a photo). For each emotion, in order to provoke more in depth thinking, participants were asked "What situations might make you feel [emotion]?" After all emotions had been presented, on the 5th day of the intervention, participants received information regarding the differences between emotions (e.g., how do fear and anxiety differ, in which situations do each of them occur).

In the control condition, participants studied six continents (Africa, Asia, Australia and Oceania, Europe, North America, and South America) and six countries (Brazil, Canada, Croatia, French Polynesia, India, and Lesotho). The information regarding these countries and continents was retrieved from the Wikipedia (n.d.) and was presented in such a way that it was very similar to how the materials were presented in the emotion knowledge intervention. The text descriptions contained the geographical information of the country or continent. For each country or continent, there were three neutral visual stimuli also retrieved from the Wikipedia (n.d.). The visual stimuli comprised a map of the country or continent, a flag of the country and a satellite view of the continent, as well as a landscape shot of the indicated area. Afterward, in order to make the materials

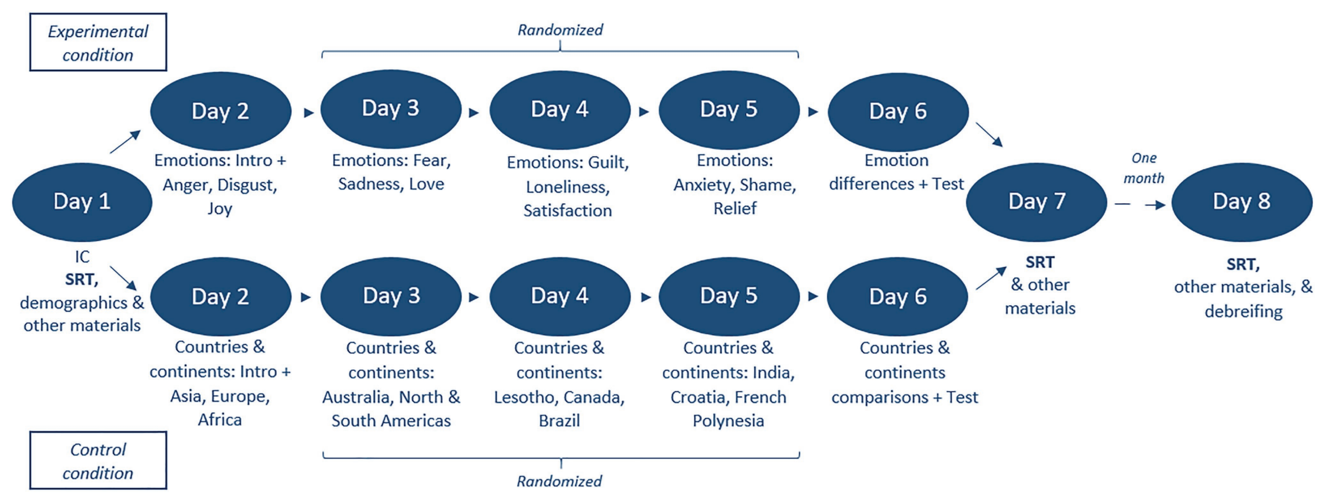

FIGURE 1 | Flowchart of the study procedure.

of the control condition similar to the materials of the experimental condition, participants were asked the question "Would you like to visit [country/continent]? Why or why not?"

On the last day of the intervention, participants received materials to learn more about the differences and similarities between countries/continents (e.g., differences or similarities in their population density, territory, and climate).

Materials for both conditions were made very similar to each other by implementing the same number of items (12 emotions or 12 countries and continents), the same structure, and the same number of pictures. All information regarding a certain concept was presented on the same page. In order to enhance attention to materials, in both conditions, participants were informed at the start that at the end of the intervention, they would be offered a test on the materials they studied. At the end of the 5th day of the intervention (day 6 of the study), they were offered the test to complete.

Attention check items (Oppenheimer et al., 2009; Berinsky et al., 2014) were included in order to control the quality of the data. "Fair" attention check items recommended by Prolific were applied. We included both open-ended and close-ended items. An example of an open-ended item is: "The color test is simple, when asked for your favorite flower you must enter the word magnolia in the text box below. Based on the text you read above, what flower have you been asked to enter?" An example of the closed-ended item is: "It's important that you pay attention to this study. Please tick 'Strongly disagree.'" Four attention check items were included in the longer surveys (which were assessed on days 1, 7, and 8) and one attention check item was included in the short surveys (which were assessed on days 2–6). Across three time points, 98.58% of attention check items were answered correctly.

Procedure

The study was created and edited on the Qualtrics Survey Platform and then conducted with Prolific – a participant pool for online experiments (Palan and Schitter, 2018). There is evidence that data recruited *via* crowd-working platforms is of good quality (Buhrmester et al., 2011).

The experiment required participation for 8 days. At pre-intervention (T1; approximately 30 min long) on day 1 participants signed informed consent and completed the SRT and other tasks and questionnaires for a larger project. Among all tasks and questionnaires, participants completed the SRT first, right after the informed consent. A known problem with online participant pools is that instead of a "real" participant, sometimes questionnaires are completed by bots (e.g., Teitcher et al., 2015; Bai, 2018). Therefore, in order to ensure that our participants were real persons and not bots, on the 1st day of the study, participants were asked to answer an open question ("what is your favorite dish?") in two full sentences. In case a participant had given a nonsensical answer, we would have not invited them to the following steps of the study. However, this was not the case for any of the participants; therefore, all participants were invited for the intervention part of the study. To control bots further in the study, the Completely Automated Public Turing test to tell Computers and Humans Apart (CAPTCHAs; von Ahn et al., 2003) were included into all 8 days of the study. On days 2–5 (approximately 15 min each) participants received information about emotions (emotion knowledge intervention in the experimental condition) or countries (control condition) one by one, with three concepts per day (e.g., anger, disgust, and joy; or Asia, Europe, and Africa). The sequence of concepts was randomized for days 3–5. On day 6 participants studied emotions (or countries) in comparison to each other and completed a test based on the received knowledge. On day 7 (T2, post-intervention) and 1 month after (T3, follow-up) participants completed the same questionnaires and tasks again (approximately 30 min each day). At follow-up (T3), which was 1 month after T2, participants additionally received the debriefing.

RESULTS

Data-Analytic Strategy

To test our hypotheses regarding emotion differentiation, we applied two mixed ANOVAs per hypothesis. Because of the drop out, we first compared T1 and T2 with a full sample and then separately we compared T1, T2, and T3 with a smaller sample. Thus, 2 (Time; within-factor) × 2 (Condition; between-factor) mixed ANOVA with the full sample of 120 participants (60 per condition) was conducted to compare T1 and T2. Then, an additional exploratory analysis of 3 (Time; within-factor) × 2 (Condition; between-factor) mixed ANOVA with 103 participants (53 of them from the experimental condition) was conducted to make a comparison across T1, T2, and T3. Scenarios from the SRT were used to compute positive and negative emotion differentiation indices. Both hypotheses H1 (between-person level) and H2 (within-person level) were tested separately for positive and negative emotion differentiation. SPSS version 26.0 (IBM Corp., 2019) was used for data analysis.

Hypotheses Testing

We conducted one-way ANOVAs on 120 individuals to compare emotion differentiation in participants of both conditions at T1. There was no effect of condition for negative emotion differentiation, $F(1,118) < 0.01$, $p = 0.977$, $\eta_p^2 < 0.001$, or for positive emotion differentiation, $F(1,118) = 1.02$, $p = 0.316$, $\eta_p^2 = 0.009$, so individuals from both conditions had approximately the same levels of emotion differentiation before the intervention.

Positive Emotion Differentiation

A mixed 2×2 ANOVA was run. There was an effect of time, $F(1,118) = 14.47$, $p < 0.001$, $\eta_p^2 = 0.109$, observed power of 0.97, with participants having higher positive emotion differentiation at T2 ($M = -1.16$, $SD = 0.42$) than at T1 ($M = -1.28$, $SD = 0.35$). There was no effect of condition, $F(1,118) = 3.00$, $p = 0.086$, $\eta_p^2 = 0.025$, observed power of 0.40, meaning that participants in the experimental condition did not differ significantly in positive emotion differentiation from the participants in the control condition. However, there was 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, $F(1{,}118) = 2.13$, $p = 0.147$, $\eta_p^2 = 0.018$, observed power was 0.30.

In order to exploratively compare T1, T2, and T3, we applied a mixed 3×2 ANOVA with 103 participants (**Figure 2**). There was an effect of time, $F(2;202) = 5.29$, $p = 0.006$, $\eta_p^2 = 0.050$, observed power of 0.83. *Post-hoc* pairwise comparisons revealed that individuals had higher positive emotion differentiation at T2 ($M = -1.19$, $SD = 0.41$) than at T1 ($M = -1.30$, $SD = 0.38$, $p = 0.011$), T2 did not differ significantly from T3 ($M = -1.18$, $SD = 0.34$, $p = 1.000$), but T1 did ($p = 0.029$). There was an effect of condition, $F(1{,}101) = 6.44$, $p = 0.013$, $\eta_p^2 = 0.060$, observed power of 0.71, with individuals in the emotion condition having higher positive emotion differentiation ($M = -1.14$, $SD = 0.46$) than participants in the country condition ($M = -1.30$, $SD = 0.48$). Contrary to both our hypotheses, there was no interaction between time and condition.

In conclusion, although positive emotion differentiation appeared to improve with time and in the emotion condition, the interaction between time and condition did not reach the significance level. Therefore, our hypotheses (H1 and H2) were not confirmed.

Negative Emotion Differentiation

A mixed 3×2 ANOVA was run on 120 individuals. There was a main effect of time, $F(1{,}118) = 18.49$, $p < 0.001$, $\eta_p^2 = 0.135$, observed power of 0.99, with people having higher negative emotion differentiation at T2 ($M = -1.28$, $SD = 0.41$) than at T1 ($M = -1.39$, $SD = 0.36$). The effect of condition was significant, $F(1{,}118) = 4.03$, $p = 0.047$, $\eta_p^2 = 0.033$, observed power of 0.51: individuals from the experimental condition ($M = -1.27$, $SD = 0.50$) had higher differentiation than individuals from the control condition ($M = -1.40$, $SD = 0.50$). There was an interaction between time and condition, $F(1{,}118) = 24.85$, $p < 0.001$, $\eta_p^2 = 0.174$, observed power of 0.99, meaning that participants in the experimental condition improved their negative emotion differentiation more than participants in the control condition. Since the interaction was significant, we conducted analyses of simple main effects, which revealed that there was an effect of time for the experimental group, $F(1{,}59) = 37.69$, $p < 0.001$, $\eta_p^2 = 0.390$ with participants having higher negative emotion differentiation at T2 ($M = -1.15$, $SD = 0.55$) compared to T1 ($M = -1.39$, $SD = 0.46$). However, that was not the case for the control group, $F(1{,}59) = 0.27$, $p = 0.603$, $\eta_p^2 = 0.005$. This indicates that our within-person hypothesis (H2) was confirmed, meaning that in the experimental condition, negative emotion differentiation improved, but in the control condition, it did not improve. As mentioned above (one-way ANOVA), the analysis of simple main effects confirmed that there was no effect of condition for T1, $F(1{,}118) = 0.01$, $p = 0.977$, $\eta_p^2 < 0.001$. However, there was an effect of condition for T2, $F(1{,}118) = 12.46$, $p = 0.001$, $\eta_p^2 = 0.095$, with people from the experimental condition having higher negative emotion differentiation ($M = -1.15$, $SD = 0.57$) than people from the control condition ($M = -1.41$, $SD = 0.57$). This indicates that our between-person hypothesis (H1) was also confirmed, meaning that before the intervention, the difference in negative emotion differentiation was not significant between the groups. However, after the intervention, the level of negative emotion differentiation was significantly higher in the experimental group than in the control group.

In order to exploratively compare T1, T2, and T3, we applied a mixed 3×2 ANOVA (**Figure 3**) with 103 effective data points (54 participants in the experimental condition, and 49 participants in the control condition). The test of sphericity was significant ($p < 0.001$) and larger than 0.75 (Greenhouse–Geisser $\varepsilon = 0.87$), therefore we used Huynh-Feldt correction. There was an effect of time, $F(1.79{,}181.24) = 6.53$, $p = 0.003$, $\eta_p^2 = 0.061$, observed power of 0.88. *Post-hoc* pairwise comparisons revealed that individuals had higher negative emotion differentiation at T2 ($M = -1.30$, $SD = 0.38$) than at T1 ($M = -1.40$, $SD = 0.36$, $p = 0.001$), T3 ($M = -1.33$, $SD = 0.44$) did not differ significantly from T1 ($p = 0.122$) and T2 ($p = 0.633$). An effect of condition was also significant, $F(1{,}101) = 8.33$, $p = 0.005$, $\eta_p^2 = 0.076$, observed power of 0.82, meaning that the experimental group was higher in negative emotion differentiation ($M = -1.24$, $SD = 0.50$) than the control group ($M = -1.44$, $SD = 0.51$). There was an interaction between time and condition, $F(1.79{,}181.24) = 11.80$, $p < 0.001$, $\eta_p^2 = 0.105$, observed power was 0.99, meaning that participants from the experimental condition improved their negative emotion differentiation more than people from the control condition. Since the interaction was significant, we conducted analyses of simple main effects, which revealed that there was indeed an effect of time for the experimental group, $F(1.86{,}96.73) = 21.37$, $p < 0.001$, $\eta_p^2 = 0.291$ with participants having higher negative emotion differentiation at T2 ($M = -1.13$, $SD = 0.53$) compared to T3 ($M = -1.22$, $SD = 0.57$) and T1 ($M = -1.38$, $SD = 0.51$). *Post-hoc* tests revealed that the level of negative emotion differentiation significantly differed between all three time points: T1 from T2 ($p < 0.001$), T1 from T3 ($p = 0.002$), and T2 from T3 ($p = 0.013$); it increased from T1 to T2 and decreased from T2 to T3, however at T3 it was still higher than at T1. There was no effect of time for the control group, $F(1.63{,}79.85) = 0.39$, $p = 0.636$, $\eta_p^2 = 0.008$, meaning that the level of negative emotion differentiation was not different between the three assessment points for the participants in the control condition. This means that our within-person hypothesis (H2) was confirmed: in the experimental condition, negative emotion differentiation improved, but in the control condition, it did not. As mentioned above, there was no effect of condition at T1, but there was at T2. A one-way ANOVA showed that there was an effect of condition also at T3, $F(1{,}101) = 6.08$, $p = 0.015$, $\eta_p^2 = 0.057$, which demonstrated that individuals from the experimental condition had higher negative emotion differentiation ($M = -1.22$, $SD = 0.62$) than individuals from the control condition ($M = -1.43$, $SD = 0.64$) at follow-up. This means that our between-person hypothesis (H1) was confirmed: meaning that before the intervention, the difference in negative emotion differentiation was not significant between the groups, but after the manipulation, the level of negative emotion differentiation was significantly higher in the experimental group than in the control group. Moreover, at follow-up, these

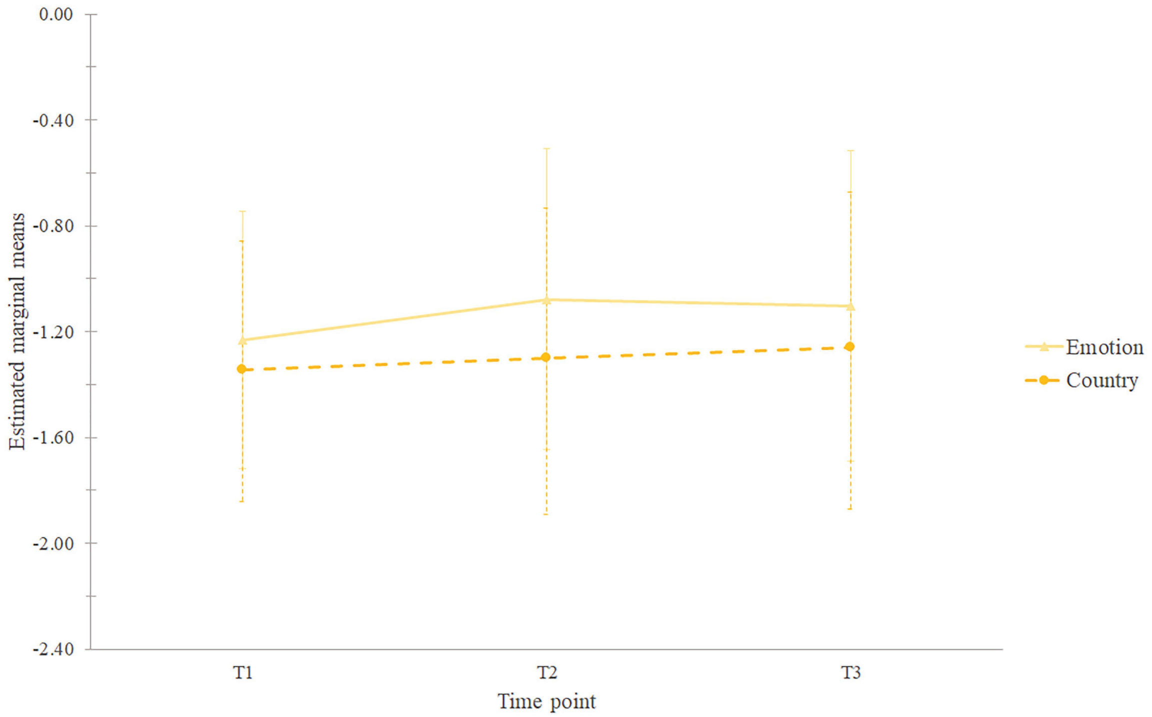

FIGURE 2 | Estimated marginal means of positive emotion differentiation. Error bars represent standard deviations.

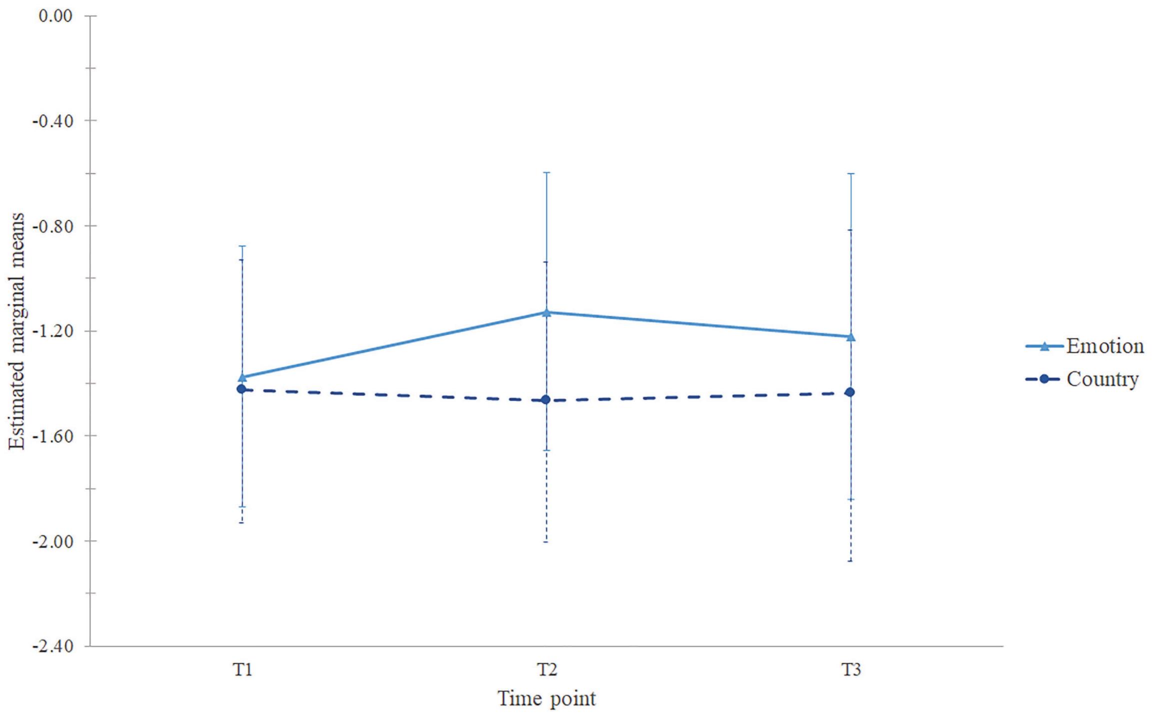

FIGURE 3 | Estimated marginal means of negative emotion differentiation. Error bars represent standard deviations.

differences were still significant, implying that the effect was lasting.

In conclusion, both between- (H1) and within-person (H2) hypotheses were confirmed for negative emotion differentiation, providing evidence for the improvement of differentiation due to the emotion knowledge intervention.

DISCUSSION

In the past years, a large number of studies have shown that lower levels of emotion differentiation are related to maladaptive outcomes. However, there is very limited evidence on the direction of this relationship. The current study is among the first to show experimentally that emotion differentiation abilities can be improved through an intervention. We hypothesized that increasing individuals' emotion knowledge would help them to better differentiate between emotions and found that the individuals who received the emotion knowledge intervention indeed improved their levels of emotion differentiation. Specifically, we found that the emotion knowledge intervention benefited emotion differentiation on both the within- and between-person level. Compared to the control group, we found that the level of negative emotion differentiation had increased significantly from baseline to post-intervention. In other words, for negative emotions, we found that the intervention increased the level of emotion differentiation, whereas there was no significant increase in the control group. Moreover, at post-intervention, the level of differentiation was significantly higher in the experimental group compared to the control group. The effect size for interaction at T2 for negative emotion differentiation was 0.174, $\eta_p^2 = 0.174$, indicating medium effect according to the rule of thumb (MRC CBU, n.d.). Importantly, this effect was still visible at the third measurement occasion, which was a month after the end of the intervention. This indicates that the effects of the intervention did not just cause a momentary increase, but that these changes were lasting (at least for a month). In sum, with regard to negative emotions, this study provides a clear direction of the effect and thus inputs to the directional literature on the topic of emotion differentiation. Considering the fact that some individuals appear to have low levels of emotion differentiation, which in turn is associated with negative outcomes such as depression, negative emotions, and maladaptive behavior (Kashdan et al., 2010; Lennarz et al., 2018; Willroth et al., 2019), improving emotion differentiation might be a promising way forward to increased well-being.

With regard to positive emotion differentiation, changes were observed in both conditions, which indicate that the increase in emotion differentiation was not due to the emotion knowledge intervention. There can be different reasons of these findings. First, maybe the mere participation in the experiment (e.g., De Vuyst et al., 2019) has increased the level of positive emotion differentiation: the participants repeatedly completed questionnaires about emotions and well-being (which were the part of a larger study; e.g., mindfulness, self-esteem, and depression scales) and the Scenario Rating Task, which might have caused them to think in more detail about their emotions overall, including positive ones. However, this effect was not observed for negative emotion differentiation (i.e., negative emotion differentiation did not increase in the control condition, instead there was an interaction between time and condition); therefore, this explanation is not very likely. Another possible reason is that the positive emotion differentiation index was less reliable than the negative emotion differentiation index, because it only consisted of four emotions, whereas the negative differentiation index consisted of eight emotions. Moreover, we included joy as one of positive emotions; however, it could be an umbrella term for positive emotions overall (Sauter and Scott, 2007; Lyubomirsky and Kurtz, 2009; Sauter, 2017; Shiota, 2017). Therefore, participants might have picked up joy as an experienced emotion instead of going into details and report relief or satisfaction. The absence of an emotion knowledge intervention effect for positive emotion differentiation may be also due to the fact that negative emotions are more necessary for the survival than positive emotions from an evolutionary point of view (Buss, 2000), and thus individuals are more motivated to improve their differentiation of negative emotions. For example, if an individual cannot differentiate sadness and fear, they might get into difficulties: if it is sadness, active actions might not be needed, but if it is fear, this individual should take actions to save their life. However, if someone cannot differentiate admiration from interest, that is much less likely to lead to detrimental consequences. Thus, although negative emotions may sometimes be considered as undesirable, they have an important function, which, for example, is highlighted in existential positive psychology (e.g., Wong and Hwang, 2021). People's lives consist not only of pleasant events, and the ability to deal with negative emotions appears to be an adaptive strategy (e.g., Diener and Seligman, 2002; Wong and Bowers, 2018; Wong et al., in press).

Overall, this study shows that increasing individuals' level of emotion knowledge can increase the level of negative emotion differentiation. This finding is important since it allows for a more directional test of the relationship between emotion differentiation and indicators of well-being in later studies. Furthermore, the current intervention, or components of this intervention, can be applied in the context of psychotherapy or clinical interventions to increase the level of emotion differentiation by making people more aware of the components of and the differences between emotions.

Apart from this practical implication, the findings from this study also have a theoretical implication. Previous research showed that there are several pathways through which emotion differentiation can be influenced. One pathway is thought to be through information processing: since stress on 1 day predicted emotion differentiation on the next day (Erbas et al., 2018), individuals' knowledge and/or perception of the environment as more or less stressful determined their ability to differentiate emotions. A second pathway is thought to be through attention: Van der Gucht et al. (2018) showed that a mindfulness-based intervention led to an increase in differentiation of positive and negative emotions. Being mindful refers to drawing novel distinctions (Langer, 1989), and in order to do so, one should be attentive to their environment, which could include their emotional state, enabling individuals to pay more attention to their emotional experience. The current findings suggest a third pathway, namely through conceptual emotion knowledge, where more knowledge about emotions appears to increase the level of emotion differentiation. Discovering new pathways allows for a better understanding of what emotion differentiation is and how it can be changed, which opens the doors to better and more effective interventions for the clinic. Furthermore, since emotion knowledge appears to influence individuals' tendency to differentiate between emotions, it may also improve emotional intelligence (Salovey and Mayer, 1990; Mayer et al., 2004) especially its emotion understanding branch. Previous research shows that negative emotion differentiation as part of the emotional complexity construct, appears to be related only to emotion understanding (and not to emotion intelligence overall), but this relationship was not significant anymore after controlling for negative affect (MacCann et al., 2020). Although the relationship between emotion differentiation and emotion intelligence appears fragile, emotion knowledge may still have an influence on other emotional intelligence branches, for example, on emotion perception (i.e., the ability to perceive emotions in the environment) or emotion facilitation (i.e., the ability to use emotions to generate thought). Future research may further examine those relationships.

In terms of future directions, it might be important to set up an intervention with a more equal number of positive and negative emotions. This will not only help to capture the effect of emotion knowledge on positive emotion differentiation more extensively, but it will also allow to compare between the effects of the emotion knowledge intervention on differently valenced emotions. While negative emotions may be more relevant for focusing and narrowing attention, positive emotions may broaden individuals' thought repertoires (Fredrickson, 2001; Fredrickson and Branigan, 2005). However, the scope of emotion differentiation research has been mostly on negative emotions, therefore examining positive emotion differentiation more extensively in future research is pertinent.

Furthermore, it is important to assess whether the current findings extend to other populations. The current study only included healthy individuals who may not particularly be in need of developing higher levels of emotion differentiation. However, individuals with for instance major depressive disorder or borderline personality disorder tend to have lower levels of emotion differentiation (Suvak et al., 2011; Demiralp et al., 2012) and might therefore benefit more from an intervention.

Furthermore, the sample of the study was not representative, since most participants reported to reside in the United Kingdom. The intervention might have different effects in other countries since there are cultural emotion differences (e.g., Boiger et al., 2018). For instance, differences can be found in behavioral and physiological aspects of emotions, with Easterners having fewer physiological activity than Westerners and Westerners experiencing emotions more actively (with higher arousal; reviewed by Lim, 2016). If individuals from different cultures are different in emotion experience and expression, they might be also different in the perception of emotion knowledge. Therefore, in order to generalize the current findings, a more culturally diverse population may be needed.

In addition, about a third of the participants completed the follow-up assessment in March 2020, when the COVID-19 pandemic had started, those circumstances were likely to affect participant's performance. Furthermore, as mentioned in the "Introduction" section, the reported study was part of a larger project that included more measures of emotional complexity (e.g., emodiversity) and well-being (e.g., depression), because we were interested in how the emotion knowledge intervention and its effect on emotion differentiation would relate to those measures. However, the findings for these other variables were very inconsistent (though the well-being measures were trending in the right direction), and it is unclear whether this was caused by the pandemic, or by other factors.

Finally, while the current intervention was successful in increasing the level of emotion differentiation, it is possible that a more personal and intensive intervention might be even more effective. For instance, the current study was conducted online, and there was no personal interaction between the researcher and the participants. Moreover, while the participants were explicitly instructed to pay attention to the materials that were presented as part of the intervention, these materials were presented online and it is possible that perhaps not all participants were equally motivated to learn all information from the screen. Furthermore, the information was presented to the participants in a passive way, whereas it may also be important that individuals get the opportunity to practice and apply the information to the real world. Therefore, a longer in person intervention, which also includes interactions between the researcher/clinician and the participants, and practice sessions with feedback from the researcher/clinician, might potentially be more effective, and could result in more structural changes in emotion processing than the current intervention.

To conclude, increasing emotion knowledge by providing individuals with information about the definitions of emotions, the circumstances when those emotions are likely to emerge and showing them related pictures appear to be beneficial for negative emotion differentiation. Individuals with low negative emotion differentiation might therefore benefit from an emotion knowledge intervention to improve their ability to make finer distinctions among their emotions and thus subtracting more granular information from their environment.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Social and Societal Ethics Committee of University of Leuven, KU Leuven, Belgium (G-2017 12 1040).

The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

EV, PK, and YE contributed to the conceptualization and design of the study. EV collected the data and performed the statistical analysis. EV wrote the first draft of the manuscript. PK and YE edited the manuscript. All authors have read and approved the submitted version.

FUNDING

During the majority of this project, YE was supported by a postdoctoral fellowship of the Research Foundation Flanders (FWO).

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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frontiers in Psychology

PERSPECTIVE
published: 01 December 2021
doi: 10.3389/fpsyg.2021.703658

Cultivating Emotional Granularity

Christine D. Wilson-Mendenhall[1]* and John D. Dunne[1,2]

[1]Center for Healthy Minds, University of Wisconsin-Madison, Madison, WI, United States, [2]Department of Asian Languages and Cultures, University of Wisconsin-Madison, Madison, WI, United States

An emerging focus in affective science is the expertise that underlies healthy emotionality. A growing literature highlights emotional granularity – the ability to make fine-grained distinctions in one's affective feelings – as an important skill. Cross-sectional evidence indicating the benefits of emotional granularity raises the question of how emotional granularity might be intentionally cultivated through training. To address this question, we present shared theoretical features of centuries-old Buddhist philosophy and modern constructionist theory that motivate the hypothesis that contemplative practices may improve granularity. We then examine the specific mindfulness-style practices originating in Buddhist traditions that are hypothesized to bolster granularity. We conclude with future directions to empirically test whether emotional granularity can be intentionally cultivated.

Keywords: emotional granularity, emotional expertise, mindfulness, Buddhist philosophy, contemplative practice, constructionist theory

OPEN ACCESS

Edited by:
Maria Gendron,
Yale University, United States

Reviewed by:
Andrea De Cesarei,
University of Bologna, Italy
Kiat Hui Khng,
Nanyang Technological University, Singapore

Correspondence:
Christine D. Wilson-Mendenhall
cwilson37@wisc.edu

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: *30 April 2021*
Accepted: *29 October 2021*
Published: *01 December 2021*

Citation:
Wilson-Mendenhall CD and Dunne JD (2021) Cultivating Emotional Granularity. Front. Psychol. 12:703658. doi: 10.3389/fpsyg.2021.703658

INTRODUCTION: GRANULARITY AS EMOTIONAL EXPERTISE

Emotional expertise involves skills for understanding, experiencing, and regulating emotions (Zeidner et al., 2012; Hoemann et al., 2020). Emotional granularity is an aspect of emotional expertise. It refers to the ability to experience emotions in a precise and context-specific manner (Barrett et al., 2001; Lee et al., 2017). Whereas highly granular individuals make fine-grained distinctions in their emotional experiences, those lower in granularity are unable to do so. For example, those higher in granularity can distinguish feeling angry from other negative feelings, such as feeling fearful, exhausted, or lonely. In contrast, those lower in granularity experience feeling bad without further distinction.

Accumulating evidence from cross-sectional studies suggests that emotional granularity is beneficial. More granular experiences of negative emotions, especially, are consistently associated with better coping and mental health (Kashdan et al., 2015; Smidt and Suvak, 2015). This evidence, along with conceptualizing emotional granularity as a skill, raises the question of how adults can cultivate this expertise. Based on shared theoretical insights in modern constructionist theory and centuries-old Buddhist philosophy, we propose that mindfulness-style practices originating in Buddhist traditions may bolster emotional granularity and that this hypothesis can be empirically tested.

THEORETICAL ACCOUNTS OF GRANULARITY

The idea that emotional granularity is a beneficial skill has emerged relatively recently in psychological science (Kashdan et al., 2015), but it is also a feature of traditional Buddhist accounts of the mind, where it is embedded within a framework that considers granularity of mental states (not just emotions) to be both beneficial and trainable (Dalai Lama et al., 2020). After introducing granularity in each tradition, we focus on shared theoretical features that motivate specific contemplative practices for cultivating granularity.

Emotional Granularity Is Beneficial: Theoretical Context

Whereas the constructionist theory discussed here largely emerged in the context of empirical investigation over the past 150 years (Gendron and Barrett, 2009), Buddhist theories emerged more than 2000 years ago. To avoid elevating one discourse over the other, we begin by illustrating how insights regarding the benefits of granularity arise in each framework.

Psychological Construction Framework: Granularity Underlies Situated Action

Psychological construction approaches to emotion assume that emotions are constructed events rather than fixed, essential entities (Barrett and Russel, 2015). Within this "family" of theories (Barrett and Russel, 2015), the Theory of Constructed Emotion (TCE; Barrett, 2017) addresses the functionality of granularity. Consider feeling afraid when a fire erupts in one's house and feeling afraid when giving a speech. In the former, swiftly escaping the house is appropriate and necessary to avoid life-threatening danger. However, fleeing is not helpful in the context of public speaking. Different, situated actions are necessary for effective responding (Barrett, 2013; Wilson-Mendenhall et al., 2013; Wilson-Mendenhall, 2017). In this context, interpreting physiological arousal as a sign that one is ready to engage and perform, instead of signaling a threat to avoid, is beneficial (Jamieson et al., 2018). Granular, context-sensitive processing is necessary to engage in the *specific* actions that will be of benefit in the particular situation,[1] including actions taken to successfully regulate emotions (Aldao, 2013; Bonanno and Burton, 2013).

Buddhist Frameworks: Granularity Enables Insight and Enhanced Regulation

Although "emotion" is not a superordinate category used by Buddhist theorists, the capacity for experiential granularity – the careful parsing of one's mental states – is a highly valued skill cultivated by meditative practices beginning with the early *Abhidharma*[2] literature. This emphasis on granular accounts of experience emerges from the perspective that ordinary persons are largely unaware of – or mistaken about – many phenomenally accessible aspects of experience, and this lack of insight into one's own experience perpetuates suffering (Dalai Lama et al., 2020). Enhanced experiential granularity enables insight into experience in ways that relieve suffering, and it also enables one to more carefully regulate aspects of experience, such as attention and affect (Anālayo, 2003, 2018; Dalai Lama et al., 2020).

[1]Even the act of fleeing physical danger ("flight") benefits from situational granularity. In fire safety training, for example, one practices getting low and going under smoke to an exit as "flight."

[2]In Pali, the canonical language of the Theravāda tradition, the equivalent term is *Abhidhamma*.

Shared Theoretical Features

Table 1 specifies shared theoretical features across the TCE and the Dharmakīrtian Revision of the Buddhist Abhidharma that motivate the hypothesis that contemplative practices improve emotional granularity. These features include (1) top-down construction, (2) granular concepts, and (3) goal-directed outcomes.

Shared Theoretical Features in the Theory of Constructed Emotion

The TCE specifies how the brain constructs emotions (Barrett, 2017). Whereas several models examine granularity in processing that occurs after an emotion emerges [e.g., *via* "identification" (Gross, 2015), "feelings-as-information" (Schwartz, 2011), or "regulation flexibility" (Pruessner et al., 2020)], the TCE characterizes granularity during the dynamic process of constructing an emotional experience.

The TCE is grounded in a predictive (vs. reactive) model of brain function (Barrett and Simmons, 2015; Chanes and Barrett, 2016; Barrett, 2017). In brief, the brain predicts forward in time to prepare for movement and anticipate the body's energy needs. Prior experiences are reinstated to predict the cause of incoming sensory changes, and the visceromotor changes and motor actions required to deal with that causal occurrence (Hoemann et al., 2019). This top-down prediction is confirmed or corrected by bottom-up sensory input. Once a prediction is confirmed, sensory input is categorized such that the brain understands what caused the sensations and how to act. This active inference constructs emotional experiences (and other mental states). Although implicit emotional habits often stabilize *via* this top-down categorization, we propose that, due to their constructed nature, emotional habits lacking granularity can be transformed (**Table 1**, feature 1).

"Concepts" is another name for the brain's predictions (i.e., its internal model; Hoemann et al., 2019). Because emotions are constructed, they can be transformed by altering concepts (**Table 1**, feature 2). The TCE points to language as a tool for granular concept construction (Barrett et al., 2007; Lindquist et al., 2015; Hoemann et al., 2019). An emotion word like "angry" constructs concepts that integrate body and world to serve a particular goal-based function, such as overcoming an obstacle (Hoemann et al., 2019).[3] Grounded in a situation, this goal-based function facilitates specific actions (e.g., protesting injustice or confronting a partner). Discrete emotion categorizations (e.g., angry, afraid, or sad) thus serve to navigate negative affect in the situation at hand (Barrett, 2013), which can include context-sensitive regulation (e.g., relationship repair after an angry argument; Barrett et al., 2014). Without such categorizations, indistinct and ineffective action may be repeated

[3]Events categorized as anger or any other discrete emotion (e.g., fear, sadness, and joy) vary widely in their features, including the context-dependent actions that facilitate goal-relevant outcomes. These situational instances can be constructed without any categorical "essence."

TABLE 1 | Shared features that motivate why specific contemplative practices may be effective for cultivating emotional granularity.

Shared feature	Psychological Science Theory of Constructed Emotion	Buddhist Philosophy Dharmakīrtian Revision	Function of Contemplative Practices Grounded in Buddhist Traditions
Feature 1 Because emotions are constructed, emotional habits can be disrupted	Emotional experiences are constructed through active inference. Prior experiences are reinstated (i.e., "concepts") to categorize sensory input such that the brain understands what caused the sensations and how to act. Emotional habits emerge *via* this top-down construction. Habits lacking granularity can result in ineffective action that does not address the situation at hand (e.g., avoidance coping). Due to the constructed nature of these habits, however, they can be transformed.	Categories of mental states appear to exist as real things in the world, but they are actually constructed through the process of concept formation. Prior experience shapes the concepts deployed in a given context, and that concept in turn shapes one's behavioral response, prompting certain behaviors while inhibiting others. Through training, one can come to recognize that concepts are constructed in this way and learn to revise them, despite prior conditioning.	*Acceptance*, *decentering,* and *dereification* practices disrupt emotional habits. Instead of avoiding feelings (especially distress), *acceptance* and *decentering* encourage observing emotional experience from a nonjudgmental, impartial perspective without deploying habitual conceptualizations. *Dereification* that involves experiencing emotions as dynamic, constructed mental states would, in theory, disrupt sensorimotor inferences and make it possible to construct experience differently.
Feature 2 Emotions can be transformed through granular concepts	Because emotions are constructed, emotional experiences can be transformed through concept construction. Precise emotion word labels, as well as language that specifies situational details, are tools for constructing granular concepts that serve a particular goal-based function, with categorization instantiating context-specific action (and regulation) to navigate the situation at hand.	Since categories of mental states are constructed through concept formation, they can be radically revised, with that revision driven especially by the efficacy of the concepts to achieve context-specific goals. Experiencing conceptual contents as mental constructs facilitates this revision, as does careful parsing of the ways that the concepts illuminate or obscure features of a given mental state.	*Decentering* and *noting* practices use labeling to precisely parse one's mental state as it changes from moment to moment. *Dereification* underlies the realization that one's emotional experience is one of many possible constructions. Thus, it invites exploring alternate constructions and observing how they unfold (*via acceptance*, *decentering*, *noting*).
Feature 3 Goals shape the outcomes of granularity	Granular categorization facilitates goal-relevant outcomes. These outcomes may not be beneficial to oneself and/or others if the goal (i.e., the purpose of categorization) is not aligned with well-being.	Concepts function to enable goal-directed behavior, and a concept's efficacy depends on its ability to accurately predict success. The goal itself, however, may not be conducive to the elimination of suffering, and goals must also be a focus of analysis.	Just as interventions derived from Buddhist practices promote various models of well-being, Buddhist practices are embedded within the larger context of relieving suffering, which is taken as a normative goal for all Buddhist traditions.

across situations involving negative affect, such as avoidance coping. Precise language further refines categorization (e.g., as annoyed, resentful, or furious) to tailor action and regulation in the situation (e.g., "letting go" of a minor annoyance). Moreover, language can specify detail such that actions (including regulation) become increasingly situated. For example, noting one's fatigue during an angry argument may serve to initiate rest before respectfully reengaging. Such details can also shift categorization. Noticing fatigue initially, for example, may shift categorization such that anger is not experienced.

In the TCE framework, granularity facilitates goal-relevant and culturally congruent outcomes (Hoemann et al., 2020). If the goal – the purpose of categorization – is not aligned with well-being, we propose that granularity may not be beneficial (**Table 1**, feature 3). During an experience of anger, for example, granular categorization with the goal of regulating one's intense feelings is more likely to support well-being than granular categorization with the goal of enacting revenge. Goals can also shape the emotion experienced. Instead of experiencing anger toward another, for example, one might experience compassion, if goals shift to recognizing others' suffering.

Shared Theoretical Features in the Dharmakīrtian Revision of the Buddhist Abhidharma

Theories and practices that promote experiential granularity emerge first in the *Abhidharma* literature, possibly dating to Buddhism's earliest period (5th century BCE). Presenting extensive lists of "mental factors" (Sanskrit, *cetasika*), including elements of attention, affect, and cognition, this literature played – and continues to play – a central role in Buddhist contemplative practice (Anālayo, 2003). These lists provide the initial Buddhist framework for carefully parsing one's experience, making experiential granularity a target of mental training.

While some *Abhidharma* traditions did not essentialize mental categories (Gethin, 1992; Heim, 2013), others employed an essentialist approach (Westerhoff, 2018) that limits granularity. For essentialists, an experiential feature belongs by virtue of its essence to a particular category (such as "anger"); thus, multiple, context-dependent categorizations of that feature are not possible. In response to this essentialism, the Indian Buddhist philosopher Dharmakīrti (7th century C.E.) promoted an anti-essentialist account of concept formation that enhances granularity. Instead of appealing to essences, Dharmakīrti maintained that concepts are constructed through the triggering of associations with past experience within a goal-oriented framework rooted in the causal capacities of whatever is being conceptualized (Dunne, 2011; Eltschinger et al., 2018; **Table 1**, feature 1). Thus, when one conceptualizes two experiential features at different times as "anger," to ordinary persons, it seems that this conceptualization is simply picking out some identical essence in both instances. The two features are actually unique, but a single concept construes them as the same. In short, given the context formed by one's goals, the process of concept formation ignores those experiences' individual differences and constructs a concept that picks out their relevant causal features. If reliable, that concept predicts the outcomes of one's behavior in ways that enable effective action (Dunne, 2004, 2011; Ganeri, 2011). Concepts are thus highly context-sensitive, and they potentially are highly flexible because an experiential feature does not *in essence* belong to any single category; it is instead open to numerous context-relevant conceptualizations (**Table 1**, feature 2). To attain that flexibility, one must be trained to recognize the process of concept formation and the illusion of essences that it creates, along with recognizing the role played by conditioning from prior experience. Trained in such a way, one can choose to radically revise the categories used to parse experience, such that an instance of "anger" might be re-conceptualized as "hunger," in the right context. Crucially, since concepts are always formed in relation to goals, the re-conceptualization of experience must occur within a framework of goals that move one along the Buddhist path, whose endpoint necessarily includes the relief of suffering (Dunne, 2015; Anālayo, 2021; **Table 1**, feature 3).

FUNCTIONS OF CONTEMPLATIVE PRACTICES GROUNDED IN BUDDHIST TRADITIONS

One can characterize a contemplative practice as a cultural practice (Hutchins, 2008) that emphasizes self-awareness, self-regulation, and/or self-inquiry for the purpose of self-transformation, with formal, seated meditation serving as a paradigmatic form (Lutz et al., 2007, 2008; Davidson and Dahl, 2017). In Buddhist cultures, mindfulness meditation has for centuries been a prominent contemplative practice that has more recently been adapted to secular interventions (Kabat-Zinn, 2011). As shown in **Table 1**, several features of mindfulness-style practices, whether in Buddhist or secular contexts, likely train the capacity for experiential granularity, including meta-awareness, decentering, and dereification (Dunne, 2015). One feature is the instruction to remain "non-averse" to experience (Buddhaghosa, 1976). In the style of mindfulness found in Buddhism-derived, secular Mindfulness-Based Interventions (MBIs), this is usually articulated as maintaining an attitude of "acceptance" or "friendliness" toward experience (Bishop et al., 2004; Kabat-Zinn, 2013), along with a "non-reactive" stance (Bernstein et al., 2015). This attitude is crucial because increased granularity requires a close examination of experience, but if one is averse to an experience that one labels as "unpleasant" or "bad," then one cannot approach and carefully observe that experience to describe it in a more nuanced fashion.

Likewise, the traditional Buddhist emphasis on deliberately parsing experience into categories, which is best exemplified by the "noting" practice promoted by the influential Burmese teacher Sayadaw (2016), also serves to enhance granularity.[4] The instruction is to "note" whatever occurs in experience through mental verbalization at each moment – such as "planning, planning, planning, pain, pain, pain." Both traditional and contemporary mindfulness practice include the instruction to not construe mental states as "belonging to me" (Sanskrit, *ātmīya*; Dalai Lama et al., 2020), often articulated in MBIs as "not identifying with" one's emotions (Bernstein et al., 2015). This "decentering" facet may enhance granularity by providing the psychological distance to deploy descriptions of experience that do not conform with one's self-concept.

Mindfulness-based interventions often emphasize the need to "let go" of the "story" that one is telling about one's experience (Kabat-Zinn, 2013), and this reflects more directly a Dharmakīrtian influence. Specifically, Dharmakīrti's non-essentialist account posits that concepts are mere mental constructs that never fully capture an object's identity. As such, concepts can be experienced just as mental events, and this contemplative technique – recognizing that thoughts are simply events in consciousness – emerges directly from Dharmakīrtian philosophy in non-dual meditation styles (Brunnhölzl, 2007; Dunne, 2015). In MBIs, this technique is central to dereification (Bernstein et al., 2015; Lutz et al., 2015), and it is crucial for enhancing emotional granularity, since it permits one to set aside habitual conceptualizations that may seem especially "real" or "true" (Dahl et al., 2020). Dharmakīrti's approach also permits the application of competing concepts to the same experience, and this promotes reappraisal – a technique that became more prevalent in Buddhist practices starting around Dharmakīrti's time, such as "Mind Training" practices (Jinpa et al., 2006; Dahl et al., 2015; Jinpa, 2015).

FUTURE DIRECTIONS

A research agenda emerges from the interdisciplinary integration illustrated in **Table 1**. Key questions for future research are presented in **Table 2**. Because only a handful of studies address these questions, we highlight findings from these studies in the context of discussing future directions.

Mindfulness-Based Interventions

Do secular MBIs improve emotional granularity? To our knowledge, only one MBI study has examined emotional granularity as it is typically measured *via* experience sampling. This study demonstrated that improved granularity of negative emotions following Mindfulness-Based Stress Reduction was mediated by acceptance and decentering skills, even when controlling for changes in negative affect (Van der Gucht et al., 2019). Consistent with **Table 1**, this finding suggests that emotional granularity may improve through engaging with negative experiences from a more impartial, precise perspective, without experiential avoidance. Because this relatively small study did not include a control group, the results need to be replicated in larger, randomized controlled trials (RCTs).

As Van der Gucht et al. showed and as posited in **Table 1**, it is important to investigate whether specific features of contemplative practice cultivate emotional granularity (e.g., acceptance, decentering, dereification, and noting). Moreover,

[4]Despite the traditional context of Burmese Vipassanā meditation and lacking direct contact with the Dharmakīrtian approach, Mahāsi Sayadaw nevertheless promoted a "noting" practice that is not constrained by such lists (Sayadaw, 2016). To the extent that MBIs encourage careful observation of experience, they also do so without normative categories.

TABLE 2 | Questions for future research on cultivating emotional granularity.

Mindfulness-Based Interventions	
1.	Do mindfulness-based interventions, such as Mindfulness-Based Stress Reduction, improve emotional granularity?
2.	Which features of MBI practices (if any) contribute to cultivating emotional granularity (e.g., acceptance, decentering, dereification, noting)?
Hybrid Interventions	
3.	Do hybrid interventions that include language-based categorization of emotions, such as Mindfulness-Based Cognitive Therapy (MBCT), provide a more comprehensive approach to cultivating emotional granularity?
4.	What novel, hybrid interventions may be effective in cultivating emotional granularity, especially in the context of preventing (vs. treating) psychopathology?
Emotional Granularity as Mediator	
5.	Does training-related improvement in emotional granularity mediate beneficial changes in emotion regulation (e.g., decreased use of maladaptive coping strategies)?
6.	Is training-related improvement in emotional granularity a mediator of beneficial changes in mental health (e.g., decreased mood disorder symptoms) and sustaining those changes (e.g., reduced relapse)?
Methods and Measurement	
7.	What forms of emotional granularity are overlooked in current measurement approaches?
8.	Does measuring goals help distinguish when emotional granularity is beneficial?

fine-grained neuroscientific accounts of how each feature contributes to enhancing emotional granularity would be valuable. To develop such accounts, it may be fruitful to integrate the constructionist model described here with relevant facets of the growing literature on mindfulness and emotion regulation, such as using awareness practice to expand beyond a narrow focus on threat and attend to other situational features (Hill and Updegraff, 2012; Roemer et al., 2015).

Hybrid Interventions

Mindfulness-based interventions are increasingly being integrated with other intervention approaches (Hayes et al., 2011; Renna et al., 2017). Evidence suggests, for example, that Mindfulness-Based Cognitive Therapy reduces risk of depressive relapse for those with recurrent depression (Kuyken et al., 2016; Segal et al., 2018). Based on **Table 1**, integration of the language-based categorization of emotional experiences involved in cognitive therapy (Beck and Haigh, 2014) with MBI practices would be a strong approach to cultivating the emotional granularity that may sustain mental health. Is the coupling of these approaches more impactful in bolstering beneficial emotional granularity than either alone?

Nonclinical populations may also benefit from integrating language-based approaches that expand the range and context-sensitive use of emotion vocabulary (Kashdan et al., 2015). We propose that situated learning is necessary to construct concepts that navigate the situation at hand (Lebois et al., 2020). Consistently labeling an emotion in a particular situation is thought to establish coherent concepts that implement context-specific, goal-directed actions (Hoemann et al., 2019). It is an open question whether integrating MBI practices with vocabulary expansion would be particularly impactful for cultivating emotional granularity.

Emotional Granularity as Mediator

It will be important to ascertain whether training-related increases in emotional granularity are beneficial and thus to consider emotional granularity in relation to other mechanisms of change. Cross-sectional studies suggest that experiencing negative emotions with greater granularity is associated with less maladaptive coping, such as binge drinking, aggression, and self-injurious behavior (Kashdan et al., 2015). These findings suggest that training-related increases in emotional granularity may mediate improvements in emotion regulation. Higher granularity of negative emotions is also related to fewer symptoms of depression and anxiety (Demiralp et al., 2012; Kashdan et al., 2015), which prompts the question of whether training-related increases in emotional granularity may mediate improved and sustained mental health.

Methods and Measurement

Dismantling RCTs experimentally manipulate elements of an intervention to systematically investigate their impact. Consistent with Van der Gught and colleagues' finding that acceptance mediated changes in emotional granularity, recent dismantling RCTs suggest that acceptance is an "active ingredient" underlying the affective benefits of MBIs (Lindsay and Creswell, 2019). This approach is promising for examining how features of contemplative practice may shape emotional granularity (e.g., acceptance and dereification), as well as how other approaches (e.g., cognitive therapy and vocabulary expansion) may interact with contemplative practice to cultivate emotional granularity.

Measures of emotional granularity primarily focus on differentiation of same-valence categories, such as fear, sadness, and anger (Kashdan et al., 2015; Smidt and Suvak, 2015). Buddhist traditions draw attention to the partitioning of emotion, cognition, and perception in Psychology. Dissolving such superordinate categories suggests measuring other forms of fine-grained granularity, including precision within the aforementioned emotion categories (Erbas et al., 2019), sensitivity to dimensions of emotional "thought" such as ruminative repetition (Nolen-Hoeksema et al., 2008; Watkins, 2008), and nuance in relation to bodily "perception" (e.g., identifying hunger as contributing to anger). Moreover, **Table 1** suggests that measuring goals may be important for distinguishing beneficial granularity. Developing precise approaches for capturing granularity and the situated actions enabled by that granularity is an important future direction.

CONCLUDING REMARKS

In conclusion, we posit that "deep integration" between constructionist approaches in affective science and scholarship in Buddhist traditions can stimulate novel research (Wilson-Mendenhall et al., 2019). Theory and initial research bolster the hypothesis that contemplative practices contribute to cultivating beneficial emotional granularity, a claim that can be empirically tested.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, and further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

CW-M and JD outlined the manuscript together, each wrote specific sections as designated during the outlining process, and contributed to revising the manuscript. CW-M led a major revision to the manuscript based on helpful reviewer comments. All authors contributed to the article and approved the submitted version.

ACKNOWLEDGMENTS

We thank Paul Condon and Lisa Feldman Barrett for many discussions in the context of a different manuscript that planted seeds for developing this manuscript.

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Conflict of Interest: CW-M has served as a consultant to the nonprofit organization Healthy Minds Innovations.

The remaining author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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frontiers in Psychology

BRIEF RESEARCH REPORT
published: 10 January 2022
doi: 10.3389/fpsyg.2021.687497

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Feel to Heal: Negative Emotion Differentiation Promotes Medication Adherence in Multiple Sclerosis

T. H. Stanley Seah, Shaima Almahmoud and Karin G. Coifman*

Department of Psychological Sciences, Kent State University, Kent, OH, United States

OPEN ACCESS

Edited by:
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University of Valencia, Spain

****Correspondence:***
T. H. Stanley Seah
tseah@kent.edu

Specialty section:
This article was submitted to Psychology for Clinical Settings, a section of the journal Frontiers in Psychology

Received: *29 March 2021*
Accepted: *08 December 2021*
Published: *10 January 2022*

Citation:
Seah THS, Almahmoud S and Coifman KG (2022) Feel to Heal: Negative Emotion Differentiation Promotes Medication Adherence in Multiple Sclerosis. Front. Psychol. 12:687497. doi: 10.3389/fpsyg.2021.687497

Multiple Sclerosis (MS) is a debilitating chronic autoimmune disease of the central nervous system that results in lower quality of life. Medication adherence is important for reducing relapse, disease progression, and MS-related symptoms, particularly during the early stages of MS. However, adherence may be impacted by negative emotional states. Therefore, it is important to identify protective factors. Past research suggests that the ability to discriminate between negative emotional states, also known as negative emotion differentiation (NED), may be protective against enactment of maladaptive risk-related behaviors. However, less is known as to how NED may promote adaptive health behaviors such as medication adherence. Utilizing weekly diaries, we investigated whether NED moderates the association between negative affect and medication adherence rates across 58 weeks among patients (n = 27) newly diagnosed with MS (following McDonald criteria). Results revealed that NED significantly moderated the relationship between negative affect and medication adherence. Specifically, greater negative affect was associated with lower adherence only for individuals reporting low NED. However, this link disappeared for those reporting moderate to high NED. Building upon past research, our findings suggest that NED may promote adaptive health behaviors and have important clinical implications for the treatment and management of chronic illness.

Keywords: emotion, emotion differentiation, health behaviors, medication adherence, multiple sclerosis, chronic illness

INTRODUCTION

Multiple Sclerosis (MS) is a chronic autoimmune disease of the central nervous system that lowers quality of life (Arnett, 2003). While there is currently no cure for MS, medication adherence is important in reducing relapse and disease progression (Goodin et al., 2002). In particular, medication adherence following initial diagnosis of MS has been found to be predictive of disease outcomes as well as future compliance rates (Kleinman et al., 2010). However, given the chronic, uncertain, and life changing nature of MS, patients often experience elevated levels of distress during the early stages of disease (Janssens et al., 2003). Importantly, the first 5–10 years following diagnosis are a time of considerable stress, emotional upheaval, in conjunction with frequent disruptions from changes in physical impairments and increased fatigue (Strober, 2018). Indeed, it is estimated that MS patients are at considerably high risk for psychiatric illness, with rates of lifetime depression approaching 50% (Siegert and Abernethy, 2005). The severe consequences of depression are well-documented, contributing to expensive disruptions in functioning (Kessler et al., 2006), greater risk for physical illness (Blume et al., 2011), and within the context of chronic illness, poor treatment compliance and prognosis (Kalsekar et al., 2006; Moussavi et al., 2007). Therefore, it is important to identify protective factors that may facilitate adherence to MS and related medications.

Research suggests that emotion differentiation (ED; also known as emotional granularity), which refers to the ability to distinguish between emotional states in a fine-grained manner (e.g., fear vs. anger; Barrett et al., 2001), may be important. Individuals who are more adept at differentiating their emotions tend to label their experiences using various terms that describe the presence and intensity of specific emotions (e.g., sadness). Conversely, poorer differentiators are more likely to experience difficulties separating between emotional states and tend to describe their experiences as generally "bad" or "unpleasant" (Kashdan et al., 2015; Smidt and Suvak, 2015). In the literature, ED is commonly assessed using experience-sampling methodology, where individuals repeatedly report their emotional experiences across time. A person-level indicator of ED is derived by calculating the intraclass correlation coefficient (ICC) between emotion ratings across the sampling duration.

Studies accumulated over the past two decades have generally shown that ED, particularly negative ED (NED), is associated with better psychosocial functioning, including lower levels of depression and anxiety (e.g., Demiralp et al., 2012; Seah et al., 2020), and decreased engagement in a wide range of maladaptive behaviors in response to negative emotion across clinical and non-clinical samples (O'Toole et al., 2020; Seah and Coifman, 2021). Indeed, there is compelling theory and evidence suggesting that NED may operate by facilitating adaptive regulation of states of distress (Kashdan et al., 2015). For example, labeling feelings precisely can decrease the intensity of emotion-related arousal (Tabibnia et al., 2008; Kircanski et al., 2012). Moreover, NED has been explicitly tied to adaptive emotion regulatory strategy use (Barrett et al., 2001; Hill and Updegraff, 2012) and has been found to mitigate the association between negative affect (NA) and maladaptive behaviors known to interfere with treatment and predict poorer prognosis, including binge drinking, social avoidance, and non-suicidal self-injury (Kashdan et al., 2010; Zaki et al., 2013; Seah et al., 2020).

While it is now increasingly clear that NED may afford some protection against maladaptive behaviors, less is known about whether it may promote adaptive health behaviors. This appears especially important in the context of chronic illness management, where negative emotional states are known to adversely impact health behaviors such as treatment adherence (Bruce et al., 2010). Results from one prior study by Coifman et al. (2014) found that NED was positively associated with adherence in Beta-Thalassemia, a congenital blood disorder. However, this study only examined attendance at routine screenings and less is known regarding other important indicators of treatment compliance such as daily medication adherence.

Therefore, the present investigation sought to replicate and extend findings by Coifman et al. (2014) in the context of MS by examining NED as a moderator of the association between NA and self-reported medication adherence in daily life. As in previous studies, we utilized sampling methodology via weekly diaries to derive person-level indices of NED, mean NA, and medication adherence rates across a 58-week period. Given its protective benefits, we hypothesized that the effects of NA on medication adherence rates would depend on levels of NED. Specifically, we predicted that NA would be negatively associated with medication adherence at low but not high levels of NED.

MATERIALS AND METHODS

Participants

Data described in the present investigation were part of a larger study investigating emotion processing related to psychological adjustment in MS. Of the total sample, 27 participants (aged 18 and above) were included in the current study as they completed the weekly diary portion that examined emotional experiences and medication adherence in daily life over a period of 1 year. These participants were English-speaking MS patients (aged 18 and above) recruited from a local clinic and/or online advertisements from the Midwestern United States (see Eligibility Criteria and Recruitment). Participants reported a mean (SD) age of 36.11 (8.88), and were mostly female (74.1%), White/Caucasian (81.5%), non-Hispanic (100%), and working full-time or part-time (51.9%). **Table 1** describes the characteristics of this sample. All participants provided informed consent prior to the start of data collection.

Eligibility Criteria

The eligibility criteria for participants in the larger study included having a diagnosis of Relapsing –Remitting MS (RRMS), largely because 85% of all MS patients are diagnosed with RRMS at disease onset (McKay et al., 2015). This diagnosis was evaluated by a neurologist according to the revised McDonald Criteria (Polman et al., 2005), which is a diagnostic scheme that provides reliable diagnoses of MS and prevents false positives. The criteria combined magnetic resonance imaging with well-established diagnostic examinations that considered neurological history and examination, and a range of other laboratory tests. Given the larger study's focus on adjustment following MS diagnosis, participants' time of MS diagnosis could not exceed 10 years prior, although nearly all (92.6%) were diagnosed within the prior 5 years. In addition, psychiatric history was assessed in a diagnostic interview using the Structured Clinical Interview for Diagnosis of Axis I Disorders in the DSM-IV-TR (SCID-I; First et al., 2002). Participants with a history of psychosis

TABLE 1 | Characteristics of study participants as a percentage of the sample (n = 27).

Characteristics	Study sample
Sex	
Female	74.1
Male	25.9
Race	
White/Caucasian	81.5
Black/African American	7.4
Other	11.1
Ethnicity	
Non-Hispanic or Latino	100
Employment status	
Work full-time	33.3
Work part-time	18.5
Retired	3.7
Unemployed	3.7
Unemployed due to disability	33.3
Other	7.4
Date of multiple sclerosis diagnosis	
Within past 5 years	92.6
Within past 10 years	7.4
Diagnostic status	
Met criteria for any psychological disorder	44.4
Major depressive disorder	7.4
Generalized anxiety disorder	14.8
Social anxiety disorder	14.8
Agoraphobia without panic disorder	11.1
Posttraumatic stress disorder	3.7

were excluded from the research. See **Table 1** for information on individuals who met criteria for current diagnosis of any psychological disorder, as well as specific diagnoses.

Recruitment

Participants were primarily recruited from an MS clinic in Northeast Ohio. Patients who met the inclusion criteria were approached by a registered nurse who was certified by the International Organization of Multiple Sclerosis Nurses, a graduate student, or a trained research assistant. Alternatively, participants responded to advertisements posted online. Phone interviews were conducted with individuals who expressed interest in the study to evaluate eligibility and explain the study's activities. For participants who were recruited online, their diagnoses were verified (with consent) through their neurologist to ensure all eligibility criteria were still met. Sixty-one percent of participants completed the initial data collection at the MS clinic and 39% completed it in a research lab at Kent State University. Ninety-five percent of participants were taking medications to decrease the number of relapses and reduce the progress of the disease and 5%[1] were not taking any medications for MS relapses. Fifty-five percent of participants who were taking a medication to decrease the number of MS relapses were taking infused/intravenous MS medication (e.g., Tysabri and Lemtrada), 25% were taking self-injection MS medication (e.g., Copaxone, Rebif, and Avonex), 18% were taking oral MS medication (e.g., Tecfidera, Gilenya, and Aubagio), and 2% did not report the delivery type of their medication. In addition to the MS medication that was taken to manage the disease course, other medications (e.g., Gabapentin and Baclofen) were taken to manage MS-related symptoms. The most frequently reported symptoms were pain, such as nerve pain, muscle spasm and spasticity, and bladder problems. The time frame for participant recruitment was from June 2013 to February 2017.

[1]These participants were still included in the study because they were also taking other medications for MS-related symptoms.

Procedure

Data collection was completed across an 18-month period. However, data for this study focused exclusively on the 12-month weekly sampling period. During the initial stage (first 3 months), all participants completed two lab sessions that included a diagnostic interview (described above), as well as other tasks, questionnaires, and assessments to determine physical and cognitive functioning in MS. Upon completion of the second session, participants received training to complete a weekly diary for the next 10–12 months (see "Measures" section for more details). During this stage of study participation, they received weekly diary reminders by the research team and returned each diary entry via addressed-stamped envelopes. Note that participants were provided with the option to opt out of this study component. Following completion of the diary, participants returned to the laboratory for two follow-up sessions, where they repeated assessments described in Stage 1. All study procedures were reviewed and approved (Protocol: #13-134) by the university Institutional Review Board before the start of data collection.

Measures

Weekly Diary

Participants were trained by a research assistant to complete weekly diaries to assess their emotional experiences and frequency of medication adherence. Participants completed these diaries for up to a maximum of 58 weeks (approximately 10–12-month period; for 58 diaries). Participants were provided with paper copies of weekly diaries after the second laboratory session. They completed these diaries once a week, typically on the same day each week (e.g., Saturday), and returned these documents to the research team via postal mail. To increase compliance, all participants received weekly reminder phone calls and/or emails from a trained research assistant and packets of paper diaries were mailed monthly to participants. Four participants were excluded from subsequent analyses because they completed less than seven diaries in total, which was less than 1.5 standard deviations from the average number of diaries completed across the sample (Bolger et al., 2003). There were no significant demographic differences (age, sex, race/ethnicity, and employment status) between excluded individuals and the final sample. The final sample (n = 23) completed a mean (SD) of 37.26 (12.55) diaries (range: 12–55; compliance: 64%).

Momentary Self-Reported Emotions

During each weekly diary, participants were asked to describe their current emotional experience by providing ratings on a 7-point Likert scale ranging from 1 ("none") to 7 ("strong"). Participants rated the extent to which they felt each of six negative emotion words (*fear*, *sadness*, *guilt*, *distress*, *anger*, *disgust*), which formed the NA scale. Unrelated to the present study, participants also rated how much they felt each of six positive emotion words (*happiness*, *enjoyment*, *affection*, *surprise*, *amusement*, *relief*). As in previous studies on ED, these emotion words were selected to reflect varying levels of activation across negative and positive valence dimensions of contemporary affective circumplex models (e.g., Russell, 1980; Rafaeli et al., 2007). To assess the reliability of the NA scale, we computed values at the between-person (R_{KF}) and within-person (R_C) levels following Cranford et al. (2006). The between-person (R_{KF} = 0.99) and within-person (R_C = 0.82) reliability for this sample were good.

Mean Negative Affect

An index of mean NA was obtained by calculating a mean score across participants' ratings of the six negative emotion words from each diary across the sampling duration. The mean (SD) level of mean NA reported in this sample was 1.53 (0.48; range: 1.01–2.79).

Negative Emotion Differentiation

As in previous studies, a person-level index of NED is obtained for each participant by computing the average ICC with absolute agreement between negative emotion ratings across all diaries (Kashdan et al., 2015). This ICC index provides a measure of how similarly (i.e., level of agreement) ratings of negative emotion words vary across time. Higher ICC values would suggest similar ratings across negative emotions at any given diary entry, while lower ICCs would suggest more differentiated responses across emotion ratings. One individual had a negative ICC (−0.02) and this value was changed to 0 and included in subsequent analyses (Erbas et al., 2014).[2] Following existing conventions in ED research, ICC values were reverse scored (i.e., subtracted from 1) so that higher values indicated greater NED for ease of interpretation (Seah and Coifman, 2021). The mean (SD) level of NED reported in this sample was 0.34 (0.25; range: 0.03–1.00), which is comparable to that reported in other clinical and community samples (e.g., Zaki et al., 2013; Seah et al., 2020).

Medication Adherence

During each weekly diary, participants were asked to record information about their medications (includes those that treated MS and MS-related symptoms) over the past week and indicated whether they completed (coded as 1) or missed (coded as 0) a dose for each day of the week. As in Coifman et al. (2014), medication adherence rates across the sampling period were derived by calculating the proportion of the total number of completed vs. missed doses across all completed diaries based on the medical records of prescribed medications. The mean (SD) rate of medication adherence reported in this sample was 0.77 (0.31; range: 0–1.00).

Data Analysis Plan

First, we examined bivariate correlations between primary outcome variables and potential covariates (e.g., age, total number of diaries completed) in the final sample. In addition, a series of one-way ANOVAs were conducted to examine whether there were any demographic differences in medication adherence in terms of sex, race, and employment status. Next, we tested the possible moderation of the association between mean NA and medication adherence by NED using the Hayes PROCESS macro (Model 1) in IBM SPSS (v. 23). This macro runs a series of Ordinary Least Squares regressions with the centered product term representing the interaction of mean NA by NED as a predictor of medication adherence. The estimated effects reported were unstandardized regression coefficients. Statistical significance was set at 0.05.

RESULTS

Preliminary Analyses

Results from correlational analyses revealed a significant negative association between mean NA and the total number of completed diaries, $r = -0.42$, $p = 0.043$. Contrary to past research, mean NA was not significantly associated with medication adherence, $r = -0.22$, $p = 0.323$. Similarly, NED was not associated with medication adherence, $r = 0.14$, $p = 0.529$ or mean NA, $r = -0.06$, $p = 0.778$. No other significant correlations were observed. Next, results from one-way ANOVAs revealed no significant differences in medication adherence due to sex, $F_{(1,21)} = 0.18$, $p = 0.679$, race, $F_{(2,20)} = 0.38$, $p = 0.687$, or employment status, $F_{(5,17)} = 0.97$, $p = 0.462$.

Primary Analyses

Results from the moderation analyses are presented in **Table 2**. As hypothesized, we found that NED significantly moderated the relationship between mean NA and medication adherence, $B = 1.12$, $\Delta R^2 = 0.18$, $F_{(1,19)} = 4.62$, $p = 0.045$, 95% CI [0.03;

TABLE 2 | Significant Two-way (Mean NA by NED) interaction predicting medication adherence (n = 23).

	Predictor	*B*	*SE*	95% CI	sr^2	R^2	ΔR^2
Step 1	Mean NA	−0.13	0.14	−0.43 to 0.16	0.04	0.06	
	NED	0.16	0.16	−0.41 to 0.72	0.02		
Step 2	Mean NA	−0.63*	0.27	−1.19 to −0.08	0.23	0.25	0.18*
	NED	−1.49	0.80	−3.17 to 0.20	0.13		
	Mean NA × NED	1.12*	0.52	0.03 to 2.22	0.18		
	$F_{(3,19)} = 2.06$, $p = 0.139$						

B, unstandardized coefficient; SE, standard error; CI, confidence interval; NA, negative affect; NED, negative emotion differentiation.
$^*p < 0.05$.

[2]Negative ICC values are common in studies of emotion differentiation. While ICCs should range between 0 and 1 in theory, they can take on small negative values in practice due to sampling error (Cohen et al., 2003). However, rather than excluding these data, Cohen et al. (2003) recommended assigning them a value of 0. Notably, our results remained the same even after excluding the individual with a negative ICC score for negative emotion differentiation.

2.22], $sr^2 = 0.18$. This suggests that the impact of mean NA on medication adherence depended on levels of NED. To examine the effects of the interaction, predicted values were plotted for individuals at the mean and ± 1 SD from the mean of NED and mean NA (refer to **Figure 1**). Follow-up tests of the simple slopes revealed that the association between mean NA and medication adherence under low NED (1 SD below the mean) was significantly different from zero, $b = -0.53$, $p = 0.029$. Therefore, among individuals with low NED, mean NA predicted poorer adherence. However, the association between mean NA and medication adherence for individuals reporting moderate (at the mean; $b = -0.25$, $p = 0.087$) to high (1 SD above the mean; $b = 0.03$, $p = 0.859$) NED was not significantly different from zero. Thus, mean NA did not appear to influence medication adherence rates among individuals with moderate to high NED. Finally, we re-ran our analyses controlling for the total number of completed diaries, as well as diagnostic status (i.e., individuals with vs. without a current diagnosis of a psychological disorder), and the pattern of results remained the same.

DISCUSSION

Our findings build upon past research demonstrating the protective effects of NED. Specifically, the results suggest that beyond its negative association with maladaptive behaviors, NED may also facilitate adaptive health behaviors, such as daily medication adherence. Moreover, these results held even after controlling for important covariates such as number of completed diaries and diagnostic status. Critically, our sample comprised patients who were recently diagnosed with MS, a period of elevated stress for most new patients, and suggests that NED affords protection even in such highly aversive contexts. This appears especially important given that treatment compliance reduces symptom exacerbations in MS, and in so doing, may help to improve patients' health in addition to psychological well-being and quality of life (Khayyat et al., 2019; Peacock et al., 2021). Finally, these results replicate prior findings associating NED with treatment compliance in patients with a congenital blood disorder (Coifman et al., 2014) and reinforce the importance of considering affective processes in chronic disease management.

Notably, the interaction term between NED and mean NA accounted for 18% of the variance in our model, suggesting that it may be most important to target emotion-related processes in patients showing elevated negative emotion in order to boost medication adherence in MS treatment. This is consistent with a growing body of work that has demonstrated the implicit emotion regulatory benefits of affect labeling, where assigning labels to one's emotions may facilitate downregulation of NA and psychophysiological indices of distress (e.g., amygdala activation; Torre and Lieberman, 2018). Moreover, past research suggests that ED may counteract maladaptive cognitive-emotional processes such as rumination that often exacerbate NA and increase propensity of maladaptive behavioral engagement (Zaki et al., 2013; Seah et al., 2020). Instead, it is possible that ED may enable one to disengage from difficult experiences (rather than staying "stuck"), and in turn facilitate greater psychological distance and adaptive regulation of negative emotion (Kross and Ayduk, 2017; Seah et al., 2021). Nevertheless, these hypotheses remain preliminary and future research should aim to explicitly test possible underlying mechanisms of ED in relation to adaptive behavioral response to increase our understanding of how it may operate.

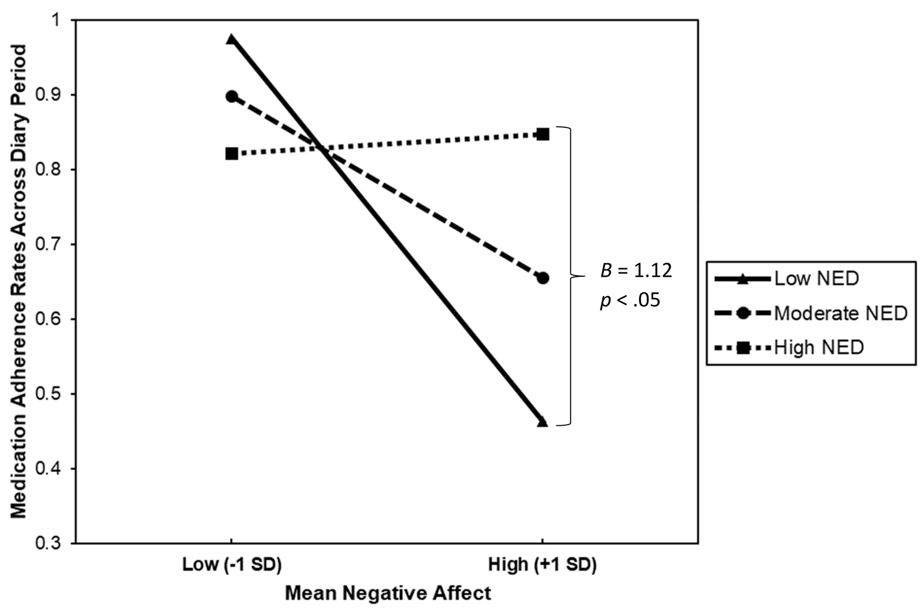

FIGURE 1 | This figure describes the interaction between mean negative affect and negative emotion differentiation (NED) when predicting medication adherence rates across the 58-week diary period among 23 patients with Multiple Sclerosis.

The findings from the current study also have clinical implications. Our results suggest that fostering the ability to differentiate and label emotions may have potential to help patients who exhibit elevated negative emotion and distress while experiencing challenges with medication adherence. Indeed, this is a skill commonly addressed in psychotherapy (Greenberg, 2004), such as dialectical behavior therapy (Linehan, 1993), where explicit training in improving patients' understanding of emotion is associated with reductions in more severe life-threatening behaviors (e.g., suicidal behaviors; DeCou et al., 2019). Given the relatively high incidence and prevalence of common psychiatric disorders in MS (e.g., mood and anxiety disorders; McKay et al., 2018), clinicians may consider identifying patients at-risk for poor adherence and providing referrals as appropriate. While our results are largely preliminary, there is potential for patients to benefit broadly from interventions aimed at developing ED skills nonetheless.

Additionally, that NED, which is derived from more subjective patient-reported outcomes, seem to be able to impact more objective clinical behavioral outcomes such as medication adherence highlights the need to consider psychological factors in medical contexts. Indeed, the effects of psychological factors such as emotion (e.g., fear) on health behaviors (e.g., health screening) have been well-documented in the literature (see review by Consedine and Moskowitz, 2007). This appears particularly important given the chronic and uncertain nature of diseases such as MS, which inflicts significant burden on patients over time. Moreover, compliance with medication regimen is likely impacted by potential negative medication side effects (e.g., pain from injections), as well as other contextual factors (e.g., fear associated with hospital visits; Lynd et al., 2018). Our findings suggest that it may be beneficial for healthcare providers to consider patient-reported outcomes as part of patient care, which may facilitate identification of risk and/or protective factors during the course of treatment.

The results from the present investigation should be considered in light of the following strengths and limitations. First, this was a relatively rare investigation of NED in a high-risk population in relation to an essential and highly adaptive behavioral response to stress (medication adherence during chronic illness). The assessment of both NED and medication adherence was robust and took place over a year-long period of sampling. Most research estimates NED from far shorter periods of time and has almost exclusively targeted maladaptive behavioral responses (Seah and Coifman, 2021). However, our study sample was small and had limited diversity in race/ethnicity and gender. Therefore, our results may not generalize to other racial/ethnic minority groups and non-female-identifying individuals. Despite the small sample, it is important to note that although not a rare disease, MS is still much less common than many other chronic illnesses and thus the total population of MS patients is also small (Evans et al., 2013). As such, our study's findings remain clinically meaningful and would benefit from future replications in larger and more diverse samples. In the present study, we assessed medication adherence broadly which limited our ability to capture variability in frequency and method of dosing for both MS and MS-related medications. Indeed, there is evidence that certain MS medications (e.g., Lemtrada; Barclay et al., 2019) have considerable variability in dosing and demand for adherence. Moreover, recall bias is possible since adherence was assessed via weekly retrospective self-report. However, it was also important to minimize participant burden particularly given the long duration of sampling (~12 months). Nevertheless, future research should consider more sensitive measurements of medication adherence. Finally, the correlational nature of our study prevents conclusive interpretations regarding causality. However, accumulating evidence from experimental studies on ED suggests that it plays a causal role in facilitating adaptive behavioral responses in laboratory provocations (Kircanski et al., 2012; Cameron et al., 2013). This remains an important question worthy of future exploration.

Despite its limitations, the current study revealed important findings that highlight the protective benefits of NED in the context of adjustment to chronic stressors such as MS. Specifically, our findings suggest that NED may facilitate enactment of adaptive health behaviors like medication adherence in patients with elevated distress, that may in turn improve patient health. The clinical implications of our results are also apparent, particularly given the uncertain and life changing nature of chronic illnesses like MS. Future replications in larger, more diverse clinical samples would bolster our findings with potential implications for improving the identification of psychological factors that may facilitate greater adaptation to life stress within vulnerable populations.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are publicly available. This data can be found here: https://osf.io/h5kyf/.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Kent State University Institutional Review Board. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

TS and KC analyzed and interpreted the results. TS drafted the initial manuscript. All authors contributed to study design, revisions of the manuscript, and approved the submitted version.

FUNDING

This investigation was supported (in part) by a PILOT Award from the National Multiple Sclerosis Society to KC.

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Psychology

MINI REVIEW
published: 22 February 2022
doi: 10.3389/fpsyg.2022.715966

Emotional Nuance: Examining Positive Emotional Granularity and Well-Being

*Tse Yen Tan, Louise Wachsmuth and Michele M. Tugade**

Vassar College, Poughkeepsie, NY, United States

The focus of this review is on positive emotional granularity. Emotional granularity is the level of specificity that characterizes verbal representations of an affective experience. Although there has been research on negative emotional granularity, relatively less attention has been given to the study of positive emotional granularity. Positive emotions are theorized to motivate an individual to "broaden and build" one's scope of cognition, attention, and behavior. Distinct positive emotion concepts may provide individuals with more informational value than that provided by global mood. Indeed, individuals who are higher in positive emotional granularity report being better at coping with stressful experiences. In this review, we discuss growing research on positive emotional granularity and well-being. Issues of measurement, interventions, and considerations for future lines of research are discussed.

Keywords: emotion, positive emotion, granularity, well-being, emotion differentiation

OPEN ACCESS

Edited by:
Jennifer Marie Binzak Fugate, Kansas City University, United States

Reviewed by:
Christine Wilson-Mendenhall, University of Wisconsin-Madison, United States
Kristen Lindquist, University of North Carolina at Chapel Hill, United States

****Correspondence:***
Michele M. Tugade
mitugade@vassar.edu

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: *27 May 2021*
Accepted: *13 January 2022*
Published: *22 February 2022*

Citation:
Tan TY, Wachsmuth L and Tugade MM (2022) Emotional Nuance: Examining Positive Emotional Granularity and Well-Being. Front. Psychol. 13:715966. doi: 10.3389/fpsyg.2022.715966

INTRODUCTION

The global pandemic has been emotional. Consider different emotional reactions in response to health and safety ordinances. One response might reflect more broad categories of feeling: "I don't want my stress level to be so high. I want this nightmare to be over." Another response might reflect more nuanced feelings: "I feel sad or I feel anxious and I don't like that feeling, so I get angry at the person (for not wearing a mask)" (Powell, 2020). Lay people, writers, poets, and scientists alike tend to agree that words like happiness, interest, gratitude, anger, sadness, and fear represent distinct kinds of experiences. Yet, people vary in the degree to which they use emotion words to represent separate, discrete experiences (Feldman, 1995; Barrett, 1998, 2004), as seen in the various responses above. This phenomenon is called "emotional granularity" (Barrett, 2004).

Emotional granularity is the level of specificity that characterizes verbal representations of an affective experience. When asked to report how they feel, some individuals use emotion words like "happy," "excited," "sad," and "angry" to represent highly differentiated experiences. These individuals are higher in emotional granularity, and report their emotional experience in more precise, differentiated terms, using discrete emotion labels like happy, sad, angry, etc., in a way that captures the distinctiveness in these words. Others represent their experiences in more global terms. These individuals are low in emotional granularity: they reported their experience in global terms,using discrete emotion labels to communicate only the most general of information (typically, pleasure and displeasure). They use words like "angry," "afraid," and "sad" interchangeably, not distinguishing between discrete emotion terms.

Recent research examining the neural mechanisms underlying granularity shows that emotional granularity extends beyond exclusively verbal representations (Lee et al., 2017). Lowly and highly granular individuals show different patterns of neural activity as their brains represent emotional experiences. When presented with emotional stimuli, highly (vs. lowly) granular individuals evidenced sustained attention and executive control to access conceptual knowledge to make meaning of affective stimuli. As such, the mechanisms of emotional granularity can be captured by neural processing beyond the labeling of emotions, *per se*. These findings show that emotional granularity is the tendency to experience emotion in a highly specific manner (e.g., Lee, et al., 2017).

Emotional granularity has been increasingly associated with social and emotional well- being, and has been theorized to be a key aspect of emotion regulation (Kalokerinos et al., 2019). For instance, individuals high in granularity have been found to possess greater emotion regulation skills (Barett et al., 2001), while low granularity is associated with poor emotion regulation strategy effectiveness (Kalokerinos et al., 2019). The role emotional granularity plays in emotion regulation may be attributed to the feelings-as-information theory(Schwarz, 2012), in that differentiation provides individuals with a better understanding of the cause of the emotion, and therefore facilitates contextually sensitive emotion regulation.

Emotional granularity can refer to the differentiation of both positive and negative emotions. Negative emotional experiences prompt individuals to narrow specific thought-action repertoires, conferring immediate adaptive effects on the individual; however, feeling angry should lead to a vastly different response than feeling afraid (e.g., fight vs. flight). The focus of this review is on positive emotional granularity. Positive emotions are theorized to motivate an individual to "broaden and build" one's thinking, attention, and behavioral repertoires (Fredrickson, 2001; Tugade et al., 2004). Much like in the case of negative emotions, discrete positive emotion concepts may provide individuals with more useful information than that provided by global mood. For instance, individuals who are higher in positive emotional granularity report being better at coping with stressors (Tugade et al., 2004).

BENEFITS OF POSITIVE EMOTIONAL GRANULARITY

Growing research in the field suggests that individual differences in emotional granularity are associated with emotion regulation and psychosocial adjustment. Individuals may differ in how emotionally granular they are. One theory cited in the literature that allows for the exploration of these differences is the Theory of Constructed Emotion, as elucidated by Barrett (2006), wherein emotional concepts are cognitively and socially constructed. Barrett (2006) notes that differences in experiences of emotion can reflect individual differences in perceived intensity and frequency of felt affect, with some individuals reporting their experiences on positive vs. negative dimensions (e.g., pleasant vs. unpleasant), while others report more nuanced, granular experiences (e.g., content, joyful, sad, angry). Studies suggest that emotional granularity may facilitate adaptive coping and successful self-regulation (Kashdan et al., 2015). Research into emotional granularity is still limited, and much of the research has focused on negative emotional granularity. However, emerging evidence shows that positive emotional granularity-though less studied - can be beneficial in its own right.

While emerging theories discuss individual differences in positive emotional granularity, other theoretical works focus on the distinct functions of discrete positive emotions. The theories described below focus on the importance of understanding the unique function of discrete positive experiences. A compelling argument for examining positive emotion differentiation can be found in Ellsworth and Smith (1988) study on positive emotions and associated patterns of appraisal. Though positive emotional experiences were found to be somewhat less differentiated than negative emotional experiences, considerable differentiation was still present, and different positive emotions were found to have distinct patterns of appraisal consistent with the emotions' proposed adaptive functions (Ellsworth and Smith, 1988). Furthermore, Shiota et al. (2014) theorize that there are distinct adaptive functions of discrete positive emotions. In their PANACEAS taxonomy (an acronym that represents eight different positive emotions: pride, amusement, nurturant love, attachment love, contentment, enthusiasm, awe, and sexual desire), Shiota et al. (2014) explore the events that the aforementioned positive emotions might be responsed to, and then posit potential adaptive responses to that event. For instance, awe is experienced when one encounters novel and complex information about the world beyond one's previous knowledge and understanding; an adaptive response to awe might be to form new schemas about the world (Shiota et al., 2014). Yet another approach is Fredrickson's Broaden-and-Build theory, which posits that positive affective experiences broaden people's momentary thought-action repertoires and serves to help individuals build personal resources (Fredrickson, 2003). For instance, Fredrickson (2003) notes the thought-action tendency and the personal resources accrued for pride to be different from joy. Taken together, the work by Ellsworth and Smith (1988), Shiota et al. (2014), and Fredrickson (2013) all point to how the appraisal, adaptive functions, and experience of different positive emotions can lead to different outcomes. Positive emotion differentiation therefore may play an important role in long-term thriving, as specific positive emotions may signal potential context-dependent benefits and can influence one's behavioral intentions (Soscia, 2007).

Positive emotional granularity may thus have benefits in terms of social relationships. Aptitude in emotional granularity may translate to one having a more accurate understanding of the emotional states of others, and facilitate interpersonal communication; studies have found

TABLE 1 | Hypothesized benefits of positive emotional granularity and supporting theoretical approaches.

Possible benefits of positive emotional granularity	Approaches/Theories
Social connections, e.g., improved relationship quality	Broaden-and-build theory (Fredrickson, 2004)
	Emotions-as-information theory (Schwarz, 2012)
Combat hedonic adaptation	Hedonic adaptation prevention model (Lyubomirsky, 2011; Bao and Lyubomirsky, 2013)
Physical health	Emodiversity (Quoidbach et al., 2014)
	Emotions-as-information theory (Schwarz, 2012)

that individuals high in emotion differentiation were more able to accurately categorize and recognize others' facial expressions, and individuals with high emotional granularity were better able to judge the emotions of their romantic partners (Erbas et al., 2016; Israelashvili et al., 2019). Though these studies focused on negative emotion differentiation, differentiating between one's positive emotions may similarly be beneficial to understanding the emotions of others.

According to the emotions-as-information theory (Schwarz, 2012) a heightened ability to differentiate between positive emotions may lead to a range of different affective and cognitive responses depending on the specific emotion. Algoe et al. (2010) found that experiencing feelings of gratitude in the context of a romantic relationship has been associated with increased feelings of relationship quality. Research shows that in individuals with anorexia, those with low positive emotional differentiation engaged in more vomiting, laxative use, exercising, weighing, restricting, and checking for fat. Furthermore, individuals who reported higher positive emotion intensity and low positive emotion differentiation engaged in even more frequent maladaptive weight-loss behaviors, suggesting that the effect of positive emotion intensity on weight-loss behaviors is moderated by low positive emotion differentiation. Selby et al. (2014) theorize that the unhealthy behaviors are due to the individuals' attribution of general positive mood about reaching their weight-loss goals to specific positive emotions such as confidence, accomplishment, and happiness. This misattribution and over association of a broad range of positive emotions with the achievement of a weight-loss goal therefore leads to the perpetuation of unhealthy behaviors. Because of the unique functions and informational value of specific positive emotions, high positive emotional granularity is especially important as the lack thereof may limit or misguide one's behavioral responses in a given situation.

Additionally, Bao and Lyubomirsky (2013) have posited that increasing the number of positive events and emotions in a relationship may combat hedonic adaptation, leading to sustained relationship well-being. One could hypothesize that experiencing a diversity of positive emotions would also be useful in building resistance to one's adaptation to a positive emotional experience, building on previous findings that suggest that novelty can reduce habituation (Leventhal et al., 2007). Positive emotional differentiation may also lead to better health outcomes: Quoidbach et al. (2014) found that positive emodiversity was negatively related to annual visits to family doctors, days spent in the hospital per year, and the mean defined daily dose of medication, in contrast to mean positive emotion, which was not significantly related to any of these indicators of health. While emodiversity and emotional granularity are different concepts, the constructs seem to be linked. To experience a diverse range, and abundance of emotions, or to have high emodiversity, likely requires that an individual be able to differentiate between varied emotions, rather than experiencing general, global moods. See **Table 1** for a summarized list of these hypothesized benefits of positive emotional granularity alongside their theoretical approaches.

POSITIVE EMOTIONAL GRANULARITY ACROSS CULTURES

Another relevant area of positive emotional granularity research is cross-cultural research, which can reflect different nuances in positive emotional experiences. Given the benefits of emotional granularity, it is likely important and present across cultures; however, it is important to consider cross-cultural factors that may reflect differences in emotional experiences, such as differences in the perceived affective valence (An et al., 2017), and physiological arousal in response to a given experience (Lim, 2016). For instance, An et al. (2017) found cross-cultural differences in the perceived degrees of "positivity" and "negativity" of six "basic" emotions (sadness, fear, disgust, anger, surprise, and happiness) Ekman, 1992. While basic emotions may be common globally, the interpretation and perception of said experience can differ: Chinese individuals view happiness as a harmonious, homeostatic state, and understand that pursuing happiness may not always be positive. In contrast, Americans describe happiness as more emotionally charged (Lu and Gilmour, 2004), and pursuing happiness is considered desirable. Drawing on the constructionist theory of emotion (Barrett, 2006; Lindquist and Barrett, 2008), language, and concepts (that may be socially learned) constitute the experience and perception of emotion, by helping one to make meaning of internal sensations and external stimuli. Taken together, the research on cultural differences in positive emotional experience has important implications for the study of positive emotional granularity. One's propensity for emotional granularity, may vary because of differences in attention to different facets of an emotional experience, which may be influenced by philosophical traditions (e.g., Confucianism, Buddhism; Lu and Gilmour, 2004; Zhou et al., 2021), education, and language. In addition, differences in emotional experiences may also have implications for subsequent behavioral responses and emotion regulation.

Positive emotional granularity might also be reflected *via* non-verbal channels. There are different ways that people might express feelings of joy, surprise, and amusement that are context-dependent, therefore differentiation of positive emotions (both in oneself and in others) must be culturally informed. For instance, Jack et al. (2012) found differences in facial expressions between individuals from Western and Eastern cultures. Eastern individuals were found to express emotional intensity primarily with eye activity (Jack et al., 2012); these results corroborate previous studies exploring cultural differences in recognizing facial expressions, where Eastern groups were found to fixate on the eye region (Jack et al., 2009). Similar to facial expressions, non-verbal emotional vocalizations are a means of communicating specific affective states. In a study conducted by Sauter et al. (2010), while "basic emotions" were recognized *between* cultural groups, vocalizations of positive emotions were specific *within* cultural groups. Noting the variability in expression and perception is important, especially when communicating differential positive emotions (Sauter, 2017). Together, these studies indicate that the study of positive emotional granularity in cultures is important because it can demonstrate that granularity is expressed and communicated differentially between individuals within a cultural group (e.g., upper face expressions, vocalizations).

MEASURING EMOTIONAL GRANULARITY

Many studies have used experiential sampling methodology to measure positive emotional granularity. Experience sampling methodology (ESM) gathers data on individuals' feelings, thoughts, and actions in the context of everyday life. Applying ESM to positive emotional granularity allows researchers to measure the differentiation of emotions as they are experienced, *in situ*, in the context of daily life. Participants rate their momentary emotional experience multiple times a day, for several weeks. Using ESM, researchers may compute an emotion differentiation index based on the interrelatedness of similarly-valenced emotion terms (Barett et al., 2001; Tugade et al., 2004). Greater interrelatedness when reporting positive emotional words would reflect lower emotional granularity (less differentiation); whereas lower interrelatedness when reporting positive emotional experience reflects higher emotional granularity (more differentiation). Such methods capture momentary emotion differentiation, in an ecologically valid context, and also makes use of new technologies at hand.

Previous measures of granularity have relied mainly on experience-sampling methods (e.g., Barett et al., 2001; Tugade et al., 2004). ESM offers an important advantage in that the measures are based on participants' actual emotional experiences as they unfold over time, revealing unique patterns of emotional experience within each individual. Even still, this approach has some limitations. First, because the experiences sampled are those that arise spontaneously across different contexts in respondents' lives, the set of experiences can vary greatly from individual to individual, sometimes rendering the scores difficult to compare across individuals. There would be considerable utility in differentiation scores derived from a common set of experiences. Second, ESM can be time-consuming, expensive, and difficult to implement. Thus, ESM can limit the range of studies to measure positive emotion granularity and associated factors.

As research on positive emotion granularity increases, researchers have developed new measures of positive emotional differentiation. One such measure is the Differentiation of Positive Emotion Scale (DOPES), wherein individuals are asked to imagine and indicate their emotional reactions to a set of eight positive emotion-eliciting vignettes (Kirby et al., 2014). Each vignette is designed to elicit a specific positive emotion, and respondents are asked to rate their emotional reaction based on eight targeted emotions: happiness, pride, gratitude, interest, hope, challenge/determination, awe, or contentment. This self-report measure can be used to assess individual differences in positive emotional granularity. For each vignette, respondents are asked to rate their imagined emotional responses in terms of each of the eight targeted emotions. The degree of emotion differentiation (granularity) for each respondent is quantified by intercorrelating the ratings for each emotion scale across the eight vignettes, then computing the mean intercorrelation. To normalize the distribution of the resulting scores, this average correlation is subjected to an *r*-to-*z* transformation. Higher mean intercorrelations reflect *lower* levels of differentiation because they indicate that the emotion ratings covary strongly across the vignettes (Kirby et al., 2014). Thus, in addition to ESM, the DOPES is another viable measure of the tendency to differentiate positive experiences.

POSITIVE EMOTIONAL GRANULARITY INTERVENTIONS

Although research on the benefits of emotional granularity is growing, there has been little focus on ways to improve emotion differentiation ability, and the research on positive emotional granularity interventions is especially sparse. Mindfulness techniques may be useful in contributing to more positive emotional differentiation. In an empirical study of a mindfulness- based intervention, Van der Gucht et al. (2019) hypothesized that mindfulness may contribute to better positive and negative emotion differentiation. Significant improvement in both positive and negative emotion differentiation was found, although the study did not include a control group. Improvements in negative emotion differentiation were found both post intervention and at a 4 month follow up, although after controlling for negative affect levels this improvement was no longer significant. Improvement in positive emotion differentiation was only significant at the 4 month follow up, and was significant even after controlling for mean positive affect levels. Van der Gucht et al. (2019) speculate that these findings may mean that positive emotion differentiation takes more time to learn as compared to negative emotion differentiation, or that there is more opportunity to improve negative emotion differentiation. While the results of this study are complex and findings may differ when including a control group, the findings indicate that mindfulness-based interventions may be useful tools in improving emotion differentiation (Van der Gucht et al., 2019). Programs focused on emotional intelligence may also be relevant to emotional granularity and often include aspects of emotion differentiation training.

Programs that promote emotional intelligence and social emotional learning often also focus on emotion labeling and differentiation. While many of these interventions do not directly measure emotional granularity, they may be useful to improve emotional granularity and often focus indirectly on emotion differentiation. Emotional intelligence training has been shown to lead to improvement in emotion identification and differentiation (Nelis et al., 2009). RULER is one such intervention that may improve emotional intelligence as well as emotional granularity. For example, the RULER feeling words curriculum focuses on teaching students about feeling or emotion words, what they mean, and how to label their emotions accurately. Each unit includes multiple different lessons and activities integrated into classroom instruction focusing on specific feeling or emotion words (Brackett et al., 2012). Integrating these types of curricula may help students correctly label and differentiate between their emotions. Broadening children's understanding and use of different emotion words and correctly labeling their emotions using the RULER feeling words curriculum has led to improved academic performance and social behavior (Brackett et al., 2012).

Interventions targeting emotional differentiation may be useful for adults in the workplace. In fact, one study found that employees who participated in an emotional intelligence intervention which included a focus on emotion differentiation had increased work performance scores after participating in the intervention (Munir and Azam, 2017). Interventions that include a focus on emotional granularity should be developed and implemented across the lifespan. A focus on positive emotion differentiation especially may have benefits in terms of social relationships. Interventions that ask individuals to differentiate between positive emotions and to reflect on the functionality of their felt emotional experiences (Shiota et al., 2014) may also be especially valuable. This approach may help individuals learn about why certain distinct positive emotions (e.g., pride vs. gratitude) can be adaptive in various contexts of one's daily life.

CONCLUSION AND FUTURE DIRECTIONS

The present paper sets the stage for future research directions. For instance, it would be fruitful to disentangle the effects of state versus trait positive emotional granularity. It may be possible that particular contexts allow one to be more emotionally granular than others, and this might have implications for emotion regulation. Second, it would be important for future work to experimentally manipulate positive emotional granularity. Experimental manipulations of emotional granularity would allow future research to make causal claims about the consequences of emotion differentiation. Indeed, because emotional granularity has been studied as an individual difference construct as measured in the context of daily life, such manipulations would be complex and require further investigation. Third, it would be important to investigate the processes that allow for positive emotional granularity. We speculate that emotional granularity may reflect individual differences in complex emotion knowledge or cognitive resources that are useful in appropriately and effectively navigating through one's daily life. Empirical work on this theory could reveal important psychological and cognitive processes that link positive emotional granularity with emotion regulation. Fourth, it would be important to examine the developmental trajectory of emotional granularity. There may be individual differences in people's capacities to be granular for positive versus negative emotional experiences. Understanding mechanisms associated with such differences would elucidate the developmental path that enables one to achieve high levels of precision in their representations of emotion.

AUTHOR CONTRIBUTIONS

MT, TT, and LW contributed to the conception and design of the manuscript and wrote sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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frontiers | Frontiers in Psychology

TYPE Methods
PUBLISHED 10 November 2022
DOI 10.3389/fpsyg.2022.690030

Check for updates

OPEN ACCESS

EDITED BY
Jennifer Marie Binzak Fugate,
Kansas City University,
United States

REVIEWED BY
Andrea De Cesarei,
University of Bologna,
Italy
Katie Hoemann,
KU Leuven,
Belgium

*CORRESPONDENCE
Sean P. Lane
lanesp@missouri.edu

SPECIALTY SECTION
This article was submitted to
Emotion Science,
a section of the journal
Frontiers in Psychology

RECEIVED 01 April 2021
ACCEPTED 21 October 2022
PUBLISHED 10 November 2022

CITATION
Lane SP and Trull TJ (2022)
Operationalizing undifferentiated affect:
Validity and utility in clinical samples.
Front. Psychol. 13:690030.
doi: 10.3389/fpsyg.2022.690030

Operationalizing undifferentiated affect: Validity and utility in clinical samples

Sean P. Lane* and Timothy J. Trull

Department of Psychological Sciences, University of Missouri, Columbia, MO, United States

Emotion differentiation is conceptualized as the process of categorizing one's general affective experiences into discrete emotions. The experience of undifferentiated affect or the inability to distinguish the particular emotion or combination of emotions that one is experiencing is often considered a hallmark of emotion dysregulation. Some past research has attempted to operationalize the general tendency to experience undifferentiated affect at the trait level using explicit questionnaire measures. More recently, indirect measures using intraclass correlation coefficients (ICCs) to estimate the consistency between simultaneous measures of different in-the-moment emotional experiences have become the favored method of quantifying undifferentiated affect. While the ICC method constitutes an advancement in estimating undifferentiated affect, which is theorized to be a dynamic process that occurs at a very granular level, prior investigations have used aggregate ICC measures or momentary ICC derivations that ignore multiple sources of dynamic variability to make inferences about in-the-moment experiences. We introduce a new, flexible method of calculating ICC measures of undifferentiated affect at different levels of experience that takes full advantage of time-intensive data measurement and more closely maps onto the theorized process. This method provides more refined estimates of undifferentiated affect and its associations with various behavioral outcomes, as well as uncovers more nuanced associations regarding the temporal process of emotional differentiation. It also elucidates potential conceptual issues in mapping empirical estimates of emotion undifferentiation onto their underlying theoretical interpretations.

KEYWORDS

ecological moment assessment, emotion differentiation, emotional granularity, generalizability theory, longitudinal data analysis

Introduction

Undifferentiated affect/emotion, alternatively characterized as the lack of emotional "granularity" or "complexity" (e.g., Suvak et al., 2011; Grühn et al., 2013; Kashdan et al., 2015), refers to an individual's tendency to experience generalized feelings of positivity or negativity instead of actively discriminating between discrete emotional experiences

(Barrett et al., 2001). This tendency is thought to inhibit one's ability to regulate emotions and adapt to stress (Barrett et al., 2001) because the experience of discrete emotions provides information regarding appropriate coping behaviors (Schwarz and Clore, 1983, 2003). Indeed, the inability to differentiate between different affective experiences, especially negative ones (Barrett et al., 2001; Kashdan et al., 2015), has been linked to various behavioral and health impairments and clinical disorders (Kashdan et al., 2010; Demiralp et al., 2012; Pond et al., 2012; Selby et al., 2013; Zaki et al., 2013).

Recently, Kashdan et al. (2015) reviewed findings from research investigating processes linked to undifferentiated affect (UA), noting the large potential impact on general well-being. They also focused on the importance of careful measurement of UA, advocating experience-sampling or ecological momentary assessment (EMA; Stone and Shiffman, 1994; Shiffman et al., 2008) methodologies, which minimize retrieval and self-belief biases (Robinson and Clore, 2002) and allow for a covert behavioral index of UA to be calculated. Such an approach also allows for estimates of UA that are reflective of individuals' actual day-to-day experiences. Moreover, others have noted that there has been a disconnect in the trait versus state theoretical conceptualization of emotion differentiation and its methodological operationalization, resulting in gaps in our empirical understanding of its effects on psychological outcomes (Thompson et al., 2021). However, depending on the conceptualization, matching the corresponding measurement allows for more robust tests of situational versus generalized hypotheses (Thompson et al., 2021). Recent meta-analyses speak to this gap, noting primarily small or nonsignificant findings between undifferentiation and well-being at the trait level and inconclusive patterns at the state level (O'Toole et al., 2020), or small but reliable negative associations between negative emotion differentiation and maladaptive behaviors specifically (Seah and Coifman, 2021).

We resonate with these reviews asserting that measurement of UA is important and that EMA is a promising way to characterize it (Kashdan et al., 2015), but that there is a limitation in pairing its conceptualization with its operationalization (Thompson et al., 2021) with emotional negativity being a particular area of interest (Seah and Coifman, 2021). The purpose of this paper is to demonstrate the limitations of commonly used analytic methods to quantify UA and how conclusions from previous ways of quantifying UA may, in fact, be misleading. Specifically, we highlight how previously used analytic methods, essentially person level analytic approaches, can result in the inflation of UA estimates because they do not separate or identify variance due to systematic changes in affect, variation in difficulty of items, and variance due to items measuring the same subscale of affect. To address these limitations, we offer an analytic method using Generalizability Theory (GT; Cronbach et al., 1972; Brennan, 1992; Cranford et al., 2006) to partition these important sources of variance. If multiple items per emotion category are administered, this method can be used to estimate UA at the *momentary level* in intensive longitudinal data, a level where UA processes are theorized to operate (Barrett et al., 2001; Erbas et al., 2019). We discuss the decision-making process regarding how to handle assessment data that include the identical ratings for items (resulting in a lack of variance), a result that is more likely when considering momentary data. Finally, we compare how the associations between UA and self-reported impulsive behaviors differ when operationalizing UA, (a) with traditional versus GT approaches, and (b) at different levels of experience (i.e., momentary-, daily-, and person-level). We also consider the implications of handling assessments with no variability in items' scores in different ways.

Generalizability theory

Generalizability Theory (GT) offers a way to systematically examine the variance in single-trial occasion measurements and identify various sources of systematic signal that can be used to estimate reliability coefficients. GT is an expansion of classical test theory (i.e., Spearman-Brown approaches), which acknowledges that the variance in an observed score is born of multiple influences (Cronbach et al., 1972). GT decomposes a true score into a researcher-specified set of constituent systematic sources of variance based on the structure of their data rather than a single true score as in classical test. In this way, GT can be used to better capture and understand not only factors conceptualized as contributors to randomness, but also how variance components of interest may affect observed scores (Shrout and Lane, 2012). Within the GT framework, the first set of analyses conducted is commonly referred to as a "G study," the goal of which is to estimate sources of potential variance in observed scores. An advantage of this approach is that the variance components included in the G study can be defined and adjusted by the researcher according to their research design and desired application. Further, the treatment of repeated measures within subjects can be specified (e.g., crossed vs. nested within subject) when estimating these variance components. G study analyses are computed as linear combinations of ANOVA mean squares.

The second set of analyses utilized in GT is commonly referred to as the "D study," wherein the variance components derived from the G Study are used to estimate reliability as a proportion of variance. Just as in classical test theory, the reliability (i.e., dependability and consistency) of a measurement represents the ratio of variance from "true" scores to the total relevant variance (i.e., true variance + variance attributable to all sources of error). Factors are treated as either fixed or random by their inclusion in the denominator of the reliability formula. These analyses are used to assess the reliability of a measurement given a study's assessment factors (e.g., survey assessments varied across raters, items, days, etc.). It is here where the ICCs that represent undifferentiated negative affect are calculated based on the set of derived variance components.

Person level UA estimation

Most investigations of UA involving intensive longitudinal assessments have relied on indirect average inter-item correlations (e.g., Zaki et al., 2013; Erbas et al., 2018; Kalokerinos et al., 2019) or intraclass correlation coefficients (ICCs; e.g., Pond et al., 2012) to evaluate the degree to which responses to items corresponding to different emotions from self-report questionnaires are consistently rated similarly in generating an index of UA. ICCs subsume inter-item correlations, so we focus on those as our point of comparison. The common design is to ask individuals to rate, using self-report, and the same series of affect items across multiple occasions or days. Then a basic two-way ANOVA model corresponding to Equation 1 can be estimated for each person where items are treated as fixed and occasions as random.

$$Ratingi_o = \mu + Ii + O_o + ei_o \tag{1}$$

Here, $Rating_{io}$ corresponds to a person's rating of item, i, at occasion, o. μ is the grand mean for all ratings. I_i is the tendency for an item to be rated higher/lower on average for that person, and O_o is the tendency for a given occasion to on average have higher/lower ratings. e_{io} is error. Once this model is estimated, a traditional ICC can be computed using the sums of squares [specifically ICC(3,1); Shrout and Fleiss, 1979]. The resulting value is an index of the consistency with which an individual rates items across occasions. Higher values indicate that an individual does not vary in the way he/she rates items at a given random occasion (i.e., high UA).

This approach seems straightforward. However, we note a few important limitations. First, if individuals are being sampled over multiple days or weeks where systematic effects on affect might be expected (i.e., weekend, morning/evening), *estimates of UA may be inflated due to the confounding of occasion and error*. Second, if certain items are systematically elevated across occasions as a result of being easier to endorse (e.g., sad vs. hopeless), *UA estimates may again be inflated because this variance is being confounded with variance estimated across items* (i.e., precisely what we are most interested in as an indicator of UA). Third, there may be *other systematic factors that contribute variance to the error*, independent of individual items and occasions, which may inflate estimates (e.g., if certain items correlate because they belong to a common subscale). Each of these factors can effect overall UA estimates as well as associations between UA and other variables to the extent to which individuals vary on their experience of each (i.e., some individuals experience more extreme diurnal and/or weekly shifts in mood than others).

To account for these potential confounding factors, we adopt a GT approach (Cronbach et al., 1972; Brennan, 1992; Cranford et al., 2006) to estimating ICCs for UA. The GT approach uses the same ANOVA structure to model variability, except it allows the basic two-way ANOVA model to be expanded to accommodate other sources of variance. Such models can then be estimated using any variance decomposition software (for examples, see Shrout and Lane, 2012) and the individual variance components used to estimate ICCs. We start by giving the analogous GT ICC estimate for UA based on the ANOVA model in Equation 1. It is given in Equation 2.

$$R_{P1} = \frac{\sigma^2_{ITEM}}{\left(\sigma^2_{ITEM} + \sigma^2_{ERROR}\right)} \tag{2}$$

This estimate gives the proportion of total variance that is accounted for by individual items (i.e., how differentiated each item is from the others across repeated measurements) and is analogous to ICC(3,1). To get an estimate of UA, we subtract this value from one. Next, we expand the ANOVA model to include other sources of variance. We do this based on an EMA design (see below) in which individuals are assessed multiple times a day for a number of consecutive days. At each assessment, they complete a set of items (e.g., negative affect) that contain item subsets corresponding to different specific emotions (e.g., sad, hostile, and fearful). Using this design, the following ANOVA model can be constructed (Equation 3).

$$\begin{aligned} Rating_{io} = \mu + I_i + S_s + O_o + D_d + (IS)_{is} + (IO)_{io} + (ID)_{id} \\ + (SO)_{so} + (SD)_{sd} + (OD)_{od} + (ISO)_{iso} \\ + (ISD)_{isd} + (IOD)_{iod} + (SOD)_{sod} + e_{isod} \end{aligned} \tag{3}$$

The interpretation is as before, except now we have the additional factors of subscale, s, and day, d. There are also the six two-way and four three-way interactions between the variables. This allows for certain subscales and certain days to have systematically higher/lower ratings than others across the repeated assessments. The two-and three-way interactions allow, for example, that certain subscales may be systematically higher/lower on specific days (e.g., if hostility is particularly low on weekends compared to sadness and fear).[1]

1 We note that there can be some ambiguity as to which terms should be included in the model. For example, the items for each subscale are likely unique to that subscale and so, formally, item is nested within subscale. In this case the terms $(IS)_{is}$, $(ISO)_{is}$, and $(ISD)_{is}$ would be removed from the model and/would be replaced with $I_{i(s)}$. However, to the extent to which the items are consistently given in the same order when presented, there may be a systematic ordering effect (e.g., the first item is disproportionately elevated; Knowles et al., 1996) that allows the interaction effect to be estimated. Similarly, conventional parlance would suggest that occasions are nested within days; however, if individuals are systematically sampled in the morning, afternoon, and evening across multiple days, occasions can be considered crossed with days (i.e., the interaction can be estimated). Some of the terms may be inestimable, such as the higher order interactions, in which case they may often be dropped with little effect. If a researcher's design does not conform to this model they may simply drop all terms containing that design element (i.e., occasions) and perform a variance decomposition as before.

After performing variance decompositions for each individual and saving the variance components, an estimate for UA can be calculated using Equation 4, where N is the number of items per subscale.[2]

$$R_{P2} = \frac{\sigma^2_{SUBSCALE} + \sigma^2_{ITEM*SUBSCALE}}{\left(\sigma^2_{SUBSCALE} + \sigma^2_{ITEM*SUBSCALE} + \frac{\sigma^2_{ERROR}}{N}\right)} \quad (4)$$

This estimate gives the proportion of total variance that is accounted for by the different subscales (i.e., how consistently an individual rates items within a subscale as compared to items that belong to different subscales). This value represents a generalized estimate of ICC(3,1) generated as the *D*-study portion of a generalizability analysis (Cronbach et al., 1972). We again subtract this value from one to get an estimate of UA. If an investigator is treating items as nested, the variance for the interaction terms in the equation would be dropped and the item nested with subscale variance ($I_{i(s)}$) may be added to the denominator.

Momentary UA estimation

It seems desirable to examine UA as it occurs in daily life, and how it, itself, may be dynamic. However, previous operationalizations of UA calculate person-level estimates to characterize this theoretically very temporally fleeting process (Barrett et al., 2001; Zaki et al., 2013; Erbas et al., 2018; Kalokerinos et al., 2019). Momentary UA can be evaluated when multiple items are used to assess each of a set of emotions in a given assessment. Then a model analogous to Equation 1 can be estimated, but instead this is done for each assessment in an individual's time series.

$$Rating_{is} = \mu + Ii + Ss + e_{is} \quad (5)$$

Equation 5 depicts the model fit for each occasion of an individual. At each time point, a rating is a function of the grand mean (μ), which item is being responded to (i), and which subscale that item belongs to (s). The corresponding estimate for the momentary ICC is as follows:

$$R_{M1} = \frac{\sigma^2_{SUBSCALE}}{\left(\sigma^2_{SUBSCALE} + \frac{\sigma^2_{ERROR}}{N}\right)} \quad (6)$$

The formula for R_{M1} is similar in structure to R_{P1} except the item variance has been replaced with subscale variance as in R_{P2}. In addition, we divide the error by the number (N) of subscale items as in R_{P2}, since our interest is in differences in ratings across subscales. Again note that if items are considered nested within subscale, item variation would be included in the denominator. As in R_{P2}, we must again subtract this value from 1 to get an estimate of UA.

Of note, and core to the labeling of the index as undifferentiated *affect*, the resulting ICC represents individuals' tendencies to disambiguate general affective categories and not the specific emotions that may comprise those categories, such as those located within the same quadrants or cluster regions of the affective circumplex (Russell, 1980). The theory of *emotion* differentiation (Barrett et al., 2001) argues for individuals' ability or tendency to isolate discrete emotional experiences, as it serves to inform emotion regulation strategies. This is how all operationalizations of emotion differentiation have proceeded to date, either at the person (i.e., trait) or occasion level. However, we consider at least two related challenges to the validity of these approaches. First is that research suggests that, at least when utilizing self-report in naturalistic environments, individuals tend not to discriminate reliably between individual emotion prompts, but rather very reliably group them into broader affective categories (e.g., Hepp et al., 2017, 2018, 2020; Erbas et al., 2019). Second, existing approaches use individual emotion items to estimate emotion differentiation indices that assume perfect reliability (i.e., no measurement error), yet psychometrically and empirically single item measures underperform (e.g., Wanous and Reichers, 1996; Wanous and Hudy, 2001). Combined, these methodological concerns would suggest that existing emotion differentiation estimation approaches are contaminated by and possibly capitalizing on considerable error, drawing into question the various empirical associations that have been observed, or at least if they represent true differentiation or some degree of response bias. By utilizing multiple items to assess broader affective categories and broadening the scope of differentiation to the disambiguation of those categories, the current proposed method addresses these issues and increases the reliability of the (un) differentiation estimate and resulting inferences. However, then the construct being measured conceptually changes.

One potential limitation of estimating UA at the momentary level is if there is no variability in ratings (e.g., if all items are rated as 0, or otherwise absent, in the moment). If all ratings are the same, at least superficially that would appear as complete undifferentiation, since an individual is not discriminating between different discrete emotion probes. This seems reasonable if all of the ratings are elevated indicating at least some emotional experience. However, it is less clear in the case that all of the ratings are at the floor of a given scale (i.e., a score of 0, or otherwise "not at all" on many scales), usually indicating the absence of experiencing the given emotion. We examine the frequency of such reports and their impact on analysis results and interpretations in the following example. At any rate, empirically,

2 If the number of items varies by subscale, a conservative estimate would be to use the smallest item set size. Alternatively, a harmonic mean could be estimated (Raudenbush and Bryk, 2002).

using our momentary method would result in missingness in each of these scenarios and decisions must be made on how to handle it. We discuss three options based on the above rationale.

Empirical example

The current example uses an EMA approach to examine the relationship between undifferentiated negative affect (UNA) and impulsivity/substance use among individuals with disorders often tied to emotion dysregulation. Past studies have found that UNA is often associated with general predispositions toward impulsivity (Tomko et al., 2015), as well as specific impulsive behaviors (Kashdan et al., 2010; Pond et al., 2012; Selby et al., 2013; Zaki et al., 2013). We estimated UNA at both the person level and momentary level using Equations 2, 4, 6, including three ways of handling missing data at the momentary level due to the absence of variability. Results from analyses predicting impulsivity and substance use are compared across the different methods. A simulation study was also conducted to corroborate empirical findings.

Materials and methods

Participants

Participants[3] included 131 individuals with borderline personality ($N=81$) and depressive ($N=50$) disorders who were recruited from local psychiatric outpatient clinics for a study examining affective instability (see Trull et al., 2008). Previous studies have reported on differences between these two diagnostic groups in terms of mean levels (e.g., Trull et al., 2008; Solhan et al., 2009; Tomko et al., 2014, 2015) and associations between (Jahng et al., 2011) variables that we include in our analyses, including UNA (Tomko et al., 2015). While there were mean level differences in some of these variables between groups, specifically UNA (Tomko et al., 2015), there were no differences in the associations between these variables across diagnostic groups in the presented analyses, so we chose to combine the data across groups. This quality, with respect to the association between emotion (un) differentiation salient outcomes speaks to its theorized transdiagnosticity as a construct across healthy and dysregulated emotional functioning (Barrett et al., 2001).

Given these two groups' chronic elevated experience of negative affect compared to the general population, we viewed analysis of their data as an example of a *minimal-impact* case of the influence of zero variance reports. Zero variance reports, for example, may result from ratings indicating no experienced negative affect (i.e., all floor reports; see Figure 1). Analysis of UNA in the general population compared to our sample would likely result in more zero-variability reports and less variability in ratings overall.

General exclusion criteria included having a psychotic disorder, history of severe head trauma, intellectual disability, severe substance dependence, or severe neurological dysfunction. Individuals were required to be between the ages of 18 and 65 to participate ($M=31.6$, $SD=11.9$). Most participants were female (92.5%), of Caucasian ethnicity (82.1%), were single/never married (53.7%), had an annual income less than $25,000 (74.6%), and had current comorbid anxiety (85.9%) or mood (63.1%) disorders.

Procedure

Participants who passed an initial eligibility screening were scheduled for an orientation session where diagnostic information was obtained from semi-structured interviews (Pfohl et al., 1994; First et al., 1995; see Trull et al., 2008 and Tomko et al., 2015, for details). After being confirmed as eligible, participants were issued an electronic diary (Palm Zire 31© handheld computer) that they carried for approximately 28 days ($M=28.8$ days). The electronic diary (ED) alarmed six times per day, prompting the individual to answer questions about current mood and a variety of different substance use. Across prompts, the item sets corresponding to different modules were always administered in the same order, as were items within each module. However, items for modules that represented scales were *a priori* randomized (e.g., intermixing positive and negative affect items and affect items within individual subscales). The alarm times were determined by a software program that stratified the participants' usual waking hours (as reported by the participant prior to the study start) into six equal intervals, and then randomly selecting a time within each interval (see Trull et al., 2008, for more details regarding the electronic diary protocol). The compliance in the sample was high ($M=85.8\%$), with participants completing an average of 147.0 prompts each. In total, 19,318 prompts were completed and included in the analyses.

Measures

Negative affect

Affect was assessed using items from the Positive and Negative Affect Schedule-Extended version (PANAS-X; Watson and Clark, 1999). Items were presented to each participant on the ED during each of the six daily momentary assessments. For each affect item, respondents were asked to rate the extent to which they felt the particular affective state on a five-point Likert scale (1 = very slightly or not at all to 5 = extremely) since the last prompt. The negative affect items composed three negative emotion scales: fear (six items; afraid, nervous, frightened, shaky scared, and jittery),

3 Results from the current sample with different foci are also published in Jahng et al., 2008, 2011; Trull et al., 2008; Solhan et al., 2009; Tomko et al., 2014,2015.

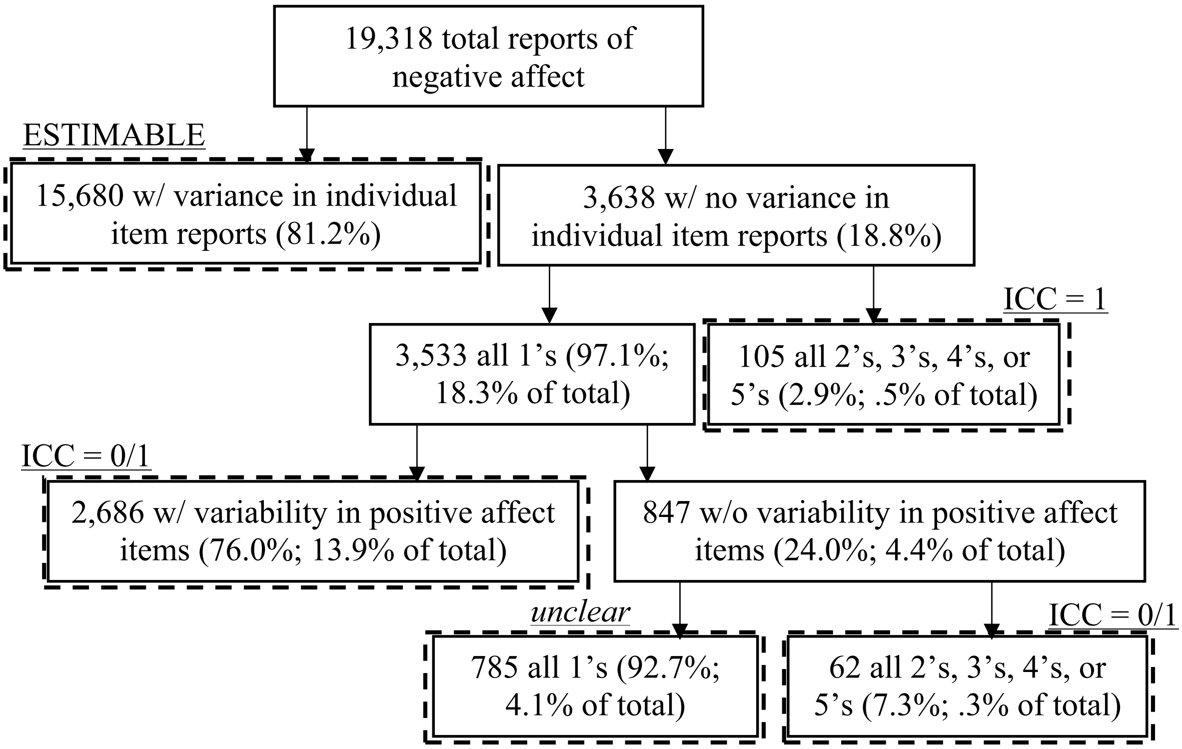

FIGURE 1
Flow diagram of affect reports with and without variability in item ratings. Undifferentiated affect cannot be estimated at the occasion level for affect reports with no variability. Therefore decisions must be made to exclude such reports from analysis, or impute them with theoretically meaningful values. We present potential options, though it is unclear how to handle occasions with no variability across all items of both positive and negative affect.

hostility (six items; angry, irritable, hostile, loathing, scornful, and disgusted), and sadness (five items; sad, blue, alone, downhearted, and lonely). Overall level of negative affect was created as an average of the 17 items. It is important to note that both the average individual differences in these subscales (R_{KF}'s > 0.95) and their reliabilities of change across time points (R_C's > 0.84) have high reliability (Shrout and Lane, 2012; Hepp et al., 2017), given that the current ICC approach explicitly parses variance assumed to be unique across items that belong to different subscales. In the case where individual item or subscale ratings were not reliable, (un) differentiation estimates would similarly not be.

Undifferentiated negative affect

To estimate an individual's negative affect undifferentiation, variance decomposition analyses were conducted at either the person-or occasion-level in accordance with Equations 2, 4, 6. At the *person level*, models were specified according to Equation 2 for the conventional UNA ICC, and Equation 4 for the GT-based UNA ICC. At the *occasion level*, a model based on Equation 6 was specified. The variance components from each model were then used to estimate person-level UNA ICCs for the conventional (Equation 2) and GT (Equation 4) approaches, as well as individual ICCs for each occasion for each individual (Equation 6). Figure 1 shows a flow diagram of occasions in which momentary ICCs were (in) estimable and potential options for imputation. In general, we note that in our sample only 4.1% of prompts were characterized by no variability across all negative and positive affect items. This suggests that the 13.9% of prompts that had no variability in negative affect ratings but some variability in positive affect ratings were likely veridical (negative and positive items were intermixed). Were instances of no variability assumed to represent complete undifferentiation, as in conventional person-level (Barrett et al., 2001) as well as newer momentary (Erbas et al., 2022) approaches, no data would be lost in analyses. We note that this is based on what is assumed by the calculation of the index, not the theoretical conceptualization of UNA. Similarly, if assumptions were made regarding what those observations theoretically represented, no data would be lost. But if researchers were unwilling to make such assumptions, up to 18% (n = 3,477) of data points would be missing and is an open area of methodological consideration (Erbas et al., 2022). We implement each of these three scenarios to examine the impact on results.

We additionally estimated undifferentiated negative *emotion* using the approach proposed by Erbas et al. (2022) as a momentary comparison index. However, in using this approach, we re-estimated disattenuated (Spearman, 1904, 1910) reliability indices for single items based on the 17 items used in our analyses, and the corresponding values indicated excellent reliability for person-level estimates ($R_{KF} = 0.99$) but substantially lower, marginal reliability for momentary estimates ($R_C = 0.52$). Moreover, we note that this approach confounds item-specific and subscale-shared variance and so where the undifferentiation signal is originating, and in what proportions, is unknown (c.f., Erbas et al., 2019). As a result, we expected potentially small associations with our momentary index, as well as small associations with conventional indices, as previously reported.

Momentary impulsivity

At each prompt, participants were asked to rate their impulsivity since the last prompt. Participants responded to four items using a five-point Likert scale (1 = very slightly or not at all; 2 = a little; 3 = moderately; 4 = quite a bit; and 5 = extremely; Momentary Impulsivity Scale; MIS; Tomko et al., 2014, 2015). The individual items were, "I made a 'spur of the moment' decision," "I said things without thinking," "I spent more money than I meant to," and "I have felt impatient." Items were summed to create a total score, which was reliable both at the between-person ($R_{KF} = 0.98$) and within-person ($R_C = 0.81$) level (Shrout and Lane, 2012).

Substance use

At each prompt, participants indicated if they had used caffeine, tobacco, alcohol, or marijuana since the last prompt (1 = yes, 0 = no). In total 128 (97.7%) individuals reported using caffeine at least once during the diary period, 75 (57.3%) reported using tobacco, 90 (68.7%) reported using alcohol, and 35 (26.7%) reported using marijuana. In total, there were 5,788 reports of caffeine use, 6,919 reports of tobacco use, 948 reports of alcohol use, and 821 reports of marijuana use.[4] Results did not differ whether we limited the analyses for each substance just to users of the specific substance or included the entire sample. We report results for analyses using the entire sample to facilitate the comparability of results across substances.

Data analysis

In all analyses, UNA was indexed using the various ICCs described above. Five sets of person level linear regressions were first conducted using aggregate measures of the dependent variables, an aggregate measure of negative affect, and either aggregated occasion level estimates of UNA or person level estimates of UNA.

Aggregates were estimated as the average across all prompts for a given individual. As a result, all substance aggregates represented the percentage of prompts that an individual reported using each individual substance. Impulsivity and negative affect were representative of the average level of each variable, reported across the entire EMA period. As denoted in Equations 2, 4, the conventional and full GT ICC estimates, respectively, were explicitly estimated at the person level, so no aggregation was necessary. The occasion level ICC estimates (Equation 6) were aggregated similar to impulsivity and negative affect. All covariates were centered on the sample means.

Next, three sets of momentary analyses were conducted using the momentary indices of UNA with different treatments of missing values (undifferentiation imputed, left missing, and conditionally imputed). When there was no variance across item ratings for a given occasion, we either (a) imputed as complete undifferentiation (i.e., a value of 1), (b) set it as missing, or (c) conditionally imputed responses as complete undifferentiation if all of the ratings were elevated but there was no variance (i.e., all negative affect items were rated as either 2, 3, 4, or 5) *but* as complete differentiation (i.e., a value of 0) if all of the item ratings were 1 (i.e., "not at all"). Given that momentary affect data were collected at multiple occasions within days and across persons, there are three levels at which UNA could be measured (c.f. Curran and Bauer, 2011). Correspondingly, we calculated ICC measures of UNA for each individual, (1) at each occasion, (2) on each day, as the average of the occasion-level ICCs for that day, and (3) as a person average across the daily averages of the diary period. We calculated similar scores for negative affect. For impulsivity we then fit a multilevel model corresponding to:

$$\begin{aligned} MIS_{ijk} = {} & (b_0 + b_{0i}) + b_1{*}ICC\_occasion_{ijk} + \\ & (b_2 + b_{2i}){*}ICC\_day_{ij} + b_3{*}ICC\_personi \\ & + (b_4 + b_{4i}){*}NA\_occasion_{ijk} + (b_5 + b_{51}){*}NA\_day_{ij} \\ & + b_6{*}NA\_personi + e_{ijk} \end{aligned} \tag{7}$$

In this equation, MIS_{ijk} is the momentary impulsiveness rating of person i on day j at occasion k. There is a global intercept (b_0) as well as a person-level intercept (b_{0i}) such that across the diary period some individuals might report more impulsivity than others on average. Next there is an effect of undifferentiated negative affect at the occasion-level (b_1) on occasion-level impulsivity. This effect describes the degree to which feeling undifferentiated negative affect in the moment relates to concurrent reports of impulsivity in the moment. Similarly, there is a between-person effect of an individual's average ICC for a given day (b_2) and the corresponding person-specific random effect (b_{2i}). These effects describe the degree to which feeling undifferentiated negative affect on average on a particular day is related to higher reports of impulsivity at some point throughout that day. Then, there is the effect of an individual's average 28-day ICC on impulsivity at a given occasion (b_3). This represents the extent to which someone who is on average undifferentiated with respect to their reports of negative emotions also reports more impulsivity at any given occasion. This is analogous to a trait-level or personality effect.

4 Of all caffeine use reports 997 (17.2%) had no variability in negative affect item reports, 1,271 (18.4%) had no variability for tobacco use reports, 179 (18.9%) had no variability for alcohol use reports, and 200 (24.4%) had no variability for marijuana use reports.

Analogous to the ICC effects, there are corresponding effects for occasion-level negative affect (b_4 and b_{4i}), day-level negative affect (b_5 and b_{5i}), and person-level negative affect (b_5). Lastly, there is an error term (e_{ijk}). Each of the covariates were centered such that occasion-level variables were centered on the person-average for that day, day-level variables were centered on the person-average of day-averages for that person across the diary period, and person-level variables were centered on the average of person-averages across the diary period (see Tomko et al., 2015, for full descriptions of parameters).

At the momentary level, since the substance use variables were binary, we opted to fit logistic models using Generalized Estimating Equations (GEE; Liang and Zeger, 1986), in which there are no random effects estimated, but instead clustering is adjusted for in the residual covariance matrix through estimation of robust standard errors (see Burton et al., 1998; Carlin et al., 2001; Hubbard et al., 2010 for discussions comparing GEE and multilevel approaches with continuous versus categorical outcomes).[5] Data preparation and analysis syntax, including example data, for the presented results are available *via* https://osf.io/ftwrs/.

Results

The BPD group had higher undifferentiated negative affect estimates using the conventional ANOVA [$M_{BPD} = 0.74$, $M_{DD} = 0.65$, $t(129) = 2.60$, $p = 0.010$], conventional GT [$M_{BPD} = 0.80$, $M_{DD} = 0.71$, $t(129) = 2.86$, $p = 0.005$], full GT [$M_{BPD} = 0.59$, $M_{DD} = 0.48$, $t(129) = 2.27$, $p = 0.025$], undifferentiation imputed [$M_{BPD} = 0.71$, $M_{DD} = 0.64$, $t(129) = 2.12$, $p = 0.036$], and imputed missing [$M_{BPD} = 0.64$, $M_{DD} = 0.59$, $t(129) = 1.79$, $p = 0.076$] estimates, but not for the conditionally imputed [$M_{BPD} = 0.51$, $M_{DD} = 0.48$, $t(129) = 0.76$, $p = 0.451$] estimates. Consistent with these results, apart from the conditional imputation, the BPD group had higher undifferentiated negative affect estimates using the Erbas et al. (2022) method [$M_{BPD} = 6.07$, $M_{DD} = 5.20$, $t(129) = 1.98$, $p = 0.050$].

BPD individuals were also more likely to be marijuana users [$\chi^2(1) = 4.74$, $p = 0.029$] and slightly more likely to be tobacco users [$\chi^2(1) = 2.83$, $p = 0.093$]. Despite these average level differences in the independent and dependent variables between the two groups, we did not observe group differences in the associations between them, and so we collapsed all reported results across the two groups for ease of presentation.

Comparing empirical undifferentiated negative affect estimates for (1) conventional person level, (2) full GT person level, and (3) person aggregated occasion level approaches

In the top portion of Table 1, we first report the person-level estimates of UNA using the conventional ANOVA-based approach as reported in other studies (Tugade et al., 2004; Kashdan et al., 2010; Pond et al., 2012; Grühn et al., 2013), followed by the analogous estimates using GT (with only item and measurement occasion as factors in the model) to demonstrate the comparability of the models, and lastly, include the estimates of the full GT model, which estimates variances for all levels of measurement, including their interactions. The conventional ANOVA and GT estimates are not different, demonstrating that the two approaches are analogous. The UNA estimates from the full GT model are substantially smaller, indicating more differentiation across individuals on average, but still do correlate quite highly with the conventional estimate ($r = 0.81$).

In the bottom portion of Table 1, we present the occasion-level undifferentiated negative affect estimates that are then aggregated to the person-level, including the method of Erbas et al. (2022) proposed for estimating undifferentiation as a comparison. However, due to the issue of inestimability when there is no variance across item ratings for a given occasion, we present the average values and correlations when those occasions were, (a) imputed as complete undifferentiation (i.e., a value of 1; $N = 3,638$, Figure 1) in line with what the person-level models implicitly assume and consistent with previous conceptualizations, (b) set to missing and effectively ignored, reducing overall sample size (Tomko et al., 2015), and (c) conditionally imputed as complete undifferentiation if all of the ratings were elevated but there was no variance (i.e., all negative affect items were rated as either 2, 3, 4, or 5; $N = 105$, Figure 1) *but* as complete differentiation (i.e., a value of 0; $N = 3,533$) if all of the item ratings were 1.[6]

When occasions with zero variance are treated as completely undifferentiated they correlate most highly with the full GT person-level estimates ($r = 0.81$) and somewhat less, but still strongly with the conventional approach ($r = 0.73$). When occasions with zero variance are excluded from the aggregated occasion-level estimates (18.8% of all occasions, Figure 1), as expected, those correlations are reduced ($r = 0.56$). However, when zero-variance occasions are conditionally imputed (i.e., 97.1% of which are coded are complete differentiation) the correlations with the undifferentiation estimates from the conventional approach are near zero ($r = 0.03$), and the correlations with the full GT estimates and conceptually similar

5 In addition to the primary variables of interest listed in the model equation, we adjusted for other factors that might be systematically related to the dependent variables. For momentary analyses, this included day of the week and time of the day. In both momentary and person level analyses, we also included reports of conflict, being rejected, being complimented, or health problems.

6 This includes the 847 occasions where there was also no variability in positive affect ratings. If we instead impute those 847 occasions as complete undifferentiation or exclude them from the analyses (i.e., missing) the pattern of results does not change.

TABLE 1 Person-level descriptive statistics and bivariate correlations for different operationalizations of undifferentiated affect.

		ICC	*M*	*SD*	1	2	3	4	5	6	7
Person level	1.	Conventional – ANOVA	0.71	0.19	1.00						
	2.	Conventional – GT	0.71	0.19	**1.00**	1.00					
	3.	Full GT	0.55	0.28	**0.81**	**0.81**	1.00				
Occasion level	4.	Erbas et al. (2022)	5.74	2.47	0.04	0.04	−0.02	1.00			
aggregated to	5.	Zero var. imputed w/ 1	0.68	0.19	**0.73**	**0.73**	**0.81**	−0.13	1.00		
person level	6.	Zero var. set to Missing	0.62	0.18	**0.56**	**0.56**	**0.76**	−0.16	**0.92**	1.00	
	7.	Zero var. imputed w/ 0 for all 1's, 1 for all 2's-5's	0.50	0.18	0.03	0.03	**0.31**	−0.06	**0.38**	**0.68**	1.00

ICC, intraclass correlation; GT, Generalizability Theory; and Var, variance. ICC values of 1 index complete undifferentiation while values of 0 index complete differentiation. Bold values are significant at $p < 0.001$.

TABLE 2 Person-level variance decompositions of emotion ratings.

Variable	Conventional		Full GT	
	M (*SD*)	%	*M* (*SD*)	%
σ^2_{Item}	0.231 (0.299)	27.5%	0.020 (0.040)	2.2%
σ^2_{Scale}	–		0.115 (0.258)	12.8%
$\sigma^2_{Scale*Item}$	–		0.139 (0.192)	15.4%
$\sigma^2_{Measurement}$	0.225 (0.271)	26.9%		
σ^2_{Occ}	–		0.004 (0.010)	0.5%
σ^2_{Day}	–		0.100 (0.178)	11.1%
$\sigma^2_{Occ*Day}$	–		0.092 (0.117)	10.2%
σ^2_{Error}	0.382 (0.269)	45.6%	0.237 (0.188)	26.4%
$\sigma^2_{Scale*Occ}$	–		0.003 (0.006)	0.2%
$\sigma^2_{Item*Occ}$	–		0.001 (0.002)	0.1%
$\sigma^2_{Scale*Day}$	–		0.042 (0.057)	4.7%
$\sigma^2_{Item*Day}$	–		0.005 (0.010)	0.6%
$\sigma^2_{Scale*Item*Occ}$	–		0.005 (0.008)	0.5%
$\sigma^2_{Scale*Item*Day}$	–		0.058 (0.065)	6.5%
$\sigma^2_{Scale*Occ*Day}$	–		0.071 (0.061)	7.9%
$\sigma^2_{Occ*Item*Day}$	–		0.007 (0.012)	0.8%
σ^2_{Total}	0.838 (0.660)	100.0%	0.899 (0.724)	100.0%
ICC	0.768 (0.174)		0.550 (0.277)	

Estimated variances will not add up exactly because they are averages of person-level estimates. However, the item variation using the conventional approach ($\sigma^2_{Item} = 0.231$) was similar to the sum of the item, type, and type-by-item variation using the GT-based approach, which mathematically it subsumes ($\sigma^2_{Item} + \sigma^2_{Type} + \sigma^2_{Type*Item} = 0.020 + 0.115 + 0.139 = 0.254$), as were the comparable measurement ($\sigma^2_{Conventional} = 0.225$; $\sigma^2_{GT} = 0.196$), error ($\sigma^2_{Conventional} = 0.382$; $\sigma^2_{GT} = 0.429$), and total variances ($\sigma^2_{Conventional} = 0.838$; $\sigma^2_{GT} = 0.899$). Using the median variances also provided similar estimates (item—$\sigma^2_{Conventional} = 0.113$; $\sigma^2_{GT} = 0.092$; measurement—$\sigma^2_{Conventional} = 0.133$; $\sigma^2_{GT} = 0.071$; error—$\sigma^2_{Conventional} = 0.328$; $\sigma^2_{GT} = 0.314$; total—$\sigma^2_{Conventional} = 0.698$; $\sigma^2_{GT} = 0.746$). Furthermore, the total variances for each method were nearly perfectly correlated ($r = 0.996$), demonstrating that although the methods obtained slightly different estimates due to the different assumed models, they provided consistent estimation across persons.

undifferentiation imputed occasion-level aggregates are small to medium (*r*s = 0.31 and.38, respectively). In general, we see that both person-level and our aggregated momentary GT estimates are generally unrelated (and possibly negatively) to the aggregated person-level estimates using the Erbas et al. (2022) approach.

The reasons for the differences between these approaches are 2-fold. The first is a result of systematic variance in item ratings that is due to other sources that are either ignored, as in the case of the conventional approach (e.g., *Scale*Item*, *Day*), or confounded with error due to the level of analysis, as in the occasion-level approach (e.g., *Subscale*Occasion*Day*). The second is due to the theoretical meaning and subsequent treatment of measurement occasions that have no variance. As shown by Figure 1, those instances, instead of communicating UNA in the cases when negative affect is in fact elevated, could be indicative of a quite differentiated *lack* of negative affect. We return to this second consideration in the discussion, as it is grounded more in theory than what is empirically estimable, and may have implications for the interpretation of previously reported results. Next, we seek to quantify the impact of not taking into account systematic factors that might affect the scale and error variance components that will then lead to bias in the UNA ICC estimates.

Simulation demonstrating the impact of additional sources of variance on undifferentiated affect estimates

We can see from Table 2 that using individual items as the level of measurement in the conventional approach leads to an overestimation of the amount of variance that is due to differences in particular negative affect subscales. This is primarily due to certain items within each subscale being systematically rated higher/lower across all ratings ($\sigma^2_{Scale*Item} = 0.139$). Similarly, using overall measurement occasion in the conventional approach ignores that there might be systematic variance due to specific days (e.g., weekends), occasions (e.g., mornings), or particular occasions given the day (e.g., Sunday night before work Monday morning). We find that day ($\sigma^2_{Day} = 0.100$; 11.1%) and occasion-by-day ($\sigma^2_{Occ*Day} = 0.092$; 10.2%) account for approximately equal amounts of variance. Lastly, there are multiple systematic sources of variance that could otherwise inflate the amount of error that is estimated using the conventional approach. The largest of those estimated using our example data was that due to certain subscales being rated higher/lower overall, on specific occasions, on certain

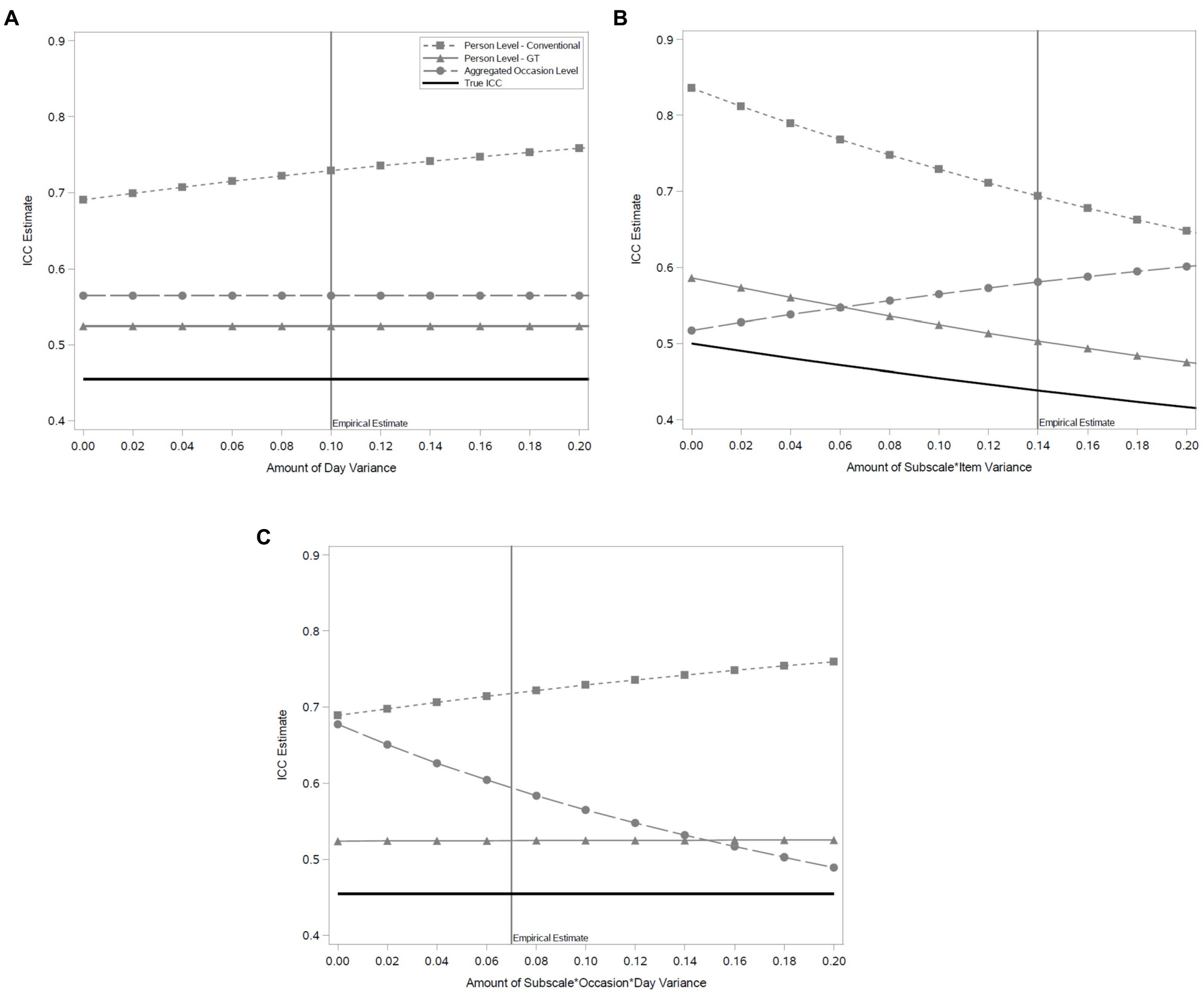

FIGURE 2
Simulation results for conventional, Generalizability Theory, and aggregated occasion level estimates of undifferentiated negative affect. **(A)** illustrates that aggregation, in general, leads to overestimation of undifferentiation, but it is minimized and constant using a Generalizability Theory approach compared to convention. **(B,C)** depict how individual item variance within subscale, and subscale variance within specific moments of different days, respectively, can bias undifferentiation estimates when unaccounted for, and this is again minimized using a GT approach. In all cases, ignoring the true momentary signal due to undifferentiation (solid black line) leads to bias, underscoring the need for momentary measures that disambiguate sources of variance.

days ($\sigma^2_{Scale*Occ*Day} = 0.071$; 7.9%). Importantly, the presence of any of these sources of variance within a given participant's data could bias the resulting estimate of person-level differentiation in different ways.

To assess the degree to which these sources of variance would bias estimates of the true underlying undifferentiation value, we simulated data based on the observed variance component structure from the full GT model in Table 2. We then independently varied the amount of systematic variance due to day, scale*item, and scale*occasion*day from zero to approximately twice of what was empirically observed, because they were the largest sources of variance contained within each of the components of the conventional model. For each level of each manipulated variance component we: (1) generated 1,000 samples of 100 individuals, (2) performed variance decompositions according to the conventional, full GT, and occasion-level (which were then aggregated) approaches, and (3) calculated estimates of UA. Based on the simulation values we also calculated the true empirical undifferentiation estimate. Figure 2 shows the results of the simulations for each manipulated variance component with vertical lines indicating the amount of variance in the specific component that was empirically observed.

In general, when there is systematic variability due to day we see that the GT estimate is a slightly biased, but consistent estimator of the underlying ICC value.[7] Similarly, the aggregated

7 This bias is due to positive skew in the underlying distributions of each of the variance components, which are bounded below by 0. Increasing the relative size of each of the variance components gradually mitigates

TABLE 3 Person-level associations between undifferentiated negative affect and impulsivity/substance use using conventional and GT-based methods.

Variable	Person Level						Occasion level aggregated to person level											
	Conventional ICC			GT-based ICC			Erbas et al. (2022)			Impute as Undifferentiation			No Imputation			Conditional Imputation		
	Est	*SE*	*β*	*Est*	*SE*	*β*	*Est*	*SE*	*β*	*Est*	*SE*	*β*	*Est*	*SE*	*β*	*Est*	*SE*	*β*
Impulsivity	1.03	1.09	0.10	0.73	0.66	0.12	0.020	0.06	0.03	1.30†	0.76	0.16	2.09**	0.71	0.24	2.51***	0.60	0.30
Alcohol	0.05	0.05	0.10	0.00	0.03	0.00	0.002	0.004	0.07	0.00	0.05	0.00	0.00	0.05	0.00	0.00	0.04	0.02
Caffeine	−0.03	0.12	−0.03	0.03	0.08	0.04	0.001	0.001	0.00	0.00	0.12	0.00	−0.04	0.12	−0.03	−0.11	0.11	−0.09
Tobacco	−0.14	0.23	−0.06	−0.11	0.15	−0.07	0.010	0.019	0.06	0.08	0.22	0.04	−0.05	0.22	−0.02	−0.16	0.20	−0.07
Marijuana	0.17*	0.08	0.21	0.07	0.05	0.15	0.009	0.007	0.14	0.19*	0.08	0.25	0.07	0.08	0.09	−0.07	0.07	−0.08

†$p < 0.10$, *$p < 0.05$, **$p < 0.01$, and ***$p < 0.001$.

occasion-level estimate is slightly more biased than the GT estimate but also is consistent. In contrast, the conventional estimate is substantially more biased (25% more variance) when there is zero day-level variability, and that bias increases as the amount of day variability in the data increases.

When instead we vary the amount of variance due to particular items within a given subscale we see again that the GT estimate is a slightly biased but still consistent estimator of the underlying ICC estimate. In contrast, we see that the aggregated occasion-level estimate is the least biased of the three when there is no subscale-by-item variance, but as that variance increases it becomes increasingly biased.

Yet another pattern is observed when we vary the amount of variance associated with scale*occasion*day. Again, the GT estimate is on average the least biased and consistent across a range of possible values. As with day variability, as scale*occasion*day variability increases so does the already large bias in the conventional estimate. By comparison, the aggregated occasion-level estimate is most biased when there is no scale*occasion*day variability, but becomes less biased as such variability increases.

Effects of undifferentiated affect on impulsivity and substance use

We next used the various UNA estimates from the example data as predictors in person-level and occasion-level regression models of impulsivity and substance use. Table 3 presents the results from the person-level analysis. UNA estimates were positively associated with reported impulsivity for each of the aggregated occasion level estimates. Importantly, the effect was weakest when occasions with zero item variance were imputed as undifferentiated ($\beta = 0.16$, $p = 0.088$), stronger when such occasions were left missing ($\beta = 0.24$, $p = 0.004$), and strongest when zero variance occasions were imputed as completely undifferentiated if negative affect was elevated and completely differentiated if negative affect was at floor levels (i.e., all 1's; $\beta = 0.30$, $p < 0.001$). UNA was also positively associated with marijuana use using the conventional ICC approach ($\beta = 0.21$, $p = 0.030$) and imputing all zero variance occasions as complete undifferentiation ($\beta = 0.25$, $p = 0.018$). Using Erbas et al. (2022) approach, none of the associations were statistically significant, though the effect on marijuana use was consistent with the other indices but smaller.

Importantly, as has been done in past research (Kashdan et al., 2010; Pond et al., 2012; Tomko et al., 2015), we explored whether UNA interacted with overall level of negative affect in predicting the various outcomes. In predicting impulsivity, the interaction was significant using the conventional ($b = 4.37$, $SE = 0.98$, $p < 0.001$, $\beta = 0.33$), GT-based ($b = 2.55$, $SE = 0.71$, $p = 0.005$, $\beta = 0.28$), complete undifferentiation ($b = 4.17$, $SE = 1.11$, $p < 0.001$, $\beta = 0.29$), and no imputation ($b = 3.15$, $SE = 1.22$, $p = 0.011$, $\beta = 0.20$) estimates, but not for the conditional imputation estimates ($b = 1.44$, $SE = 1.19$, $p = 0.229$, $\beta = 0.09$), which we note recodes occasions with all 1's ("not at all") for the negative affect items as completely differentiated. For all of the substances, all of the interaction effects were non-significant (all p's > 0.100) except when using the conditionally imputed estimates to predict marijuana use ($b = 0.43$, $SE = 0.13$, $p = 0.001$, $\beta = 0.29$).

To further demonstrate the potential utility of our GT-based approach to calculating UA we also conducted momentary analyses, which included effects at the momentary, day, and person level in predicting momentary impulsivity and substance use—something that could not previously be done using conventional approaches. Table 4 shows the results of these analyses in which impulsivity was modeled continuously, whereas substance use was modeled dichotomously. UNA at all three levels of analysis (momentary, day, and person) was associated with momentary impulsivity, and this was generally robust to the different ways of handling the zero variance occasions. As in the person level analyses, the interaction between UNA and level of negative affect was significant, but only at the person level, and only for the undifferentiation imputed ($b = 4.17$, $SE = 1.10$,

this, but we elected to retain more realistic values so that the results may be more meaningfully compared.

TABLE 4 Occasion-level associations between undifferentiated negative affect and impulsivity/substance use using occasion level ICC.

Variable	Level	Impute as Undifferentiation		No imputation		Conditional imputation		Erbas et al. (2022)	
		Est	*95% CI*	*Est*	*95% CI*	*Est*	*95% CI*	*Est*	*95% CI*
Impulsivity	Occasion	0.20**	[0.07, 0.33]	0.22**	[0.08, 0.37]	0.27***	[0.16, 0.37]	−0.006*	[−0.011,-0.000]
	Day	0.42***	[0.20, 0.65]	0.70***	[0.42, 0.98]	0.61***	[−0.34, 0.87]	−0.004	[−0.014,0.007]
	Person	1.31†	[−0.19, 2.82]	2.27**	[0.79, 3.75]	2.51***	[1.31, 3.72]	0.018	[−0.095,0.131]
Alcohol[a]	Occasion	1.24	[0.92, 1.68]	1.12	[0.82, 1.52]	1.01	[0.81, 1.25]	0.997	[0.991,1.004]
	Day	1.42†	[0.94, 2.12]	1.47†	[0.99, 2.20]	1.35	[0.91, 2.01]	1.003	[0.989,1.017]
	Person	1.06	[0.15, 7.60]	1.32	[0.20, 8.85]	1.43	[0.33, 6.13]	1.038	[0.923,1.168]
Caffeine[a]	Occasion	0.82**	[0.72, 0.93]	0.86*	[0.74, 0.99]	1.08	[0.97, 1.20]	0.995*	[0.990,0.999]
	Day	0.86	[0.72, 1.03]	0.96	[0.80, 1.15]	1.05	[0.91, 1.22]	0.996	[0.988,1.004]
	Person	1.01	[0.34, 2.94]	0.84	[0.30, 2.33]	0.55	[0.21, 1.42]	1.009	[0.924,1.102]
Tobacco[a]	Occasion	0.95	[0.88, 1.03]	0.98	[0.90, 1.07]	1.02	[0.96, 1.09]	0.999	[0.995,1.002]
	Day	0.84**	[0.74, 0.96]	0.86*	[0.75, 0.98]	1.00	[0.89, 1.12]	1.002	[0.989,1.014]
	Person	1.56	[0.22, 10.81]	1.18	[0.16, 8.52]	0.54	[0.09, 3.20]	1.005	[0.861,1.174]
Marijuana[a]	Occasion	0.80	[0.60, 1.07]	0.91	[0.68, 1.22]	1.15	[0.95, 1.39]	0.995	[0.986,1.003]
	Day	0.77	[0.46, 1.27]	0.90	[0.54, 1.52]	1.13	[0.72, 1.75]	1.002	[0.981,1.024]
	Person	390.92***	[13.59, 11244.11]	26.87†	[0.73, 989.01]	0.35	[0.01, 11.27]	1.195	[0.929,1.538]

†$p<0.10$, *$p<0.05$, **$p<0.01$, ***$p<0.001$. CI, confidence interval. [a]Parameter estimates and confidence intervals are odds ratios.

$p<0.001$) and no imputation ($b=3.23$, $SE=1.27$, $p=0.013$) methods. The exception was for the Erbas et al. (2022) method where only momentary undifferentiation was significant in the opposing direction ($b=-0.006$, $SE=0.003$, $p=0.039$), but the momentary interaction was significant ($b=0.008$, $SE=0.002$, $p<0.001$) such that the overall effect becomes positive at approximately positive one half of a standard deviation of momentary variability.

Although in the person-level analyses we did not observe associations between UNA and either alcohol, caffeine, or tobacco use, when we analyzed the data at a more granular level we did observe a number of significant effects. There was a trend such that on days when individuals felt more undifferentiated than average they were more likely to drink alcohol for both the undifferentiation imputed ($OR=1.42$, 95% $CI=[0.94, 2.12]$, $p=0.093$) and no imputation ($OR=1.47$, 95% $CI=[0.99, 2.20]$, $p=0.059$) operationalizations. This was not the case for the conditional imputation method ($OR=1.35$, 95% $CI=[0.91, 2.01]$, $p=0.140$), though the effect was in the same direction, suggesting that the recoding did not have a strong impact on this effect. This was corroborated by the absence of an interaction effect between UNA and overall level of negative affect at the day level ($OR=1.07$, 95% $CI=[0.33, 3.45]$, $p=0.915$).

Also at the day level, when individuals were feeling more undifferentiated on a given day they were less likely to smoke tobacco for the undifferentiation imputed ($OR=0.84$, 95% $CI=[0.74, 0.96]$, $p=0.008$) and no imputation ($OR=0.86$, 95% $CI=[0.75, 0.98]$, $p=0.025$) operationalizations, but not for the conditional imputation method ($OR=1.00$, 95% $CI=[0.89, 1.12]$, $p=0.978$). Again, we did not observe an interaction effect between undifferentiated negative affect and level of negative affect for this effect when using the conditional imputation ($OR=0.94$, 95% $CI=[0.21, 4.14]$, $p=0.933$).

In a similar direction as tobacco but at the momentary level, we did observe a significant effect for increased momentary feelings of UNA being associated with less caffeine use, again for the undifferentiation imputed ($OR=0.82$, 95% $CI=[0.74, 0.93]$, $p=0.003$), no imputation ($OR=0.86$, 95% $CI=[0.74, 0.99]$, $p=0.035$), and (Erbas et al., 2022 $OR=0.995$, 95% $CI=[0.990, 0.999]$, $p=0.019$) methods. Interestingly, the same effect for the conditional imputation began to trend in the *opposite* direction ($OR=1.08$, 95% $CI=[0.97, 1.20]$, $p=0.155$), as did the corresponding interaction between UNA and level of negative affect ($OR=0.77$, 95% $CI=[0.53, 1.12]$, $p=0.167$), which, consistent with the other two imputation methods, would suggest a decrease in caffeine use at higher levels of UNA and higher overall negative affect.

Replicating the person level analyses, we observed a significant effect such that people who, across the EMA period, were more undifferentiated were also more likely to smoke marijuana at any given occasion for both the undifferentiation imputed ($OR=390.92$, 95% $CI=[13.59, 11244.11]$, $p<0.001$) and no imputation ($OR=26.87$, 95% $CI=[0.73, 989.01]$, $p=0.074$) methods, but not for the conditional imputation ($OR=0.35$, 95% $CI=[0.01, 11.27]$, $p=0.557$) variation. This last effect, however, as in the person level analyses, was qualified by a significant interaction with level of negative affect ($OR=5727.303$, 95% $CI=[41.17, 796912.37]$, $p<0.001$) while the other two were not (p's>0.325).

Figure 3 illustrates the interaction effects at the person level for momentary impulsivity (Panels A and B) and marijuana use (Panels C and D) when using undifferentiated imputation (Panels

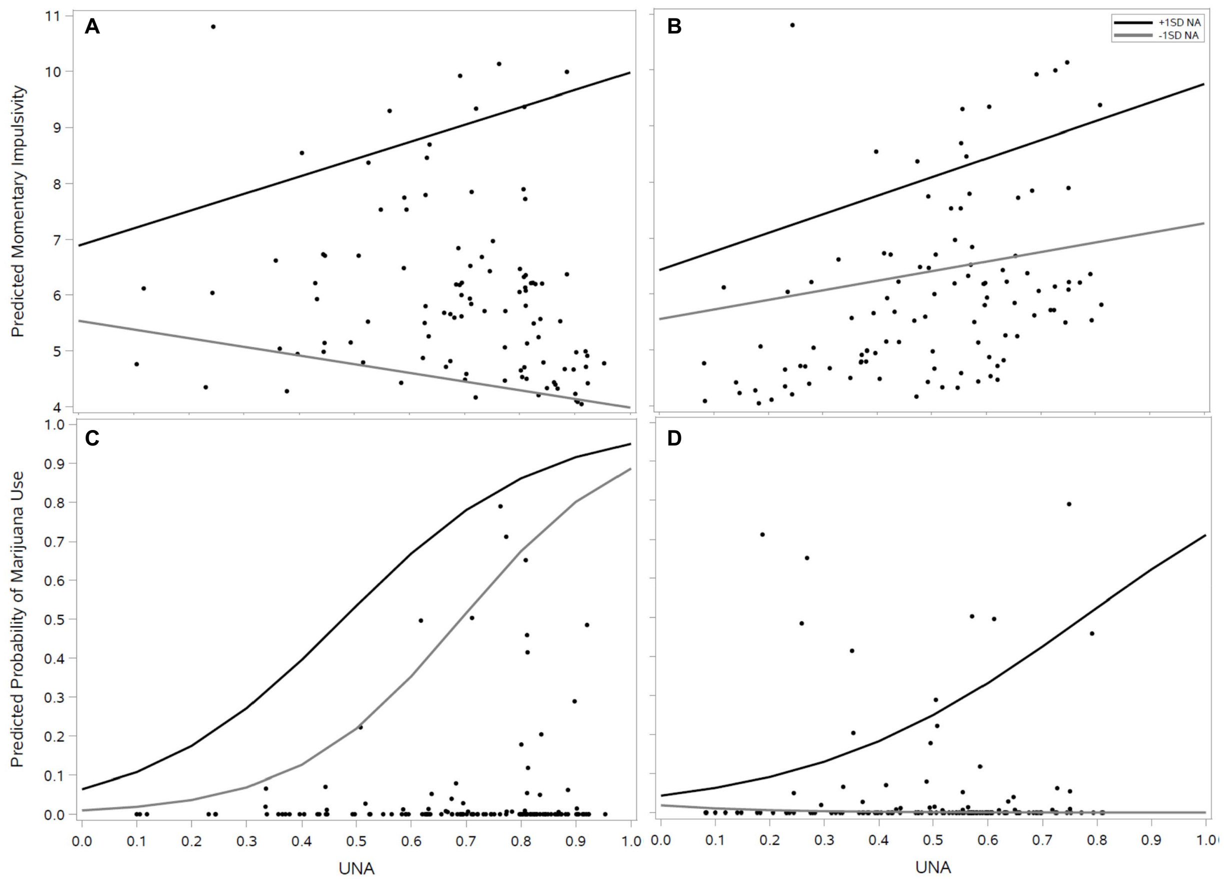

FIGURE 3
Interaction plots (undifferentiated negative affect by level of negative affect) for impulsivity **(A,B)** and marijuana use **(C,D)** using either undifferentiated imputation **(A,C)** or conditional imputation **(B,D)**. **(A,B)** depict the interaction **(A)** versus main **(C)** effect of negative affect in tandem with undifferentiated negative affect when treating zero variance floor responses as complete undifferentiation **(A)** versus differentiation **(C)**, respectively. **(C,D)** show the same comparison but with respect to marijuana use, and how an interaction that is not otherwise observed in the traditional treatment (equivocating zero variance with undifferentiation); **(C)** is revealed when treating zero variance floor ratings as being differentiated **(D)**.

A and C) versus conditional imputation (Panels B and D), because the two methods represent contrasting ways of coding zero variance occasions. The analogous plots of the interaction effects for the aggregated between-person analyses looked very similar. Individual data points represent raw person-level aggregates to minimize saturation while illustrating the impact of the different methods for handling zero variance occasions. For impulsivity, zero variance occasions coded as completely undifferentiated lead to a cluster of points in the bottom right of Panel A, which have high average UNA and drive the interaction effect. In contrast, when those occasions that have zero variability and are at the floor of the scale are instead coded as complete differentiation (with elevated zero variance occasions being coded as complete undifferentiation) the distribution of points become more evenly spread and we observe two positive main effects for UNA and level of negative affect.

For marijuana use, we see that the positive effect of undifferentiated negative affect is largely driven by a group of 10 individuals who used marijuana daily and tended to have high UNA (Panel C). However, these individuals were more than twice as likely to have zero variance occasions rated at the floor of the scale ($OR = 2.42$, 95% $CI = [1.02, 5.75]$, $p = 0.045$), which drove the main effect. When those occasions are instead coded as completely differentiated that group of individuals is more evenly distributed across the UNA range, and we can more clearly see that the impact of UNA is conditional on NA levels being higher.[8]

Discussion

In the current empirical example and simulations we sought to, (1) refine the estimation methods previously used to characterize UA, (2) extend those methods beyond the

8 The group of 10 individuals who were daily marijuana users also had a marginal tendency to report elevated negative affect ($b = 0.52$, $SE = 0.29$, $p = 0.076$).

person-level to more granular levels of experience where UA is theorized to operate, and (3) consider how certain consequences of the statistical estimation of UA may have more nuanced implications for its theoretical interpretation. We next discuss our findings with respect to each of these goals and make suggestions for future research on UA.

Refining the estimation of undifferentiated affect

In general, we observed that conventional estimates of UA may be inflated as a result of confounding other systematic sources of variance with that observed at the item level. We would argue that these sources of variance should not be included in what is considered signal for UA because they may be more parsimoniously explained by other emotion regulation processes such as circadian rhythms (e.g., Larsen, 1985; Rusting and Larsen, 1998) or by individual differences in reporting bias (Podsakoff et al., 2003). Furthermore, such external sources of variance may distort observed associations between UA and other variables. Our procedure for calculating UA at the person level did produce estimates that correlate highly with conventional approaches; however, based on the presented simulations this does not have to be the case, and our approach would be preferred because it is both more precise and robust. At the momentary level, our procedure correlated less highly with conventional approaches, both because of differences in the level of estimation and limiting factors implicit in estimating UA at the momentary level (i.e., empirically cannot estimate day level variation). We suggest that researchers use the approach that corresponds to their desired level of analysis (i.e., person level GT for person level hypotheses, occasion level GT for more dynamic or contextualized occasion level hypotheses). For occasion level applications, adjusting for known influences like time of the day and day of the week will mitigate variance confounded within the estimate of the error for individual UA values.

Extending UA measurement to the momentary level

Past studies have attempted to estimate UA at the level of the person, often aggregating across multiple daily reports and/or reports within a given day (e.g., Demiralp et al., 2012; Erbas et al., 2018; Kalokerinos et al., 2019). Recently, methods have been proposed to estimate differentiation at the momentary level, though still focusing on individual emotion items (Erbas et al., 2022). However, in light of the fact that many affect scales contain multiple items that correspond to individual subscales, we were able to leverage between-and within-subscale variation to estimate UA at the momentary level whereas other momentary indices explicitly confound them. To that end, the proposed approach can be used in other contexts outside of EMA, including experimental studies, panel studies, and even one-shot observational/correlational studies. Because the method can be used to estimate undifferentiated affect within a given moment, what constitutes a "moment" can be very general with respect to timing. Importantly, this requires multiple items to be assessed for each subscale so that consistency in ratings across subscales can be compared to that which is observed within them for a given reporting occasion. In our example, we assessed between five and six items for the hostility, sadness, and fear subscales within overall negative affect. In contrast, the 10 items also collected in the protocol corresponding to positive affect were not *a priori* chosen to assess multiple positive affect subscales. As a result, we would not be able to estimate undifferentiated positive affect at the momentary level without grouping those items into at least two subscales. We note however, that we would be able to estimate *daily* undifferentiated positive affect given that those items were each assessed approximately six times per day, allowing us to cross item and occasion in decomposing the variance.

We believe estimating UA at the momentary (and also daily) level confers distinct advantages because that is where the process of reflecting on one's emotional state and choosing appropriate regulation strategies is theorized to operate (Barrett et al., 2001). This allows for the moment-to-moment dynamics of emotion differentiation as a process to be investigated and modeled, and for situational correlates of its experience to be explored. In our example, we demonstrated that only impulsivity and marijuana use correlated with UNA at the person level. However, moving to the momentary level, we observed at least trends between UNA and alcohol, caffeine, and tobacco use as well. That is, while being a high UNA person on average was not associated with substance use other than marijuana, we did observe that if people were higher in UNA on a particular day compared to their usual daily UNA they were somewhat more likely to drink alcohol and less likely to smoke tobacco. Furthermore, within a given day, if someone was experiencing more UNA compared to their UNA across the rest of the day he/she was less likely to consume caffeine. These are potentially interesting effects that give insight into the situation-specific versus diffuse aspects of UA itself, and how UA may be composed of a set of regulatory processes (e.g., Tomko et al., 2015). Critically, conventional person-level approaches would miss these more fine-grained associations, unless researchers had specific person-level hypotheses, in which case the conventional and GT approaches produce similar results in our empirical analyses while our simulations show that conventional ICC effect sizes will be attenuated. Though preliminary, these results suggest countervailing associations between UNA and alcohol/marijuana compared to UNA and caffeine/tobacco. We can speculate that this may relate to the initial sedative but combined sedative/stimulant effects of alcohol (Chung and Martin, 2009) and marijuana (Block et al., 1998) as a coping response to experiencing UNA, while the primarily stimulant effects of nicotine (Corrigall et al., 1992) and caffeine (Biaggioni et al., 1991) may be motivationally inhibiting when experiencing UNA. Other researchers have reported positive associations between alcohol use emotion differentiation (Kashdan et al., 2010), which lends credence to part of this interpretation, but further research and replication are necessary.

Interpreting estimates of undifferentiated affect in the absence of elevated affect

In calculating UA at the momentary level, we encountered an estimation issue not encountered by other UA researchers who in the past have created estimates only at the person level. Namely, there were a large proportion of occasions (18.8%) with no variability in ratings, and so no estimate could be empirically derived. The absence of variability at the person level, over the course of multiple days or weeks, is unlikely, and so would rarely be expected to present a problem for person level estimation. However, the likelihood of sampling a person randomly during the day and he/she reporting that there is nothing negatively emotion-inducing going on (18.3% in our data) seems quite possible. These empirically "difficult" observations may also have theoretical ramifications for the conceptualization of UA. From a person level approach, these observations are implicitly counted as completely undifferentiated because they do not contribute any variance to systematic between-subscale differences, which will magnify estimates of UA (see Table 1). However, conceptually it is unclear if such instances correspond to the lack of emotional clarity/granularity (Suvak et al., 2011; Grühn et al., 2013) or generalized feelings of negativity (Barrett et al., 2001) on which UA is defined. We suggest that reporting floor responses of "Not at all" to all negative affect items may in fact indicate a *highly differentiated* absence of negativity.[9] This alternate view, when recoded in the data, can greatly change the apparent pattern of results. The observation that this occurs so frequently in a sample of individuals with disorders characterized by chronic elevated negativity (American Psychiatric Association, 2013), suggests that it is likely more prevalent in healthy samples and could therefore be even more impactful. Moreover, as Figure 1 suggests, such floor responses across both all positive and negative items (4.1%) might constitute a separate affective state that might require additional considerations of imputation or missingness.

Past research has dutifully noted and replicated that there is often an interaction effect between UA and level of negative affect (Barrett et al., 2001; Kashdan et al., 2010; Pond et al., 2012; Selby et al., 2013; Zaki et al., 2013). This interaction effect in each of the reported studies is predominantly driven by an association between UA and the outcome of interest when affect intensity is elevated, with little to no (and sometimes reversed) association observed at low levels of affect. We suggest that the absence (or reversal) of an association at low levels of affective intensity may be because high UA is simply identifying a lack of variance at the floor of the affect scale (i.e., a participant consistently reporting that he/she is not feeling any affect). This could also explain possible reversals of identified associations in that highly "undifferentiated" scores at low affect levels may actually be more precise while lower scores at low affect levels may be the result of random slight elevations in a single affect item of a scale (i.e., it represents the only variance available, gets relegated to error, and results in a high estimate of UA).[10]

This is precisely the result observed in our example with impulsivity (Figures 3A,B). Panel A, which codes zero variance occasions as complete UA, displays the same interaction pattern observed in previous investigations.[11] However, when zero variance occasions at the floor of the scale are coded as completely differentiated the result is two main effects. As mentioned earlier, the apparent reversal of this pattern for marijuana use is largely due to the tendency for daily marijuana users to increasingly report "Not at all" for all negative affect items on a given occasion, an effect that was otherwise attributed to all individuals when coding such observations as complete UA.

In sum, we do not contest previously reported interaction effects between UA and affect intensity, but suggest that rather than an interesting theoretical interaction, it may simply be driven by an absence of variance. Regardless, if investigators are using person level estimates of UA in analyses, or otherwise coding zero variance reports as complete undifferentiation, it is essential to also include the main effect of level of affect and their interaction. The alternative approach of coding zero variance occasions as complete differentiation may simplify interpretations, but the interaction should still be tested. We have no specific preference concerning which approach to use. Our goal is to elucidate an empirical wrinkle in the estimation of UA that may lead to alternative interpretations of some UA findings.

Limitations

Despite the potential advantages of the suggested approach with respect to measuring affective differentiation more reliably and more in line with moment to moment experiential dynamics than previous operationalizations, there are inherent limitations with respect to conceptualization and generalizability. Undifferentiated emotion pertains to individual, specific emotion labels and individuals' ability or tendency to disambiguate them when they experience an affectively arousing and valenced stimulus (Barrett et al., 2001). The current measure pertains to

9 This interpretation is supported and suggests that these reports are valid given the vast majority of them that are paired with positive affect reports that have variability (Figure 1).

10 This scenario composed 21.0% (*n* =4,064) of all occasions in our example data set, in addition to the 18.3% of rating sets as all 1's.

11 Note that the person level analysis (see Table 3 and results section), which does not explicitly code zero variance occasions as UA but rather does so implicitly, produces nearly identical results. This effect is not due to the level of analysis.

undifferentiated affect, which is broader in that it includes sets of neighboring individual emotions (Russell, 1980) and is inherently less well-defined theoretically. As a result, based on the construction of the PANAS-X, our conceptualization of undifferentiated affect is constrained to broader distinctions between hostility, fear, and sadness, and importantly also excludes other important categories of negative emotions such as guilt or jealousy. Our method cannot reliably disentangle specific differentiation across more individualized, nuanced emotions that are measured with single items, which we know to be inherently less reliable (Spearman, 1904, 1910). However, one option, if researchers collected data with the appropriate structure as illustrated using the GT framework, is to decompose the variance of ratings in this case at the day level since each item will then be assessed multiple times. The inherent limitation of this approach would be that undifferentiation is then necessarily estimated as a day level construct as opposed to a momentary one and lower level dynamics may be obscured. This could still have empirical utility to the extent that individuals do experience undifferentiation at the day level across contexts. Alternatively, researchers could expand or develop new measures that attempt to do what the PANAS-X does in terms of achieving relative consistency in ratings within subscales but with respect to more specific emotions.

In the current example context we are also limited in our possible generalization of the UA estimation method in terms of the affect measure (17 items) and the momentary assessment design (6 prompts per day over 28 days). Other common scales (e.g., POMS, McNair et al., 1992; MDMQ, Wilhelm and Schoebi, 2007) and designs include many fewer items and assessments (e.g., fixed, sparser, event-contingent), respectively, which may have systematic, unappreciated effects on UA estimation as a function of diurnal or weekly cycles when calculated at the person versus momentary level. These factors are also expected to be related to considerations regarding participant burden when deciding on measures and sampling schemes beyond appropriately capturing affective processes (Eisele et al., 2021). Moreover, if the specific affect differentiation of interest is broader (e.g., positive versus negative) or with respect to specific emotion categories (e.g., hostility, anxiety) fewer items may be necessary.

Conclusion

The construct of emotion differentiation is receiving more attention as a core component of emotion regulation in both healthy and clinical individuals (Kashdan et al., 2015). It is viewed as a critical gateway toward the identification and mobilization of emotional coping and eventual mental health. The precise measurement of emotion differentiation and understanding the connection between its theoretical conceptualization and empirical operationalization is essential for characterizing *how* emotion differentiation facilitates such processes in everyday life. We suggest refinements in how emotion differentiation is estimated and present a new method for estimating it at the level of individual experience. These advancements allow researchers to rule out correlated regulatory processes, make fuller use of available data, and map out emotion differentiation as its own dynamic process that may change across different environmental contexts.

Data availability statement

The data analyzed in this study are subject to the following licenses/restrictions: Data are still held under the aims of the granting agency. Requests to access these datasets should be directed to trullt@missouri.edu.

Ethics statement

The studies involving human participants were reviewed and approved by University of Missouri Institutional Review Board. The patients/participants provided their written informed consent to participate in this study.

Author contributions

SL designed and performed the research and analyzed the data. SL and TT interpreted the results and wrote the paper. All authors contributed to the article and approved the submitted version.

Funding

This research was supported by the National Institutes of Health grants R21 MH069472 (TT), P60 AA1198 (Heath), T32 AA013526 (Sher), and R01 AA027264 (SL and Hennes).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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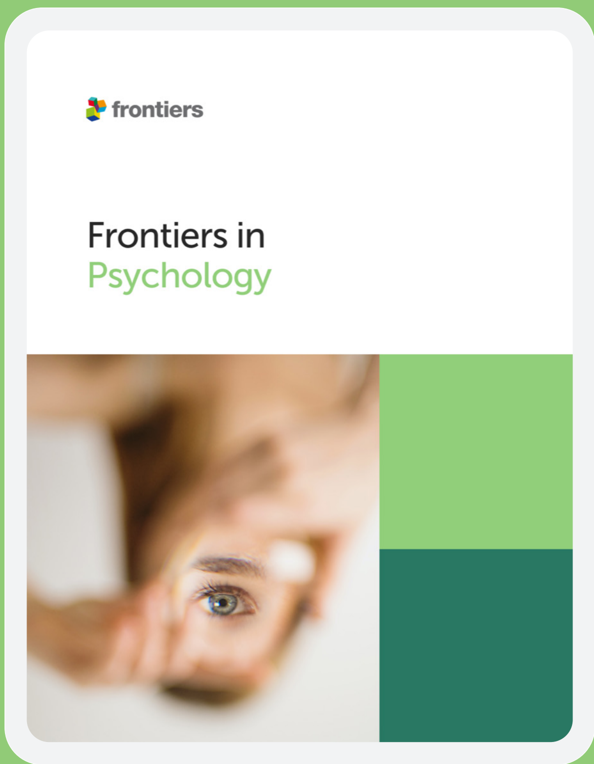

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