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ORIGINAL ARTICLE

# Low Emotional Complexity as a Transdiagnostic Risk Factor: Comparing Idiographic Markers of Emotional Complexity to Emotional Granularity as Predictors of Anxiety, Depression, and Personality Pathology

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## Abstract

**Background** Individuals vary widely in emotional complexity (EC), the ways in which they represent and experience emotions. Emotional granularity, the degree to which individuals discriminate between emotions within positive or negative categories in daily experiences, is a widely studied form of EC linked to anxiety, depression, and personality pathology. However, less research has examined idiographic measures that index EC in terms of person-specific components of emotional experience, as well as links to psychopathology.

**Methods** This study examined the relationship between two relatively novel idiographic indexes of EC in relation to granularity and measures of psychopathology. Participants ($N = 177$, 54% above moderate levels of anxiety, depression, and/or personality pathology) reported perceptions of their emotional components, a qualitative idiographic index of EC. They also completed a 50-day emotion diary.

**Results** Dynamic factor analyses yielded the number of emotion factors for each person over time, a quantitative idiographic measure of EC. Intraclass correlations on diary data measured emotional granularity. Results suggested that each measure was distinct and explained unique variance in predicting anxiety, depression, and/or personality pathology.

**Conclusions** The results highlight the importance of studying both idiographic and existing nomothetic measures of EC as potential transdiagnostic risk factors for psychopathology.

**Keywords** Emotion differentiation · Idiographic analyses · Idiography · Depression · Anxiety

## Introduction

Emotional dysfunction constitutes the core of anxiety, depressive, and personality disorders (American Psychiatric Association, 2013; Gratz et al., 2011; Stanton & Watson, 2014; Watson & Naragon-Gainey, 2010). Consequently, understanding how individuals experience emotional states is essential to recognizing and treating psychopathology (Gross, 1998). However, most research assumes that the factor structure of emotional states is identical between individuals and limited to two dimensions of positive and negative affect or valence and arousal. Clinical experience, however, implies the possibility that individuals vary in how many dimensions capture their emotional experience, suggesting person-specific or idiographic features. For one person, valence and arousal might capture the variance in their experiences, whereas another might require many more dimensions to account for them. In contrast, the authors have encountered patients who anecdotally reported experiencing only a single valence dimension of positive versus negative emotion (e.g., "I either feel fine or terrible!"; "Feeling anger or nothing at all."). Moreover, experiencing emotions in more complex and differentiated forms may be adaptive, implying lower dysfunction. The present study examined idiographic measures of emotional complexity vis-à-vis a more established measure of emotional granularity, as well as the extent to which these differentially predict emotional and

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personality dysfunction. First, we review relevant literature and reasons to attend to idiographic approaches.

## Emotional Complexity

Many forms of psychopathology are comprised of continuous emotional symptom dimensions on which individuals differ (e.g., Kotov et al., 2017). However, although these dimensional models represent general tendencies, not all individuals experience their emotions in the same way. A range of constructs related to individual differences in experiencing emotions can be subsumed under the broader meta-construct of *emotional complexity* (EC), which, although not completely agreed upon in terms of definition, reflects greater nuance in emotional experience (Grossmann et al., 2016; Grühn et al., 2013; O'Toole et al., 2019). For instance, individuals vary in *emotional awareness* (Cameron et al., 2013) and *emotional intelligence* (Petrides et al., 2001). *Emotional clarity* reflects differences in ability to understand and distinguish feelings (Gohm & Clore, 2002). *Emotion covariation* or *dialecticism* (O'Toole et al., 2019) captures the capacity to experience and articulate both positive and negative emotions at the same time. *Emotion differentiation* or *granularity* has been conceptualized as the degree to which one distinguishes between similarly-valenced (e.g., negative) states over time, suggesting specificity in discriminating momentary experiences of sadness versus anger, for example (Barrett et al., 2001). In contrast, *alexithymia* has been conceptualized as inability to understand and delineate one's emotions (Parker et al., 2001), implying lack of emotional granularity (Hoemann et al., 2021a). These overlapping constructs tap individual differences in ability to feel, understand, and distinguish one's emotions (i.e., "expertise in emotion"; Hoemann et al., 2021b), but are not necessarily redundant. For instance, measures of emotional clarity and granularity only modestly correlated (Boden et al., 2013; Erbas et al., 2014), despite reflecting aspects of the broader notion of emotional complexity.

Theories about the purpose of emotion imply that the capacity to experience emotions with complexity and specificity may be important for mental health. For instance, appraisal theories of emotion (Clore & Ortony, 2000; Frijda, 1986) associate emotions with cognitive interpretations of situations, implying the importance of accuracy for such pursuits. Particular emotions may facilitate adaptation to specific goals or tasks (Izard, 2009). Negative emotions alert people to threats, whereas positive emotions orient them to specific classes of rewards (Shiota et al., 2014). Constructionist theories (Barrett, 2009) emphasize emotion in predicting opportunities in specific contexts, portraying precision as useful. These theories imply that emotional experiences are adaptive when facilitating responses to situational contexts.

Moreover, ability to differentiate emotions and represent them in complex ways may be important for mental health. Psychotherapy is thought to help individuals differentiate emotions and associated triggers, motivations, and needs, facilitating growth (Pascual-Leone & Greenberg, 2007). Accordingly, low emotional granularity, for instance, has been linked to symptoms of anxiety (Kashdan & Farmer, 2014), depression (Demiralp et al., 2012; Erbas et al., 2014, 2018; Starr et al., 2017), and borderline personality pathology (Dixon-Gordon et al., 2014; Suvak et al., 2011; Zaki et al., 2013), suggesting a possible transdiagnostic risk factor.

## Reasons to Examine Idiographic Measures of Emotional Complexity

Research on granularity provides a promising way to measure ability to differentiate emotions and its implications for psychopathology but may not be the only fruitful approach for several reasons. Specifically, granularity has been operationalized as the intraclass correlation coefficient (ICC) of diary ratings of emotions, calculated separately for negative and positive items (Emery et al., 2014; Erbas et al., 2014; Kashdan & Farmer, 2014; Starr et al., 2017; Tong & Keng, 2017). It reflects rating emotions similarly across time relative to emotions within a single time point (then reverse-scored so that high scores indicate rating unique emotion only in specific contexts—higher granularity or differentiation). On one hand, meta-analyses show negative affect (NA) and positive affect (PA) granularity scores to correlate differentially with outcomes (O'Toole et al., 2019), implying utility in distinguishing them. However, these ICC-based indexes of granularity make the "nomothetic" assumption (i.e., law-like generalization) of the same two building blocks of emotion for all individuals. However, some individuals might vary on *more* than two dimensions of emotion. Someone able only to report diffuse distress versus euthymia would score low on granularity (Thompson et al., 2021), but also might vary day-to-day on relatively fewer dimensions than someone who distinguishes more shades of emotion. We do not challenge the importance of distinguishing positive versus negative valence in emotions, but rather the assumption that two factors always capture all the important valence in self-reported emotions.

In contrast, some aspects of emotional experience might represent unique, person-specific, *idiographic* phenomena. There is a long tradition in personality science on person-specific behavioral signatures (e.g., Shoda et al., 2015) and individual patterns in clinical case formulation. Furthermore, many disorders incorporate polythetic criteria such that individuals with highly heterogeneous symptoms may meet criteria for the same diagnosis. For example, symptom constellations vary dramatically among depressed individuals (Monden et al., 2015); sadness cooccurs with weight gain in some people, but weight loss in others (Fried, 2017). Whereas nomothetic approaches start from common categories of experience and analyze group-level data, idiographic approaches first examine person-specific experiences and may subsequently aggregate data to examine group-level patterns, providing a personalized view into psychopathology (Hayes et al., 2019; Hofmann et al., 2020). Idiographic approaches to EC would permit examination of unique variability in how individuals differentiate their emotions.

One proposed method is to adopt a multilevel modeling approach which treats the association between PA and NA as a random effect that varies between people (*affective synchrony* or *emotion covariation*). This moves closer to ideographic relationships between emotions; for some people, NA and PA correlate inversely, whereas others exhibit no correlation between PA and NA. Studies in nonclinical (Wilt et al., 2011) and clinical (Schoenleber et al., 2016) samples attest to such variability in NA–PA relationships across individuals. However, this approach still assumes PA and NA as identical building blocks of emotion for everyone.

In contrast, a more ideographic approach to EC may be to examine individuals' person-specific "building blocks" or categories of emotion. Grühn et al. (2013) suggested that individuals' *factorial components* of emotion represent an aspect of EC, which Brose et al. (2015) described as an alternative way to operationalize differentiation. We assume that the number of components indexes an aspect of EC not identical to differentiation/granularity. From a cognitive-developmental theoretical framework, as individuals mature and gain richer models for representing experience, they are assumed to require more emotional components to represent their internal states (Labouvie-Vief et al., 2010). At the simplest level, inviting individuals to report their perceived number of emotion factors may provide a *qualitative idiographic* approach. Presumably, individuals who can identify and label more of their own meaningful types of emotion may possess more ability to differentiate emotions. Very few studies have utilized this method. For instance, Russell (1980) asked participants to generate and populate their own idiosyncratic categories of emotional experience. Similarly, in another study, participants sorted 135 emotions into similar categories; higher numbers correlated with a self-report measure of emotional complexity (Kang & Shaver, 2004). Although likely not redundant, one's self-reported number of emotion factors might covary with the ICC-based (*quantitative nomothetic*) granularity given that, someone unable to differentiate between negative emotions in specific contexts may also possess few categories for understanding emotions. Moreover, each may uniquely predict lower psychopathology.

However, a qualitative index of EC (self-reported emotion factors), although idiographic, does not speak to situation-specific emotion perceptions indexed over time by granularity. Emotional experiences involve dynamic changes (Frank et al., 2017; Roche & Jacobson, 2018) both over moments and over large time spans. However, even in diary studies, emotional states have usually been measured on scales derived from between-person factor analyses at a single occasion (i.e., Watson et al., 1988), assuming similar structure among individuals (Fisher & Boswell, 2016). *Ergodicity*—the assumption that this sort of interindividual variability (IEV) generalizes to all within-person or intraindividual variability (IAV; Molenaar, 2004, 2008) often does not hold in practice (Molenaar & Campbell, 2009). Fisher et al. (2018) found different means, variances, and relationships with other constructs for PA and NA when comparing IEV and IAV. Similar evidence for person-specific intraindividual relationships came from samples with anxiety, depression, or personality disorders (Fisher et al., 2017, 2018).

By extension, though a two-factor structure derived from IEV may apply to most people on average, examinations of IAV might suggest that some people require more factors to adequately capture their daily emotional experiences. Examining within-person repeated-measures emotion components requires *person-specific factor analysis* (or dynamic factor models; Ram et al., 2013) to derive a *quantitative idiographic* index of EC based on IAV (i.e., number of factors), which may predict between-person differences in symptoms. This approach, although not common, has existed for some time. In a small sample study of "affective complexity," Wessman and Ricks (1966) found that participants' daily emotions were explained by between one and seven emotion factors, whereas Larsen and Cutler (1996) found that participants required between two and five factors to account for 50% of the with-person variance in daily emotion ratings. Studies coming from a developmental perspective found that higher number of emotion components in adults or older adults—viewed as indicators of a more complex emotional life—correlated with lower neuroticism (Carstensen et al., 2000; Ong & Bergeman, 2004). More recent research showed that the number of emotion factors correlated positively with granularity (Grühn et al., 2013), suggested possible overlap. However, scant research has examined the number of emotion factors in relationship to established measures of granularity and incremental, unique links of each to symptoms.

Given the theoretical assumption that a greater number of idiographic emotion factors may indicate more complex emotional life and greater adaptive functioning (Labouvie-Vief et al., 2010), more research is needed to examine unique relationships of idiographic markers of complexity (number of components) to clinical distress symptoms and personality dysfunction. Dynamic factor models are fit to IAV over time, and have demonstrated person-specific patterns among symptoms in daily life for anxiety and depression (Fisher, 2015; Fisher & Boswell, 2016), as well as borderline personality symptoms (Wright et al., 2016). However, with the exception of borderline personality traits (linked to lower granularity; Dixon-Gordon et al., 2014; Suvak et al., 2011; Zaki et al., 2013), few studies have examined EC markers and personality pathology. Personality dysfunction can involve undifferentiated views of self and others (e.g., Zaki et al., 2013) and concomitant emotional constriction or lability (Erickson et al., 2015; Schoenleber et al., 2016). Larsen and Cutler (1996) found that possessing more emotion factors (i.e., *idiographic quantitative* index) had mixed personality correlates, especially for men, in whom more factors correlated with lower neuroticism, but also lower happiness and extraversion. Personality dysfunction can be conceptualized as five dimensions including negative affect (i.e., emotional lability and separation insecurity), antagonism (i.e., manipulativeness), detachment (i.e., extreme introversion), disinhibition (i.e., impulsivity), and psychoticism (i.e., unusual beliefs). Idiographic EC indices may relate to these traits, given, for instance, links to disinhibition in the context of alcohol-related problems (Emery et al., 2014). In addition, they might covary with self-reported and observer-reported levels of personality functioning (American Psychiatric Association, 2013), which serve as markers of personality dysfunction (Roche et al., 2016, 2018).

### The Present Study

Recent theory in individual process-based therapy necessitates assessment strategies which conceptualize emotional dysfunction at the individual level, but also relate these idiographic factors to nomothetic processes; this approach will be key to advancing beyond single-syndrome treatment protocols (Hayes & Hofmann, 2021; Hayes et al., 2019; Hofmann et al., 2020). The present study examined both *qualitative* and *quantitative ideographic* measures of individuals' emotion factors as an alternative measure of EC alongside the more established (*quantitative nomothetic*) ICC-based granularity, as well as the unique variance each may explain in symptoms of anxiety, depression, and personality dysfunction. At baseline, participants completed online measures of self-reported idiographic structure of emotion, as well as anxiety, depression symptoms, and pathological personality traits (via self-report and independent rater), followed by 50 days of experience sampling of emotion ratings.

### Hypotheses

1. Hypothesizing idiographic experiences of emotion, we expected significant variability in indices of EC. We hypothesized that the number of emotional building blocks (i.e., factors) would vary between persons for *idiographic quantitative* and *idiographic qualitative* indices of EC. We also expected significant variance in granularity scores as the *quantitative nomothetic* index.
2. Given the idea that all three measures tap aspects of EC (Grühn et al., 2013), we expected all to correlate positively. However, we also expected unique variance in each index.
3. Given previous psychopathology research, we hypothesized that higher scores on each index would predict lower anxiety, depression, and self- and observer-rated personality pathology levels.

## Methods

### Participants

Participants [$N = 177$; 18% Male, 81% Female; 1% Transgender; $M_{age} = 19.90$ (range 18–31); 66% White/Caucasian, 7% African American/Black, 7% Hispanic/Latinx, 1% Arab/Middle Eastern/Arab American, 14% Asian/Asian-American, 2% Asian Indian, 1% Pacific Islander, 2% Multiple/Mixed Ethnicities, 1% Other] were recruited from personality psychology courses (Jacobson et al., 2021; Roche et al., 2017, 2018; Shin et al. 2022). Based on the psychopathology measures below, 53% of the sample was at moderate to severe levels of anxiety (66%), depression (25%), and/or personality pathology (67%), suggesting elevated distress in this non-clinical sample.[1]

### Measures

#### Positive Affect Negative Affect Scales (PANAS)

The PANAS is a widely used 20-item scale assessing feelings in adjectival format (Watson et al., 1988). Participants rated each emotion daily ("today") for approximately 50 days, on a 0 (*Not at All*) to 100 (*Extremely*) continuous slider scale (adapted to represent a broader range of levels of emotion). We randomized items to limit response sets based upon item order. Dynamic factor models of each participants' PANAS data provided our *quantitative idiographic* index of EC, whereas ICCs on the PANAS provided a *quantitative nomothetic* index of granularity (described below).

[1] Note that moderate anxiety pathology was assessed based on the PROMIS anxiety scale norms (Pilkonis et al., 2011). Moderate depressive pathology was assessed via PROMIS depression scale norms ibid. Moderate personality pathology was based on the PID-5 pathology subdomain in nationally representative sample norms (Krueger et al., 2012), using the procedure adopted by Samuel et al. (2013), with *t*-score of 65 or above reflecting moderate to severe.

#### Self-reported Idiographic Structure of Emotion

Based on the theory that emotions can be defined by a person's categorization of their experiences (Kang & Shaver, 2004; Russell & Barrett, 1999), participants were asked to organize the 20 PANAS emotion terms into their own self-defined emotional "building blocks" (i.e., if they experienced "nervous" and "jittery" as part of the same underlying feeling, they were asked to group these together). Informed by Russell (1980), we invited participants to choose (1) the number of building blocks and (2) a label for each. Participants were told that there were no "right" answers, and they could identify as few as one building block or as many as best captured their emotional experiences. For example, one participant grouped upset, irritable, nervous, jittery, and afraid together under a label of "anxious." Another participant grouped excited, strong, enthusiastic, proud, and active under the label of "sense of accomplishment." This provided our *qualitative idiographic* index of ED.

#### PROMIS Anxiety Scale-Short Form

The PROMIS Anxiety Scale-Short Form is a 7-item questionnaire on a 1 (*never*) to 5 (*always*) Likert scale measuring anxiety symptoms in the past 7 days (e.g., "I found it hard to focus on anything other than my anxiety") (Pilkonis et al., 2011). This scale showed strong convergent validity ($r=0.80$; Pilkonis et al., 2011) and internal consistency ($\alpha=0.93$ in the present study).

#### PROMIS Depression Scale-Short Form

The PROMIS Depression Scale-Short Form measures depression symptoms in the past week via eight items on a 1 (*never*) to 5 (*always*) scale (e.g. "I felt hopeless"; Pilkonis et al., 2011). This measure had strong convergent validity ($r=0.83$) with the Center for Epidemiologic Studies Depression Scale (Pilkonis et al., 2011) and excellent internal consistency for the present data ($\alpha=0.95$).

#### Level of Personality Functioning-Self Report (LPFS-SRA)

Participants completed a 12-item self-report measure of personality functioning (American Psychiatric Association, 2013), which has been demonstrated predictive validity (Roche et al., 2016, 2018). Internal consistency was excellent for the present dataset ($\alpha=0.85$).

#### Level of Personality Functioning-Observer Report (LPFS-OR)

Independent raters rated participants' self-written psychological life-history narratives using the abbreviated version of the Life Stories Interview (McAdams, 2008); a team of undergraduate observers rated these narratives using the level of personality functioning (American Psychiatric Association, 2013) via the same 12 items in the LPFS. Raters achieved good interrater reliability (average ICC = 0.74–0.78 across teams for the total), and this method demonstrated predictive validity (see Roche et al., 2018). Responses were internally consistent ($\alpha=0.94$).

#### Personality Inventory for DSM-5-Brief Form (PID-5-BF)

Participants completed 25 items measuring dimensional pathological personality traits of negative affect, antagonism, psychoticism, detachment, and disinhibition (American Psychiatric Association, 2013). The PID-5-BF uses a 4-point scale ranging from 0 (*very false or often false*) to 3 (*very true or often true*). Internal consistency was adequate for negative affect ($\alpha=0.77$), antagonism ($\alpha=0.69$), psychoticism ($\alpha=0.76$), detachment ($\alpha=0.69$), and disinhibition ($\alpha=0.85$).

### Procedure

On a single baseline in-person assessment day, participants completed the Self-Reported Idiographic Structure of Affect measure, PROMIS Anxiety, PROMIS Depression, LPFSR-SRA, a life history interview (for the LPFS-OR), and the PID-5-BF. They subsequently completed the PANAS at the end of each day for 50 days using a Qualtrics survey. Participants completed an average of 89.3% of the surveys ($M=44.7$ surveys, range 30–50). Participants received extra credit or could opt for an alternative credit opportunity if not interested in participating.

### Analysis Plan

#### Computing Measures of Emotion Differentiation

We computed three measures of EC: (1) quantitative nomothetic, (2) qualitative idiographic, and (3) quantitative idiographic.

(1) *Quantitative nomothetic measure of granularity* As with prior research (Emery et al., 2014; Erbas et al., 2014; Kashdan & Farmer, 2014; Starr et al., 2017; Tong & Keng, 2017), granularity/emotion differentiation was operationalized using ICC calculated separately for negative and positive affect PANAS scales (diary data). ICCs were calculated as the degree of convergence between items (i.e. each item was considered a separate "rater"). Thus, the ICC for PA reflected greater convergence between PA items, whereas the ICC for NA indicated rating NA items similarly. Typi-

cally, researchers reverse ICC scores by subtracting ICC from 1 (e.g., Grühn et al., 2013) or in some cases by multiplying ICC times − 1 (Hoemann et al., 2021a; Kashdan & Farmer, 2014) for ease of interpretation, such that higher levels reflect greater granularity. We chose the latter method.

(2) *Qualitative idiographic measure of emotional complexity* For the qualitative idiographic conceptualization, we summed the number of self-reported idiographic structures (i.e., the self-reported number of emotional building blocks identified by participants), with low numbers reflecting less EC, and higher numbers reflecting greater EC.

(3) *Quantitative idiographic measure of emotional complexity* We utilized dynamic factor models on PANAS diaries to create a quantitative idiographic measure across subjects.

**Daily Diary Data Preparation** Dynamic factor models apply to intraindividual variation over time, requiring within-personal temporal variability in order to converge. Thus we ensured that only items contributing information to the model were included, preventing non-convergence. Items with no or very low IAV for a given participant were removed, as recommended (Ram et al., 2005). We first calculated within-person standard deviation of all remaining PANAS items for each participant. A one sample chi-square test of variance determined whether a given individual standard deviation for each PANAS item was significantly below the 25th quantile of the variance for the given person (i.e., the item was relatively invariant compared to all other items for that person)—a conservative requirement for within-person variability (Millard & Neerchal, 2000; Van Belle et al., 2004; Zar, 2010). After removal of all invariant or low-variance items, we person-standardized each item to capture within-person variation (e.g., subtracted each daily item score from the aggregate person mean of the item across all days, divided by the within-person standard deviation of the item across time).

**Dynamic Factor Analysis of Diary Data** Next, we conducted exploratory and confirmatory dynamic factor analysis using state-space models (i.e. a combination of latent variable models with vector autoregressive models), utilizing the structural equation modeling package *OpenMx* in R (Molenaar, 1985). Unlike p-technique factor analysis which ignores the temporal interdependence of observations over time, state-space models incorporate temporal dynamics when determining whether a given solution provides a good fit to the data which, accounting for temporal interdependence of nearby datapoints using lags (Jacobson et al., 2019).

Model fit was examined using cutoffs from prior simulation studies: Root Mean Square Error of Approximation (RMSEA) ≤ 0.06; Confirmatory Fit Index (CFI) ≥ 0.95; and Tucker Lewis Index (TLI) ≥ 0.95 (Hu & Bentler, 1998). Model estimation proceeded by first estimating a one-factor model and then increasing the number of factors for a given person until an acceptable fit was achieved. When a model would run out of degrees of freedom in the factor estimation, items with low factor loadings (below 0.15) were fixed to 0 prior to adding an additional factor. After an exploratory factor model yielded acceptable fit, oblimin factor rotation was given that emotion factors were expected to be non-orthogonal. Next, all low factor loadings (below 0.15) were fixed to zero, and a confirmatory model was run. Note that all prior exploratory and confirmatory models fit autoregressive lags of 1 day. Additionally, cross-regressive lags between one factor on another on the next day were freed based on modification indices that indicated that freeing a cross-regressive lag would result in a significantly better fit. In most cases, missing data (10.7%) was estimated using full information maximum likelihood. However, in a minority of cases, models did not converge using full information maximum likelihood, and estimation proceeded using multiple imputation chained equations (mice) (Ji et al., 2018). The final idiographic number of factors extracted from the final confirmatory factor model fit for each person served as our *quantitative idiographic* measure of EC (with higher numbers reflecting greater complexity). See Supplemental Files for a depiction of a dynamic factor model, including a depiction of factor loadings, time-lagged factor predictions, residual associations among factor scores, and a plot of factor scores over time for an example participant and the model fit indices for all participants. Also see, Supplemental Files for a depiction of all factor loadings for each subject.

### Heterogeneity of Emotional Complexity

Descriptive statistics of the EC indices were first computed (see Table 1). One-sample *t*-tests were used to determine whether the idiographic measures had significantly more than 1 factor. Likewise, one-sample *t*-tests were used to determine whether scores for the nomothetic measure of granularity were significantly different from − 1 (i.e., which would represent total agreement and therefore complete lack of granularity, given that the ICCs were inversed). In addition, one-sample chi-squared tests on the variance tested whether the variance of each measure was significantly greater than 0.01 (a test of 0 was not possible with this type of test).

**Table 1** Means, standard deviations, and correlations of emotion differentiation constructs

| Variable | *M* | *SD* | Min | Max | 25th | Med | 75th | 1 | 2 | 3 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1. Qualitative idiographic | 5.26* | 1.49* | 2 | 12 | 4 | 5 | 6 | | | |
| 2. Quantitative idiographic | 4.79* | 1.98* | 2 | 12 | 3 | 4 | 6 | 0.03 | | |
| 3. Quantitative nomothetic: negative emotions | − 0.22* | 0.13* | − 0.57 | 0.09 | − 0.29 | − 0.21 | − 0.12 | 0.03 | − 0.16 | |
| 4. Quantitative nomothetic: positive emotions | − 0.31* | 0.16* | − 0.85 | − 0.00 | − 0.43 | − 0.29 | − .20 | − 0.00 | − 0.24* | 0.44* |

*Qualitative idiographic* self-reported number of emotion factors; *quantitative idiographic* the number of emotion factors derived from dynamic factor models; *quantitative nomothetic* negative and positive refer to the ICC for negative and positive emotion items, respectively (inversed such that the M of − 0.22 responded to a 0.22 intraclass correlation). The significance around the means for the idiographic measures was based on a one-sample *t*-test to determine whether the number of items was significantly greater than 1 (i.e. significantly greater than 1 factor). For the nomothetic measures, the significance around the means was based on a one-sample *t*-test of whether the items were significantly different than − 1 (i.e. the ICCs had less than perfect agreement). All standard deviations were tested to see if they were significantly different from 0.01 based on a one-sample chi-squared test on variance

*$p < .05$

### Relationship Between Emotional Complexity and Psychopathology

Commonality analysis (Nimon & Oswald, 2013) was utilized to determine the unique percentage of variation explained by each measure of EC predicting the level of anxiety, depression, level of personality functioning (both self- and observer reports), and pathological traits of negative affect, detachment, antagonism, disinhibition, and psychoticism. Commonality analysis is based on multiple regression, but robust to potential collinearity among predictors.

## Results

### Descriptive Statistics of Emotional Complexity Measures

As hypothesized, the one-sample *t*-tests of both the *qualitative* and *quantitative idiographic* measures indicated that the average participant had significantly more than 1 factor on average, averaging approximately 5 factors each (see Table 1). Likewise, *t*-tests for granularity showed that ICC-based scores were significantly greater than − 1, suggesting that the average participant had at least some degree of granularity. Moreover, the one-sample chi-squared tests showed that all variances were significantly greater than 0.01, attesting to variance across persons.

As expected, positive and negative *quantitative nomothetic* measures of granularity correlated positively. Contrary to hypotheses, the granularity for positive emotions correlated negatively with the *quantitative idiographic* measure, suggesting that those with more emotion factors in daily life experienced lower granularity as indexed by the ICC approach. Interestingly this association was not present for negative granularity, and the *qualitative idiographic* index did not correlate with the other indices, suggesting an independent process.

### Relationship Between Indices and Psychopathology

As hypothesized, all types of psychopathology were significantly predicted by at least one EC variable (see Table 2). *Qualitative idiographic* EC predicted an average of 32.98% of the total relationships between EC and psychopathology, such that higher scores predicted lower anxiety, depression, and self-reported personality dysfunction. *Quantitative idiographic* EC predicted an average of 13.18% of the total covariation between EC and psychopathology, with higher levels predicting greater antagonism, contrasting the hypothesis of predicting lower personality dysfunction. *Quantitative nomothetic* granularity for negative emotions predicted an average of 21.37% of the total covariation between EC and psychopathology, with higher granularity predicting lower levels of antagonism as hypothesized, but also greater detachment (contrary to hypotheses). *Quantitative nomothetic* granularity for positive emotions predicted an average of 20.30% of the total association between EC and psychopathology, with higher levels predicting lower disinhibition, as hypothesized.

## Discussion

The current investigation explored idiographic operationalizations of EC, their relationship to the widely-used ICC-based emotional granularity index (as a distinct form of EC), and their differential prediction of dimensional psychopathology. Despite prior research on the person-specific nature of emotion (Boswell et al., 2014; Fisher & Boswell, 2016; Wright et al., 2016) and the nomothetic measure of granularity (e.g., Erbas et al., 2018; Kashdan & Farmer, 2014; Nook

**Table 2** Commonality analysis

| Predictor | Outcome | $R^2$ | % of total $R^2$ | $r$ |
|---|---|---|---|---|
| Qual idiographic | Anxiety | **0.024*** | **49.205** | **− 0.154*** |
| Quant idiographic | Anxiety | 0.002 | 4.268 | 0.044 |
| Quant nomothetic negative | Anxiety | 0.018 | 40.395 | − 0.133 |
| Quant nomothetic positive | Anxiety | 0.002 | 3.936 | − 0.041 |
| All predictors | Anxiety | **0.046*** | **100.00** | |
| Qual idiographic | Depression | **0.025*** | **62.655** | **− 0.157*** |
| Quant idiographic | Depression | 0.001 | 2.552 | 0.030 |
| Quant nomothetic negative | Depression | 0.002 | 5.663 | 0.043 |
| Quant nomothetic positive | Depression | 0.005 | 14.791 | 0.073 |
| All predictors | Depression | **0.038*** | **100.00** | |
| Qual idiographic | LPFS-OR | 0.004 | 12.161 | − 0.062 |
| Quant idiographic | LPFS-OR | 0.005 | 15.220 | 0.072 |
| Quant nomothetic negative | LPFS-OR | 0.000 | 0.661 | − 0.014 |
| Quant nomothetic positive | LPFS-OR | 0.012 | 45.159 | − 0.110 |
| All predictors | LPFS-OR | **0.029*** | **100.00** | |
| Qual idiographic | LPFS-SR | **0.039*** | **72.553** | **− 0.198*** |
| Quant idiographic | LPFS-SR | 0.005 | 9.507 | 0.071 |
| Quant nomothetic negative | LPFS-SR | 0.003 | 5.746 | − 0.054 |
| Quant nomothetic positive | LPFS-SR | 0.004 | 9.807 | − 0.065 |
| All predictors | LPFS-SR | **0.052*** | **100.00** | |
| Qual idiographic | Negative affective personality | 0.021 | 55.908 | − 0.144 |
| Quant idiographic | Negative affective personality | 0.011 | 28.033 | 0.105 |
| Quant nomothetic negative | Negative affective personality | 0.002 | 9.286 | − 0.043 |
| Quant nomothetic positive | Negative affective personality | 0.002 | 5.715 | − 0.043 |
| All predictors | Negative affective personality | **0.035*** | **100.00** | |
| Qual idiographic | Antagonistic personality | 0.021 | 23.907 | − 0.143 |
| Quant idiographic | Antagonistic personality | **0.022*** | **23.838** | **0.149*** |
| Quant nomothetic negative | Antagonistic personality | **0.036*** | **39.675** | **− 0.188*** |
| Quant nomothetic positive | Antagonistic personality | 0.004 | 5.949 | − 0.067 |
| All predictors | Antagonistic personality | **0.090*** | **100.00** | |
| Qual idiographic | Psychotic personality | 0.002 | 5.613 | 0.039 |
| Quant idiographic | Psychotic personality | 0.005 | 12.983 | 0.070 |
| Quant nomothetic negative | Psychotic personality | 0.006 | 18.178 | − 0.075 |
| Quant nomothetic positive | Psychotic personality | 0.021 | 61.188 | − 0.146 |
| All predictors | Psychotic personality | **0.035*** | **100.00** | |
| Qual idiographic | Detachment personality | 0.003 | 8.663 | − 0.052 |
| Quant idiographic | Detachment personality | 0.005 | 15.806 | − 0.067 |
| Quant nomothetic negative | Detachment personality | **0.023*** | **56.065** | **0.151*** |
| Quant nomothetic positive | Detachment personality | 0.003 | 8.032 | 0.057 |
| All predictors | Detachment personality | **0.038*** | **100.00** | |
| Qual idiographic | Disinhibition personality | 0.006 | 6.196 | 0.079 |
| Quant idiographic | Disinhibition personality | 0.007 | 6.447 | 0.084 |
| Quant nomothetic negative | Disinhibition personality | 0.018 | 16.622 | − 0.135 |
| Quant nomothetic positive | Disinhibition personality | **0.030*** | **28.138** | **− 0.172*** |
| All predictors | Disinhibition personality | **0.107*** | **100.00** | |

*Qual Idiographic* qualitative idiographic (self-reported number of emotion factors); *Quant Idiographic* Quantitative Idiographic (number of emotion factors from dynamic factor analyses); *Quant Nomothetic* Quantitative Nomothetic (emotional granularity). These results display the commonality analysis of the emotion differentiation predicting psychopathology. Note that $r$ represents the partial correlation coefficient. The term “all predictors” describe the percentage of variation in the outcome explained by all predictors together in the model. Note that the models with multiple variables simultaneously are not presented here for spatial constraints (which is why all predictors do not sum to 100% of the $R^2$)

* and bolded, $p < .05$

et al., 2018; Starr et al., 2017), studies have rarely examined these variables simultaneously. Overall, results suggest unique variance in EC measures and potential relevance to anxiety, depression, and personality pathology symptoms.

Interrelationships between EC variables suggested that each reflect non-redundant processes. As expected, (*quantitative nomothetic*) ICC-based granularity measures for positive and negative emotions correlated positively. In other words, people who differentiated among positive emotions in daily life also tended to differentiate among negative emotions. However, contrary to our hypothesis, granularity variables were not associated with our *qualitative idiographic* measure, and our *quantitative idiographic* measure correlated negatively with positive emotion granularity, contrary to Grühn et al. (2013); individuals with more discrete emotion factors in daily life were slightly less likely to differentiate among specific positive emotion terms. Though unexpected, this association might be partially understood by associations to external variables. Namely, the *quantitative idiographic* measure's unique links to higher antagonism, and links of the *quantitative nomothetic* granularity measure for PA to lower disinhibition, may provide a clue. Given that high antagonism and disinhibition are associated with externalizing personality features (Sleep et al., 2018), these findings may suggest that those with more daily emotion factors were those prone to externalizing traits. If so, the *quantitative idiographic* index may serve as a marker for such traits. For instance, it is possible that a person high in externalizing traits might experience daily resentment, boredom, and contempt as unique factors, thereby scoring higher on this index. Future research should examine the content of daily emotion factors to elucidate this association. Nonetheless, the finding (in within-person dynamic factor models) of significant variability between individuals in how many factors captured their daily emotional experiences supported hypotheses and was consistent with past findings of person-specific emotion structures (Feldman, 1995; Fisher & Boswell, 2016). Also, despite the idea that multiple measures of emotional experiencing, understanding, and structure are subsumed under the concept of emotional complexity (Grühn et al., 2013), the small or nonsignificant associations between idiographic measures and granularity support suggest that our indices were largely distinct. Different forms of emotional expertise deserve to be studied in their own right (Hoemann et al., 2021a, 2021b).

Similarly, the *qualitative idiographic* measure of EC appeared to be unrelated to other measures of ED, counter to hypotheses and to previous research in which the number of sorted emotion categories correlated with self-reported emotion differentiation (Kang & Shaver, 2004). Nonetheless, significant variability in individuals' self-reported sense of how many emotional "building blocks" were needed to capture their emotional experiences was as expected and consistent with significant variability in person-specific factors in the *quantitative idiographic* measure. Lack of association with other indices and findings of links to psychopathology scales (discussed below) suggests that the *qualitative idiographic* measure provided a novel, distinct index. Our study describes the first known example where participants' self-reported and labeled structure of their emotions (Russell, 1980; Russell & Barrett, 1999) was used to predict psychopathology. Each of the three indices may represent unique variance and may vary in adaptive vs. maladaptive features, implying the need to move understand multiple EC processes.

Despite weak relationships among our three indices, each explained unique variance in symptom outcomes, providing predictive validity and suggesting that they reflect distinct processes. Specifically, the *qualitative idiographic* measure was the most robust predictor of psychopathology, predicting approximately a third of the total variance of links of EC measures to psychopathology. Next, *quantitative nomothetic* negative and positive granularity predicted about one fifth of the total variance each, in line with studies of these ICC-based indices predicting psychopathology (Demiralp et al., 2012; Dixon-Gordon et al., 2014; Erbas et al., 2014, 2018; Kashdan & Farmer, 2014; Nook et al., 2018; Starr et al., 2017; Suvak et al., 2011; Zaki et al., 2013). Lastly, the *quantitative idiographic* index, the most methodologically advanced method (i.e., dynamic factor analysis), explained roughly one seventh of the relationship of EC to psychopathology.

In addition to the average proportion of total variance explained, the direction of relationships between EC indices and dimensions of psychopathology suggests unique processes. In particular, only the *qualitative idiographic* index predicted lower anxiety, depression, and self-reported personality dysfunction, implying transdiagnostic risk. Thus, participants identified more types of distinct emotional experiences endorsed lower symptoms, in parallel to studies finding *quantitative nomothetic* (e.g., ICC) indices predicting less anxiety (Kashdan & Farmer, 2014), depression (Demiralp et al., 2012; Erbas et al., 2014, 2018; Starr et al., 2017), and borderline personality pathology (Dixon-Gordon et al., 2014; Suvak et al., 2011; Zaki et al., 2013). Whereas indices based on ICCs and dynamic factor models would be harder to fake and less open to conscious awareness, these results imply the potential relevance of consciously available mental representations of one's emotion categories for mental health. One might imagine clinical interventions emphasizing learning to identify one's own idiographic emotion categories. For instance, repeated diary assessments of mood might, over time, lead to differentiating more emotion factors in daily life, similar to how repeated assessments is linked to changes in granularity (Hoemann et al., 2021a).

Alternatively, inviting clients to sort emotions into categories in session might provide a novel way to develop expertise in emotion identification. The non-redundancy of idiographic indices and granularity might suggest the need to help clients learn both to differentiate distinct categories of emotion as well as between narrow emotion terms. Future research is warranted to test these notions.

Surprisingly, granularity measures did not predict anxiety, depression, or general personality functioning. However, the fact that granularity for positive and negative emotions predicted lower disinhibition and antagonism, respectively, supports a conceptualization of ICC-based indices as measuring an adaptive process relevant to externalizing. In contrast, the link of the negative granularity index to higher detachment was unexpected. Perhaps some individuals who chronically maintain coldness and social distance from others are relatively able to distinguish between and/or ruminate on their various negative emotions. Alternatively, this unexpected finding might be explained by use of immature defenses (i.e. denial) related to negative emotions when they are experienced somewhat separately (Roche et al., 2016), enabling detachment from separate negative emotions (Tong & Keng, 2017).

The *quantitative idiographic* measure of EC predicted higher antagonism. Although not hypothesized, this was consistent with finding that number of emotion components correlated with low agreeableness and high neuroticism (Grühn et al., 2013). It is possible that whether a greater number of daily emotion dimensions is adaptive depends on other factors. For instance, it may be that antagonistic individuals may experience a broader arrange of maladaptive or conflicting emotions that are outside the normal range of experience (e.g., pronounced greed or envy, hubristic pride, positive emotions when others fail, cynicism, and anger). Alternatively, high antagonism individuals may distinguish their self-related negative emotions (i.e. anxiety, guilt) from their anger and their sense of pride, as suggested in empirical and theoretical accounts of narcissism (Dawood & Pincus, 2018). Similarly, the number of idiographic factors correlated with poorer wellbeing in men (Larsen & Cutler, 1996) and in older adults (Brose et al., 2015), but lower neuroticism in some studies (Carstensen et al., 2000; Ong & Bergeman, 2004). Future research should examine possible moderators of the relationship between *quantitative idiographic* EC and symptoms, including type of psychopathology, gender, age, cognitive styles, and situational context. Our results provide preliminary evidence that the predictive ability of EC measures depends on both the index and type of psychopathology being predicted.

Although the EC indices varied in predicting psychopathology, each method uniquely predicted psychopathology. This is particularly salient given that the level of personality dysfunction (observer report), negative affective personality pathology, and psychotic personality pathology were not significantly predicted by any form of ED individually, but were significantly predicted by the forms of ED together. Given limited shared variance and unique links to symptoms, future studies should jointly examine each index in predicting mental health.

Our idiographic measures provide considerations for studies of within-person variation. In particular, the nomothetic theory of PA and NA as sufficient to represent emotional experiences did not match participants qualitative reports or their quantitative results in dynamic factor models; instead, participants tended toward more factors and these were person-specific. This fits the idea that conceptualizations derived from between-person IEV do not always generalize to phenomena within individuals over time (e.g., Fisher, 2015; Molenaar & Campbell, 2009). Future research must unpack the implications of this idea, which poses a challenge to common assumptions of emotion research as well as clinical practices of assessing PA and NA but not person-specific emotion constellations. Clinical interviews and self-report measures typically rely on one-time assessments, but would benefit from repeated administration to capture within-person variability (Jacobson et al., 2016).

Several limitations warrant mention. First, because we assessed emotions once per day, it remains difficulty to distinguish multiple possible means of cooccurring emotions (e.g., two emotions experienced at once; two emotions experienced at different times of day; one causing the other), suggesting the need for more frequent momentary assessment. Future studies should examine the content of person-specific emotion factors, which was beyond the scope of this paper. Also, although over half of the sample was at moderate to severe levels of symptoms, generalizability to treatment-seeking samples remains unknown. Future studies should examine idiographic measures of EC in treatment-seeking participants, and in groups varying in primary diagnoses to directly test transdiagnostic relevance. Importantly, beyond links between emotions at a given moment, emotional experiences are also interrelated over time (Jacobson & Newman, 2014, 2016, 2017; Jacobson et al., 2017), and future studies should examine prospective, cross-lagged effects of idiographic and nomothetic conceptualizations of EC across time on psychopathology. Although we argued the case for the idiographic quantitative measure by referencing the problem of ergodicity, we did not examine equivalence of EC measures at both between- and within-person levels—an important future task. Our focus was on using within-person variability to examine an IAV-based index of EC and its links to other individual differences. Additionally, we note that ICC-based granularity is nomothetic when applied to universal PA and NA categories, but could easily be idiographically calculated in person-specific emotion factors. Additionally, the models assume stationarity and that the factor structure itself was fixed and not time-varying, which is a limitation as EC develops across the lifespan. Lastly, despite the strong model fit, it is possible that more than 50 time points would provide greater stability of factor models.

Ultimately, we hope that this work spurs new dialogue about the measurement of distinct forms of EC and the need for idiographic, translational emotion science that takes seriously person-specific data and its relevance to both individual and group outcomes (Hayes & Hofmann, 2021; Hofmann et al., 2020).

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## Declarations

**Conflict of Interest** Nicholas C. Jacobson, Thane M. Erickson, Christina M. Quach, and Narayan B. Singh have no conflict of interest to report.

**Informed Consent** All participants gave their informed consent to participate in the following research.

**Animal Rights** No animal studies were carried out by the authors for this article.

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