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A Latent Variable Approach to Affect Variability in Daily Life Accurately Predicts Psychopathology, Especially Depression Symptoms in a Non-Clinical Sample

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Abstract

Background: Ecological momentary assessments (EMA) have contributed to an increase in research correlating affect dynamics to mental health and wellbeing. While many metrics can be calculated to characterize affect dynamics from EMA data, researchers often opt for a 'battle royale' approach whereby only the best individual predictor is kept. The present work addresses the possibility that shared variance across indicators, namely for affect variability, may be better captured using latent models that also could better predict psychopathology. *Methods:* A 14-day EMA protocol was used to examine affect dynamics in 109 college-aged participants. Measures of psychopathology were collected on the first and last days. A minimum of 12 observations of the Positive and Negative Affect Schedule reports were needed for each participant. Measures of affect variability, granularity, and co-occurrence were derived. *Results:* Depression, anxiety, stress, and neuroticism were positively associated with latent negative affect variability and negatively associated with latent positive affect variability. Granularity and co-occurrence were not significant predictors. Importantly, latent factors were significantly stronger predictors of depression than within-person mean and standard deviations. *Limitations:* As with any latent variable study, the factorization is sample-specific and may have limited generalizability. Replication with a clinical sample and larger battery of psychopathology assessments is recommended. *Conclusions:* Latent factors coalesce the strengths of several EMA-derived indicators while maintaining statistical and construct validity. Clinical implications are discussed regarding short-burst daily affect assessments to track potential risk for depression onset.

Keywords: Daily affect, latent variability, affect variability, mental health.

Introduction

Emotions are adaptive thanks to their ability to motivate behavior such as responding to threats and challenges, thus fluctuating naturally in response to environmental or internal changes (Levenson, 1999). However, an abundance of negative or poorly regulated emotions have consistently been associated with more experiences of psychopathology, namely anxiety and depression symptoms (Joormann & Stanton, 2016). Myriad theoretical positions have emerged regarding the nature of affect (e.g., Cacioppo & Berntson, 1994; Feldman et al., 1998; Fredrickson, 1998; Larsen & Diener, 1987; Rafaeli & Revelle, 2006; Russell et al., 1980; Watson & Tellegen, 1985). However, all models posit that *affect dynamics*—defined here as intensity, variability, and specificity of positive affect (PA) and

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negative affect (NA) based on an amalgamation of past work—vary across individuals and are often best assessed via intraindividual (i.e., within-person) methodologies.

Work on affect dynamics has dramatically expanded since the introduction of ecological momentary assessment (EMA) technologies and their increasing ease of use (Houben et al., 2015). While many metrics of affect dynamics can be calculated (e.g., variability, instability, granularity, complexity, co-occurrence), much of the work connecting affect dynamics to psychopathology has prioritized identifying those relevant to the emergence or experience of specific mental health conditions (Bosley et al., 2019). Low NA and high PA are consistently associated with better psychological wellbeing (e.g., Bradley et al., 2011; Dua, 1993; Larsen, 2009; Lonigan et al., 2003). Yet, there have been calls for more comprehensive explorations of affect dynamics and psychopathology (Kuppens, 2015) as researchers may inadvertently overlook complex and interrelated elements of affect beyond the mean (Trull et al., 2015). While mean affect commands a significant amount of the shared statistical variance between affect dynamics with some wellbeing outcomes (e.g., depressive symptoms, life satisfaction: Dejonckheere et al., 2019), clinically useful information may be lost if researchers overlook all other indicators of affect dynamics as seen in meta-analytic work (e.g., Seah & Coifman, 2021).

Depression is dynamic with symptoms changing over time (Beck et al., 1979; Wichers, 2014) and episodes fluctuating from depression to euthymia and remission, further fluctuating over months and years (Fried et al., 2016; Iacoviello et al., 2010; Vergunst et al., 2013). Evidence strongly implicates affect dynamics as being interwoven for people experiencing depression (i.e., Bos et al., 2019; Crowe et al., 2019; Koval et al., 2013; Nelson et al., 2020), and some work has tied NA variability to anxiety (i.e., Gruber et al., 2013; Jenkins et al., 2019; Scott et al., 2020) as well as other, more general risk factors for mental health problems (e.g., neuroticism: Hisler et al., 2020; Wenzel et al., 2022; general stress: Colgan et al., 2019). Some have even called for affect dynamics to be included as a diagnostic criterion for depressive disorders (Bowen et al., 2013; Crowe et al., 2019). Thus, the present work investigates how EMA data can be leveraged to understand how affect dynamics may be related to depression, anxiety, stress, and neuroticism. Specifically, we use a latent variable approach whereby the shared variance between affect measures (i.e., Dejonckheere et al., 2019) is condensed into a single latent variable. Rather than pitting metrics against one other, we aim to allow for the strengths of each indicator to be composited together while retaining high statistical value and minimally decreasing the interpretation of results.

Affect Variability

Affect variability is perhaps the most commonly studies EMA derived indicator and is defined as intraindividual fluctuations in the intensity of affect across observations, though scholars argue about its relative stability and its utility as a state or trait measure (Cacioppo & Berntson, 1994; Feldman et al., 1998; Fredrickson, 1998; Larsen & Diener, 1987; Rafaeli & Revelle, 2006; Russell et al., 1980; Watson & Tellegen, 1985). Regardless, the consensus is that higher variability in daily affect is indicative of poor self-regulation and is a risk factor for developing symptoms of various psychological conditions (Crocker, 2002; Ebner-Priemer et al., 2009). Across laboratory settings and in EMA studies, variability in NA is positively correlated with depression symptoms in non-clinical (Koval et al., 2013) and clinical samples measured over 4 days (Nelson et al., 2020), 6 days (Crowe et al., 2019), and even over the course of a month (Bos et al., 2019). Higher NA variability also predicts relapse in depression (Wichers et al., 2010). Moreover, variability in PA has been associated with worse psychological well-being, life satisfaction, and more depression and anxiety symptoms (Gruber et al., 2013; Jenkins et al., 2019). High levels of affect variability have been associated with mental illness incidence (Chan et al., 2016), and these patterns are further supported by meta-analytic evidence from 79 studies that found affect variability to be positively correlated with depression and anxiety symptoms in clinical and non-clinical samples (Houben et al., 2015).

A variety of analytic techniques have been developed to study affect variability. Specifically, there has been an exploration of dynamic structural equation modeling that models intraindividual differences

in affect over time with a high degree of specificity (Hamaker et al., 2018; Scott et al., 2020). Implementing such refined statistical approaches within any EMA study may be difficult, however, when considering the major issue of participant adherence over the course of extended data collection periods which directly influences data quality issues (i.e., attrition, missingness, careless or non-diligent responding). A minimum of 100 participants with a minimum of 10 observations (or 50 participants with 20 observations) appears to only be acceptable for between- and within-person analyses if missingness is very limited across all cases (Fang & Wang, 2024). While this may be achievable if the goal is to use dynamic structural equation modelling, researchers and clinicians may be ill-equipped for these analyses and/or want to prioritize shorter evaluation protocols for expediting diagnosis and intervention.

A final important note regarding affect variability is the tendency in the literature toward a statistical "battle royale" approach whereby overlapping indicators of variability (i.e., standard deviation, interquartile range, root mean square of successive differences) are weighed against each other to uncover which indicator is the most predictive above and beyond all others (e.g., Dejonckheere et al., 2019). For instance, some work has endeavored to remove the statistical influence of mean affect (Mestdagh et al., 2018) yet still remain susceptible to the response biases of participants such as floor effects. Thus, additional weight must be given to non-respondence, whether through a statistical correction or through a direct evaluation of how frequently emotion items are simply rated as not being felt at all (as is the case in this work). Given the well-established line of work connecting affect variability to psychopathology, the present work employs a novel latent variable technique to better understand whether a general indicator of affect variability demonstrates these associations by adequately capturing the shared underlying variance across key indicators including non-respondence.

Affect Granularity

Beyond variability over time, past work has shown how response tendencies can be indicators of within-person variation in emotional experiences. Defined as the ability to differentiate between unique affective terms (i.e., joy vs. excitement, disgust vs. anger), affect granularity represents an individualized internal representation of emotion (Barrett, 1998), often used interchangeably with terms such as complexity or differentiation (Labouvie-Vief et al., 2007; Tugade et al., 2004). Meta-analytic evidence shows that affect granularity is positively related to engaging in adaptive coping behaviors such as exercise (O'Toole et al., 2019) and negatively associated to maladaptive behaviors such as substance use in both clinical and non-clinical samples (Seah & Coifman, 2022). It has been suggested that people with higher affect granularity are able to better recognize and regulate emotion due to better recognition of their emotions (Kashdan et al., 2015) which could explain why people with higher affect granularity display less aggressive behavior (Pond et al., 2012) and how affect granularity relates to transdiagnostic risk factors for internalizing disorders (Jacobson et al., 2023). Indeed, lower emotional granularity has been correlated with anxiety (Matt et al., 2016), depression (Demiralp et al., 2012; Quoidbach et al., 2014; Starr et al., 2020), social anxiety disorder (Kashdan & Farmer, 2014), and substance use disorders (Emery et al., 2014).

However, the measurement of granularity can often be complicated by the nature of data collected and the research question being investigated. Most methods are highly data-driven approaches ranging from autoregressive correlations across a set of emotion items (e.g., Bringmann et al., 2013; Schneider et al., 2020), emotion network estimation (e.g., Hamilton & Allard, 2022; Lange & Zickfeld, 2021), intraclass correlation coefficients for each valence (ICC: Demiralp et al., 2012; Erbas et al., 2018), or within-person principal components analyses (Grühn et al., 2013; Hay & Diehl, 2010; Hoemann et al., 2021). As was the case with affect variability and dynamic structural equation modelling, there are other constraints to be considered in selecting indicators for affect granularity. The first two methods require a sizeable amount of data points for each person (see Hecht & Zitzmann, 2020 and Hamilton & Allard, 2022, respectively). Conversely, ICC and within-person principal components analyses can operate reliably on fewer data points for each person (e.g., Erbas et al., 2018; Grühn et al., 2013). Thus, the

latter are the most methodologically feasible approaches with added benefits in their interpretability and potential applications in an intervention.

Affect Co-Occurrence

Theoretical models and empirical evidence suggest that PA and NA are separable aspects of emotion and not inherently juxtaposed, potentially co-occurring at any given state (Cacioppo & Berntson, 1994; Larsen et al., 2017). In fact, some models have suggested that coactivated PA and NA in the face of stress may promote positive psychological responses (Folkman, 2008; Folkman & Moskowitz, 2000; Larsen et al., 2003). Studies of within-person variability in co-occurring PA and NA have shown that less co-occurrence is associated with greater symptoms of depression in young adults when measured over one week (Dejonckheere et al., 2018), 100 days (Hamaker et al., 2018), and even with one-week bursts recurring five and 10 years after initial measurement (Hershfield et al., 2013). Thus, greater co-occurrence (i.e., high PA and NA) may represent intrinsic regulatory process that may ameliorate the psychological effects of high NA states during periods of intense stress, as hypothesized elsewhere (Larsen et al., 2003).

However, PA and NA are often negatively correlated (i.e., one increases, one decreases) indicating greater polarization when measured across multiple observations (e.g., Rafaeli et al., 2007; Schneider & Stone, 2015). Several crucial caveats to the use of within-person correlations as a sole indicator of co-occurrence, especially regarding temporality, have been raised by prominent researchers in this area (see Larsen et al., 2017). Instead, ambivalence indices have been shown to be equally, if not better suited, to evaluate moment-to-moment co-occurrence (Berrios et al., 2015) and are often used for testing relationships between affect co-occurrence and a variety of health outcomes (e.g., Adler & Hershfield, 2012; Berrios et al., 2018; Carstensen et al., 2011; Hershfield et al., 2013). Specifically, these indices attempt to quantify the relative intensity of affect co-occurrence, with the most used technique being the minimum value (i.e., MIN) of each rating (e.g., minimum value index, see Schimmack, 2001), only requiring two items with the smaller rating out of two targets (e.g., PA and NA). Higher MIN scores (i.e., more co-occurrence) relate to better physical health (e.g., Hershfield et al., 2013); alleviating depression and anxiety symptoms (Adler & Hershfield, 2012), greater meaning in life (see Baumeister et al., 2013; Berrios et al., 2018), and general affect dynamics across the lifespan (e.g., Carstensen et al., 2011; Hay & Diehl, 2010).

While potentially captured in multiple ways, it remains clear that greater co-occurrence may be somewhat protective and relate to better psychological health, namely lower levels of depression and anxiety symptoms. Crucially, work consistently shows that affect co-occurrence does not occur very often in daily life (Barford et al., 2020; Schneider & Stone, 2015), although this may not hold true as much in young adults (e.g., Riediger et al., 2009, 2014). Moreover, emerging evidence suggests instances of high co-occurrence in daily life may actually be related to trait neuroticism (e.g., Barford et al., 2020; Wrzus et al., 2021). Thus, an important contribution of this work, beyond relating affect co-occurrence to depression and anxiety symptoms, will be to ascertain how affect co-occurrence relates to both psychopathology as well as broader person-level factors known to produce higher risk for developing certain disorders.

The Present Study

The existing literature suggests that affect dynamics are related to the intensity and/or propensity to experience symptoms of depression and anxiety. While high-volume EMA studies have provided complex and nuanced analyses that demonstrate clear associations between within-person affect dynamics and psychopathology (e.g., Hamaker et al., 2018; Scott et al., 2020), a primary goal of this work is to evaluate whether a shorter, two-week protocol can show relative similarities in the patterns of findings. However, the literature remains somewhat agnostic regarding what specific indicators of affect dynamics are the most useful for indicating potential dysregulation (e.g., Dejonckheere et al., 2019). Some work suggests that within-person standard deviations can adequately address variability and best predict psychopathology (e.g., Wendt et al., 2020) yet this depreciates the value of rich EMA

datasets that can handle much more rigorous analytic techniques (see Hamaker et al., 2018 or Scott et al., 2020 for examples). Instead, we aim to use a more nuanced approach via a latent variable estimation to reconcile slight differences across indicators to create a single composite score.

Two hypotheses were proposed for the current research. Following empirical precedent (Bos et al., 2019; Crowe et al., 2019; Koval et al., 2013; Nelson et al., 2020; Wichers, 2014), psychopathology (i.e., depression and anxiety symptom severity) and risk factors for psychopathology (Barlow et al., 2014, 2021) (i.e., neuroticism) were expected to be predicted most strongly by latent affect variability with higher NA variability and lower PA variability corresponding to higher levels of depression, anxiety, neuroticism, and general stress (*Hypothesis 1*). Second, other aspects of affect dynamics were expected to predict psychopathology, specifically higher granularity and co-occurrence were anticipated to be predictive of lower levels of depression, anxiety, neuroticism, and general stress (*Hypothesis 2*). As an exploratory step, significant predictors will be compared to evaluate whether the overall magnitude of effects differ, irrespective of directionality.

Method

Participants

A total of 136 adults provided digital written informed consent to participate in this two-week study; however, only 109 participants completed more than half of the daily assessment protocol (i.e., observations > 12) as well as first and last day sessions. Participants were sampled from two distinct sources: (1) a psychology student subject pool at a large Midwestern university (n = 62), and (2) a paid study where individuals were recruited through the university online classifieds ads and through flyers around campus (n = 74). In the second version of the study, participants could earn up to $60 for completing the 14-day EMA if at least 70% of assessments were complete. Inclusionary criteria were having a university email address and being 18 years of age. Exclusionary criteria were being under 18 or over age 35. Thus, the sample of 109 participants comprised of younger adults (M_{age} = 20.87, SD = 3.05, range: 18-33) in the campus community with 22 first-year students, 25 sophomores, 26 juniors, 20 seniors, and 16 graduate students. There was an uneven balance across gender categories with 83 women (76%), 24 men (22%), and 2 (2%) non-binary participants. There was also a lack of racial/ethnic representativeness with 68 White (62%), 25 Asian (23%), 8 Black (7%), 7 Hispanic (6%), and 1 Middle Eastern (1%) participant, which is consistent with the sampled population and discussed as a limitation below.

Participants were asked to self-report whether they have or have not received an official psychiatric diagnosis of Major Depressive Disorder or Generalized Anxiety Disorder. We also included options of "*I don't know*" and "*No, but I should be*" to account for individuals who were undiagnosed but experienced high levels of symptoms. As shown elsewhere (Rutter et al., 2023), people who choose the option of "*No, but I should be* [sic] diagnosed*"* are statistically similar to those with an official diagnosis of depression and anxiety, but different from those who report no diagnosis. We confirmed these same patterns for depression symptoms, but not so robustly for anxiety (see Supplemental Materials). Nevertheless, we combined "*Yes*" and "*No, but should be*" responses for analytic simplicity and interpretability. As a result, there were a total of 53 participants (49%) reporting no psychiatric history, 15 with a history of major depression (14%), 13 with a history of generalized anxiety (12%), and 28 reporting both major depression and generalized anxiety disorder diagnoses (26%). This work received all necessary approvals from institutional review boards prior to data collection. Deidentified data and code for analyses can be found at https://osf.io/zjtxd/.

Psychopathology Measures

Three measures were used to capture symptoms of psychopathology, which participants completed on the first (Day 1) and last day (Day 14) of the two-week protocol. Importantly, we were utilized data collected on Day 14 as the outcomes across all inferential models that were tested. The Multidimensional Emotional Disorder Inventory (MEDI: Rosellini & Brown, 2019) was used to capture

nine aspects of emotional disorders (anxiety, mood, and related disorders) including neuroticism (Cronbach's α = .74) and depression (Cronbach's α = .88). Taking a transdiagnostic approach to dimensions of psychopathology, the MEDI contains 49 items that evaluate phenotypic representations of key traits/experiences across emotional disorders (e.g., "loss of interest" for the depression subscale). The psychometric properties of the MEDI have been shown to be acceptable in research samples--its reliability, convergent, and discriminant validity are all supported (Rosellini & Brown, 2019). Scoring adhered to the previously published factorization (see Rosellini & Brown, 2019) by summing items together to create a composite variable for each construct.

To juxtapose this more novel measurement tool, we also administered the well-known Depression, Anxiety and Stress Scale (DASS-21: Lovibond & Lovibond, 1995) as well as the General Anxiety Disorder – 7 (GAD-7: Spitzer et al., 2006). The GAD-7 reliably measures anxiety in a variety of clinical and nonclinical samples across the world (e.g., Beard & Björgvinsson, 2014; Dear et al., 2011; Hinz et al., 2017; Löwe et al., 2008; Rutter & Brown, 2017) and showed excellent reliability in our sample (Cronbach's α = .90). The DASS-21 has subscales for depression (Cronbach's α = .91), anxiety (Cronbach's α = .81), and overall stress (Cronbach's α = .82) with each comprised of 7 items. Thus, we used two scores for both depression (MEDI depression scale, DASS-D) and anxiety (GAD-7 and DASS-A) to confirm the validity of findings across multiple measures along with scores for neuroticism and stress.

Concerning the prevalence of mental health symptoms, this sample had mild levels of general anxiety based on the GAD-7 (M = 6.74, SD = 5.11) and DASS-21 anxiety subscale (M = 8.11, SD = 7.79). Depression was within normal ranges for the DASS-21 (M = 9.51, SD = 9.11) and the MEDI (M = 10.75, SD = 8.92). Moreover, DASS stress subscale scores were between accepted cutoffs for normal and mild general stress (M = 13.05, SD = 8.12), and neuroticism scores from the MEDI were somewhat low (M = 16.40, SD = 7.88) compared to past literature (e.g., Rosellini & Brown, 2019).

Ecological Momentary Assessments

Participants completed online consent to the study and completed their baseline battery (Day 1), which included the questionnaires described above in addition to a larger battery of questions on emotional disorder symptoms, social media use, and an online battery of cognitive tests. Following this, they were enrolled in the EMA portion of the study, during which they received twice daily Positive and Negative Affect Schedule (PANAS) to assess daily affect and twice daily cognitive tasks, which are not the focus of the current study. The PANAS is a 20-item self-report scale assessing positive affect and negative affect on a 5-point Likert scale ranging from 1 "*Very slightly or not at all*" to 5 "*Extremely*" yielding scores from 10 to 50 for Positive Affect (PA) and 10 to 50 for Negative Affect (NA). Psychometric evaluations demonstrate that the PANAS is a reliable and valid measure of momentary affect (Watson et al., 1988; Watson & Clark, 1994). Participants completed the PANAS once on Day 1 (baseline) and Day 14 (the last day) and twice on Days 2-13[1]. Participants were told to complete the PANAS based on how they felt in the past week on Day 1 and how they felt "right now" on Days 2-14. On Day 14, participants completed another large battery of mental health questionnaires and online cognitive tasks assessing a variety of domains.

Affect Variability

Daily assessments of emotion across the two-week measurement window were first averaged to create positive and negative affect for every time point for each participant. Then, six within-person indicators were computed using all observations for each participant: (1) mean affect, (2) mean square of successive differences (MSSD; see von Neumann et al., 1941), (3) standard deviation (SD), (4) interquartile range (IQR), (5) average daily deviations, and (6) the total number of non-zero items. See Figure 1 for visualization and equations. Calculating the number of non-zero items offers statistical

[1] A programming error resulted in incorrect administration of the Day 10 evening survey; thus, this particular observation has a high amount of missingness.

control for low levels of responding (Bylsma & Rottenberg, 2011) which can occlude how various affect dynamics relate to one another (e.g., Schneider et al., 2020). Counting the number of non-responses across the protocol ("*Very slightly or not at all*", scored as 0 out of 4), the number of non-zero items was subtracted from 10 to provide the number of PA and NA items that were rated as non-zero at least once across the study.

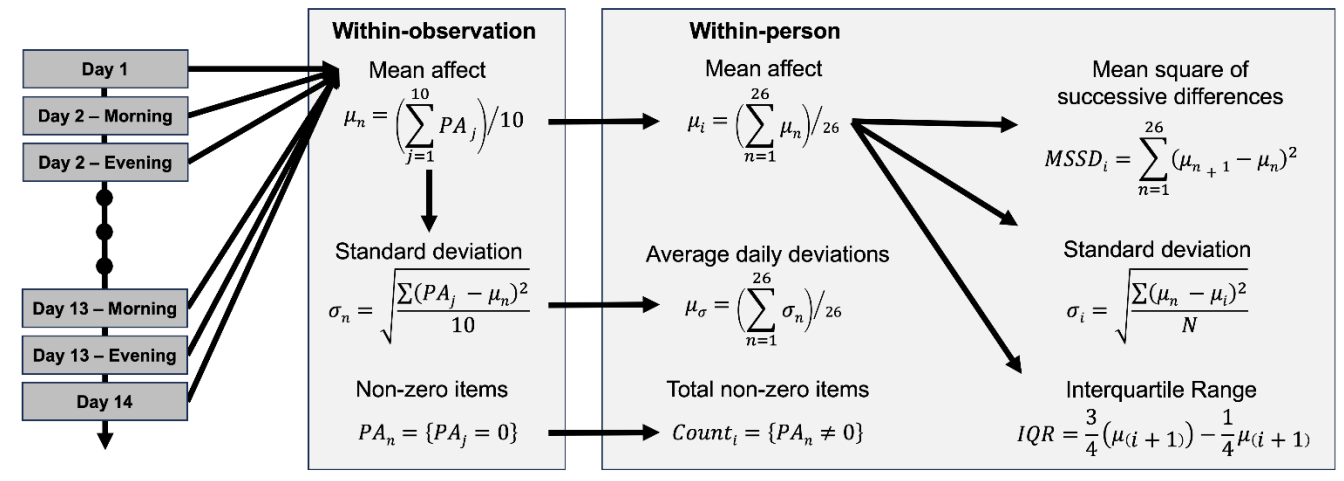

Figure 1. A visualization of the data reduction technique and the corresponding equations that were applied to the ecological momentary assessment data. Although positive affect (PA) items are shown here, the exact same procedure was applied to negative PANAS items. *j* = PANAS items with a total of 10 for PA and NA, respectively. *n* = observations, total of 26. *i* = individuals.

Latent variable estimation

Commensurate with existing frameworks for latent variable estimation (Marsh et al., 2014), we first conducted exploratory factor analyses for PA and NA with extracted factors constrained to those with eigenvalues greater than 1. Within-person mean, standard deviation, MSSD, IQR, daily standard deviation, and number of non-zero items were included. Only a single factor was extracted in both models; however, a large amount of variance was explained across the derived indicators for PA (72% variance explained; KMO = .799, $\chi^2 = 328.5$, $p < .001$) and NA (86% variance explained; KMO = .835, $\chi^2 = 543.9$, $p < .001$). See Figure 2 for a visualization and resultant factor loadings.

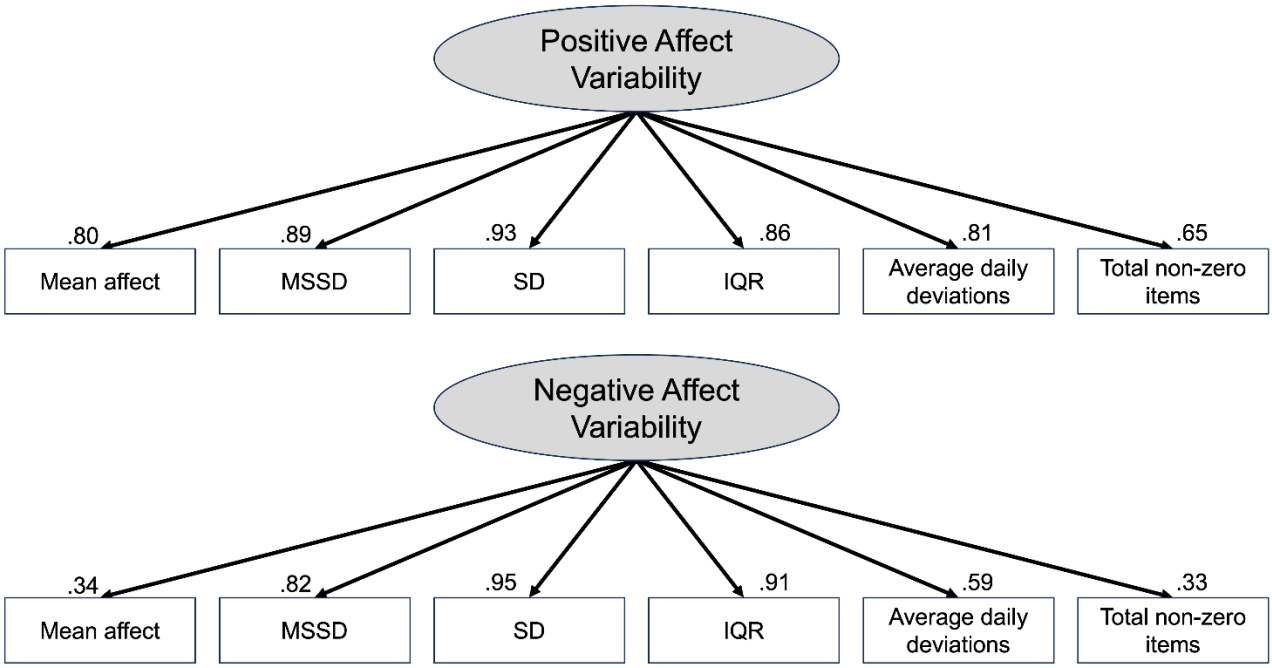

Figure 2. Factor structures revealed from the exploratory factor analyses that were used to estimate latent affect variability.

We then conducted a confirmatory factor analysis via structural equation modeling. Here, we estimated an unconstrained latent factor while modeling covariance among indicators (see https://osf.io/zjtxd/ for code). This offers greater analytic control in latent variable estimation and, as a result, may be more restrictive in its convergence on a latent factor solution (Marsh et al., 2014). Excellent fit was achieved for both PA variability (CFI = 1.000, TLI = 1.003, RMSEA < .001, CD = .939) and NA variability (CFI = .998, TLI = .992, RMSEA = .052, CD = .940). Scores from this method were nearly perfectly correlated with the factor analysis scores (r = .996 for PA; r = .993 for NA). Thus, the latent factor approach held firm across two robust analyses. As there were no meaningful statistical differences, the latent variable estimated from the exploratory factor analysis (see Figure 1) was used for all inferential tests.

Affect Granularity

Following prior literature (e.g., Tugade et al., 2004), we estimated granularity as an intraclass correlation coefficient (ICC)[2] wherein higher values indicate greater shared variance among item ratings. We calculated within-participant ICCs for positive and negative items separately and excluded all negative values from analysis following (Erbas et al., 2018). ICCs were then Fisher r-to-z transformed to fit the variable to a normal probability distribution and then multiplied by −1, such that lower ICCs indicate lower granularity and vice versa.

Following procedures outlined in Hay & Diehl (2011) and Grühn et al. (2013), we also utilized a principal components analysis conducted for each participant's PANAS ratings across all available observations. For every participant, the number of principal components with eigenvalues ≥ 1 were extracted. Thus, a higher number rendered from the within-person principal components analysis indicates that more components are necessary for explaining variation in ratings. Aligning with past literature (Grühn et al., 2013; Hay & Diehl, 2010; Hoemann et al., 2021), this means that a higher number of extracted factors indicates better emotion differentiation. While an omnibus principal

[2] Special thanks to the anonymous reviewer who suggested this calculation for greater valence-specificity in evaluating affect granularity and consistency with other work cited here.

components analysis across all participants and observations clearly separated into 2 distinct factors and aligned with the PA and NA subscales of the PANAS, no participant matched this outcome. In fact, the number of extracted factors ranged from 3 to 8 with an average of 5.54 and a standard deviation of 1.13, meaning that over 95% of participants had 4 or more principal components extracted from their individual PANAS ratings tendencies. This variable had minimal skew (-.12) and kurtosis (2.67), which are quite close to 0 and 3, respectively (i.e., a normal distribution). Thus, affect granularity was represented by the number of factors generated from a within-person principal components analysis of all their PANAS data (i.e., across observations).

Affect co-occurrence

Positive and negative emotions are usually negatively correlated when evaluated as zero-order coefficients, which is a common method of measuring co-occurrence (e.g., Larsen et al., 2017; Schneider & Stone, 2015). Thus, one indicator was the within-person correlation coefficient between positive and negative affect, which was then transformed using Fisher's *r*-to-*z* methodology for the purpose of statistical validity for inferential tests. However, the nature of affect co-occurrence has been marked by debate on theory and measurement (see Larsen, 2017), and correlation coefficients do not stand alone nor are they the most used metric.

Co-occurrence scores (also called ambivalence indices, see Schimmack, 2001) are valuable indicators of mixed emotions that aim to quantify mixed affect intensity. Co-occurrence scores are calculated by taking the minimum value of two ratings (i.e., MIN scores: Carstensen et al., 2011) with analytic data showing that simple MIN scores provide more conservative estimates of effect sizes and confidence intervals with fewer Type I error probabilities (Berrios et al., 2015). MIN scores tend to be the only common assessment across mixed emotions literature since its estimation remains valid in most measurement contexts. Yet, these scores have limitations including a two-item stratification and an issue with floor effects (Hamilton & Allard, 2022; Larsen et al., 2017; Larsen & Green, 2013). Nevertheless, we calculated MIN scores for each observation, and then averaged across all observations for each participant to represent average co-occurrence.

Transparency and Openness

This study and the present analyses were not preregistered; however, all data cleaning procedures and transformations are described here. All analyses were conducted in Stata SE 17.0 with *a priori* power analyses conducted in G*Power 3.1 (Faul et al., 2007). Control variables included age, gender (omitting 2 non-binary participants), and current psychiatric diagnoses of Major Depressive Disorder, Generalized Anxiety Disorder, or both. With these model specifications (i.e., five control variables) and using an R^2 increase as the primary metric to indicate better model fit, a minimum sample size of 73 is needed to detect a single, significant coefficient beyond control variables with a small effect size (R^2_p = .10, effect size f^2 = .11) with a = .05 and β = .80. Testing seven predictors simultaneously requires 137 people; however, if we increase the expected effect size to R^2_p = .15 as observed in Dejonckheere et al. (2019) for mean affect, this number drops to 90. Thus, adequate power was present for all inferential tests presuming a moderate effect size. Nevertheless, family-wise error was controlled using adjusted *p*-values from the Romano-Wolf multiple hypothesis correction algorithm (Clarke et al., 2019).

Results

To test our primary hypotheses, regression analyses were conducted across the various outcomes of interest controlling for key demographic items. All models used variance clustering to adjust standard errors at the subject-level. Please see the supplemental material found in the OSF link in the author note for correlation and regression output tables. Figure 3 displays results using unstandardized predictors and outcomes. As hypothesized, NA variability was significantly predictive of greater symptom scores including higher depression (b = 4.60, adjusted p < .01 for DASS; b = 5.13, adjusted p < .01 for MEDI),

neuroticism (b = 4.74, adjusted p < .05), stress (b = 2.73, adjusted p < .05) and partially for anxiety (b = 2.77, adjusted p < .01 for GAD-7; b = 1.76, adjusted p = .16 for DASS-A).

In the opposite way, PA variability significantly predictor in all models such that higher PA variability predicted less depression (b = -3.16, adjusted p < .01 for DASS-D; b = -3.25, adjusted p < .05 for MEDI), less anxiety (b = -1.77, adjusted p < .05 for DASS-A; b = -2.29, adjusted p < .01 for GAD-7), less stress (b = -2.05, adjusted p < .05), and lower levels of neuroticism (b = -2.99, adjusted p < .01). All other associations did not survive corrections for family-wise error or did not initially meet the *a priori* cut-off of α = .05 with the exception being an association between MIN scores and DASS-A scores (b = 1.40, adjusted p < .05).

To further explore differences between the relative importance of PA and NA variability, we plotted standardized coefficients (i.e., β-weights) in models using standardized predictors and outcomes, see Figure 3. Then, we conducted a postestimation test of similarity (i.e., Wald tests) to evaluate whether the standardized effects for PA and NA variability differed in magnitude, not directionality. Significant magnitude differences were not present in any of the models after applying corrections for multiple comparison (Bonferroni-corrected threshold of p > .10). Thus, both NA variability and PA variability were important predictors, albeit in opposite directions. As a final note, these models explained a large amount of variance in anxiety (71% and 49%) and depression (54% and 51%) as well as stress (55%) and neuroticism (50%) indicating the robustness of their association with affect dynamics, particularly affect variability.

As a final confirmation of the robustness of our latent factor approach for measuring variability and its relationship to psychopathology, we reconstructed these regression models using mean and standard deviation for PA and NA in place of the latent factor scores. If simple standard deviations and average affect could predict psychopathology at the same magnitude, there would be no need for the latent factor approach. Results remained largely unchanged; however, see online supplement for full results. We used seemingly unrelated estimation (i.e., -suest-) to compute cross-model comparison between estimated β-weights to test whether magnitude of effects for latent variability and simple standard deviations significantly differed. Results showed that latent PA variability was significantly stronger for depression (χ^2 = 8.13, p = .004 for DASS-D; χ^2 = 6.93, p = .009 for MEDI-Depression) with the same pattern evident for latent NA variability (χ^2 = 8.30, p = .004 for DASS-D; χ^2 = 9.33, p = .002 for MEDI-Depression). Additional differences emerged in MEDI Neuroticism scores for PA variability (χ^2 = 7.23, p = .007) and NA variability (χ^2 = 7.47, p = .006), but all other effects did not statistically differ. Thus, a latent approach to affect variability is a significant improvement over means and standard deviations, especially when predicting depression symptoms.

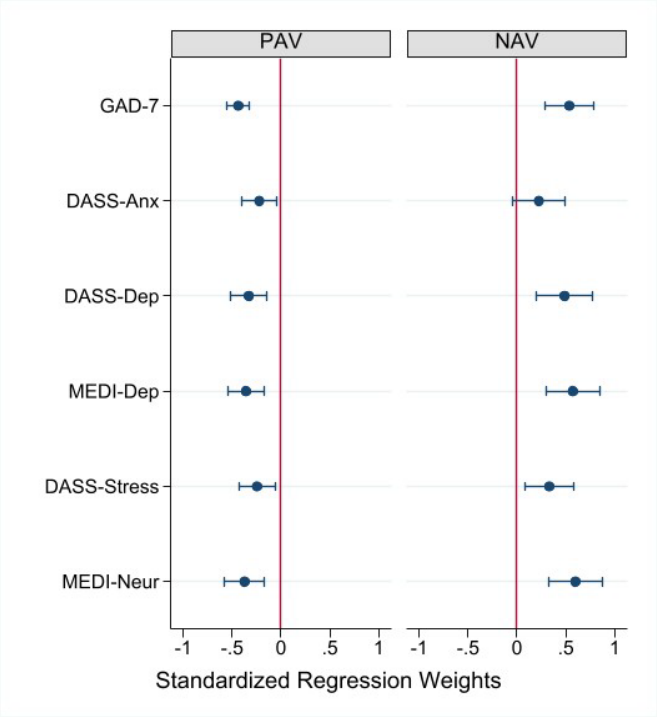

Figure 3. Comparing β-weights for positive and negative affect variability.

Discussion

While there are many ways to measure affect dynamics, with pros and cons of each that are specific to the research question at hand, researchers can consider using factor analysis whenever possible to reduce multiple dimensions of affect dynamics in a more analysis-friendly and interpretable way. Comparing each individual metric of variability (i.e., mean, standard deviation, within-observation deviations, probability of maintaining high levels of affect, non-zero item-level responding) also produces issues with multicollinearity and within-subjects variance clustering. Moreover, this approach would clutter analytic models and reduce power except for studies with a large number of participants (i.e., N > 500) or many more observations (i.e., 100 days of EMA as in Hamaker et al., 2018). Thus, the construction of a latent factor (which can be reproduced in a sample-specific manner) aids in our understanding of the interconnections of each affect variability dimension, addresses multicollinearity, and potentially increases analytic power in smaller studies by decreasing the number of predictors.

Concerning the clinical implications of this work, it is fair to wonder if knowing that a person has a high degree of NA variability elucidates objective treatment targets. Our findings support the idea that the dynamics of emotional experiences, even in healthy adults, are robustly related to symptoms of depression and anxiety. The sensitivity in detecting these effects is noteworthy, given that we did not specifically recruit a clinical sample; however, it remains to be tested if our results would replicate in clinical samples. In initial studies, predicting the course of an individual's symptoms by measuring their daily affect with brief measures has been useful in some populations including, for example, suicidal adults (Armey et al., 2011) adolescents (Forbes et al., 2012), and adult outpatients with depression (Husen et al., 2016).

Nevertheless, more work is needed to use individual affect dynamics to personalize treatments. For instance, it is possible that upon entering treatment, people could report their affect throughout the day for a week or two. After this initial period, all scores reported could be generated and their personalized "affect dynamic profile" could be characterized against normed data using non-clinical (i.e., this sample) and clinical data. If a person enters treatment for depression symptoms, we would expect to see high NA variability; however, if they display low NA variability and also low granularity, this could

result in a clinical emphasis on building emotional literacy (i.e., putting words to feelings) to enhance their recognizing of their affect states. Of course, this is speculative, but does suggest a precision medicine approach to mental health care that could be useful with increasing mental health care needs. Idiographic affect dynamics may also be used to track warning signs into symptom relapse or recurrence, in line with personalized medicine approaches to mental illness detection and prevention. While some research has begun to personalize depression treatments based on experience sampling methods (Riese et al., 2021), more hypothesis-driven work is needed to detect early warning signs (Helmich et al., 2021) and return of depression symptoms after remission (Smit et al., 2023), and to examine the interplay of depression, anxiety, and related symptoms (Schreuder et al., 2020).

Despite the strengths of the current study, we must acknowledge the potential lack of generalizability. Our sample was predominantly white, female, young, and generally healthy. Future work should recruit more diverse samples with a higher degree of racial diversity, gender diversity, a larger range of ages, and more severe symptoms of emotional disorders and emotion dysregulation. This is important, as gender plays a role in emotion regulation and affect dynamics (McRae et al., 2008). Moreover, it is unclear if these findings can be extended to clinical samples with a larger range of ages particularly given that older adults symptom presentation for depression manifests somewhat differently (Fiske et al., 2009).

Therefore, future work should prioritize replication of our latent factor approach with larger and more representative samples. This includes scale representativeness such that the PANAS has been criticized for its potential lack of specificity in measuring precise emotions which gives rise to curious relationships such as correlations between PA on the PANAS and anger intensity (e.g., Harmon-Jones et al., 2009). Alternative scales such as the modified Differential Emotions Scale (mDES; Fredrickson, 2013) have been intentionally created to assess a wider array of positive emotions with success in EMA studies (e.g., Kiken et al., 2017). Confirming that this latent factor approach to affect variability is robust against measurement variance would be an important direction for future work.

Another line of inquiry that deserves mentioning is the exact robustness of a latent factor that somewhat occludes theoretical distinctions in affect dynamics. Specifically, within-person SD and MSSD have been typically treated as indicators of variability and instability, respectively (e.g., Houben et al., 2015). While the large factor loadings for both indicators support our decision, we may have occluded important theoretical distinctions in the process of affect dynamics. Future analyses should interrogate the benefits of hyper-specific latent modelling (e.g., one latent factor for variability, one for instability, etc.) to non-specific modelling that may even include a single factor that includes all derived indicators. Yet, this work will need to also address to the aforementioned sample limitations to make meaningful steps forward.

Conclusion

These findings support the use of brief EMA protocols to capture affect dynamics in a robust way through the use of factor analysis. With our approach of creating latent variability factors, we were able to measure their effect on psychopathology symptoms (i.e., depression, anxiety, stress, neuroticism). Our main finding is that, even while modeling multiple affect dynamics that could be at play in anxiety and depression along with actual clinical diagnoses, NA variability is strongly related to reported symptoms above and beyond all measures. Future work should seek to model affect dynamics, particularly changes in variability, and how that corresponds with actual symptoms of mental disorders, both in treatment and naturalistically. Affect dynamics, once they are more clearly understood, can be used to suggest treatment type, predict treatment response, and as a marker of treatment effectiveness.

Additional Information

Supplementary Material

https://osf.io/zjtxd/

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Conflict of Interest

None.

Ethical approval

This study was approved by the Indiana University IRB (approval numbers **2011722518 and 12537**) on January 08, 2020 and September 02, 2022, respectively.

Data Availability

Not available.

Author CRediT Statement

Lauren A. Rutter: Supervision, Conceptualization, Project Administration, Writing – Review & Editing. Lucas J. Hamilton: Conceptualization, Formal Analysis, Writing – Original Draft, Writing – Review & Editing, Visualization. Prabhvir Lakhan: Data Curation, Writing – Original Draft

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