Journal of Abnormal Psychology

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Online First Publication, March 29, 2021. http://dx.doi.org/10.1037/abn0000670

AMERICAN PSYCHOLOGICAL ASSOCIATION

Journal of Abnormal Psychology

ISSN: 0021-843X

https://doi.org/10.1037/abn0000670

The Distribution of Daily Affect Distinguishes Internalizing and Externalizing Spectra and Subfactors

Aaron S. Heller[1], Caitlin A. Stamatis[1, 2], Nikki A. Puccetti[1], and Kiara R. Timpano[1]

[1] Department of Psychology, University of Miami

[2] NewYork-Presbyterian Hospital, Weill Cornell Medical College

There has been increasing recognition that classically defined psychiatric disorders cluster hierarchically. However, the degree to which this hierarchical taxonomy manifests in the distribution of one's daily affective experience is unknown. In 462 young adults, we assessed psychiatric symptoms across internalizing and externalizing disorders and then used cell-phone-based ecological momentary assessment (EMA) to assess the distribution (mean, standard deviation, skew, kurtosis) of one's positive and negative affect over 3–4 months. Psychiatric symptoms were modeled using a higher-order factor model that estimated internalizing and externalizing spectra as well as specific disorders. Individualized factor loadings were extracted, and path models assessed associations between spectra and syndromes, and daily affect. Internalizing and externalizing spectra displayed broad differences in the distribution of affective experiences, while within the internalizing spectrum, syndromes loading onto fear and distress subfactors were associated with distinct patterns of affective experiences.

General Scientific Summary

Psychiatric syndromes cluster hierarchically, but how they manifest in daily emotional experiences is unknown. Combining experience sampling of emotion with assessment of a range of psychiatric symptoms, we demonstrate that unique features of the distribution of daily emotional experience predicts individual differences in psychiatric syndromes. Identifying affect–syndrome links will aid in mapping nosology as well as in treatment selection.

Keywords: ecological momentary assessment, HiTOP, emotion, affective dynamics, internalizing

Supplemental materials: https://doi.org/10.1037/abn0000670.supp

Decades of research on current psychiatric classifications, including the International Classification of Diseases (World Health Organization, 2018) and the *Diagnostic and Statistical Manual of Mental Disorders* (American Psychiatric Association, 2013), indicates that comorbidity of psychiatric diagnoses is the rule rather than the exception (Hankin et al., 2016). Comorbidity is present at both diagnostic and criterion levels due to overlapping and nonspecific symptoms across diagnoses (Jacobi et al., 2004; Kessler et al., 2005). In conjunction with low diagnostic reliability (Chmielewski et al., 2015) and heterogeneity within diagnostic categories, the clinical utility and construct validity of the established psychiatric nosology is questionable (Angold et al., 1999; Krueger & Markon, 2006; Zachar, 2009).

The concerns about the prevailing psychiatric classification systems have led efforts to identify better nosologies using data-driven approaches. These analyses support the existence of higher-order latent factors that capture common variance across internalizing and externalizing disorders, referred to as *spectra* (Achenbach, 1966; Caspi et al., 2014; Lahey et al., 2012). This nosology, captured by the Hierarchical Taxonomy of Psychopathology (HiTOP; Kotov et al., 2017), is organized hierarchically with spectra (e.g., internalizing, externalizing) at, or near the top, with subfactors (e.g., fear, distress, substance use) and syndromes/disorders (e.g., generalized anxiety, social anxiety, bipolar disorder, depression) below. Levels lower on the hierarchy reflect an increasing degree of distinctiveness and specificity. These nosologies have gained traction, with efforts to assess their clinical utility (Ruggero et al., 2019).

Yet, because most psychiatric nosology research relies on structured psychiatric interviews, it remains unknown whether distinct taxonomic levels (i.e., spectra, subfactors, and syndromes) or entities at the same level manifest in similar or dissimilar day-to-day affective experiences. Linking the distribution of one's daily

This study was approved by the University of Miami Institutional Review Board (Protocols: 20170756 "Healthy U Study" and 20180529 "Temporal dynamics of emotion and neural activity"). These results have not been disseminated elsewhere.

Correspondence concerning this article should be addressed to Aaron S. Heller, Department of Psychology, University of Miami, P.O. Box 248185, Coral Gables, FL 33124, United States. Email: aheller@miami.edu

experiences with this hierarchical psychiatric nosology is critical to determine whether these classification systems reflect an idiosyncrasy of method (i.e., structured interview from a single timepoint, requiring an individual to integrate across a broad timescale) or reflect individuals' momentary affect, cognition, and behavior. Furthermore, incorporating daily experiences into models of nosology can help clarify the role of contextual factors that exacerbate or diminish the expressions of psychopathology (Lapate & Heller, 2020), something that retrospective structured interviews struggle to assess. Incorporating daily experience into models of nosology may also help refine connections between distinct spectra, subfactors, or syndromes and suggest novel avenues for intervention.

One way to measure individuals' day-to-day affective experiences is via ecological momentary assessment (EMA; Trull & Ebner-Priemer, 2013). EMA data collection is typically longitudinal, permitting researchers to derive idiographic distributions of momentary affective experiences. EMA research to date has most frequently examined the mean and standard deviation of one's negative and positive affective (NA, PA) experiences, demonstrating that both tend to relate to many psychiatric symptoms (Houben et al., 2015). More recently, EMA research has begun to examine whether other EMA metrics of affect predict psychopathology (Trull et al., 2015). These metrics include inertia (first-order autoregression (Thompson et al., 2012; van de Leemput et al., 2014); instability (mean-square of successive difference [*MSSD*]; Santangelo et al., 2014; Thompson et al., 2012); and emotional diversity (within EMA entropy; Vuillier et al., 2018). Importantly, however, a recent paper (Dejonckheere et al., 2019) suggested that many of these newer metrics share substantial variance with mean and standard deviation and are not predictive of depression or well-being net of the simpler distributional (mean and standard deviation) metrics. Thus, psychopathology risk is defined by an affective profile of higher baseline NA, lower baseline PA, and higher affective variability, perhaps reflecting maladaptive emotional reactivity and regulation (Davidson, 1998). Using situational triggers to determine affective reactivity and regulation would be ideal (Villano et al., 2020), but in the absence of contextual information, statistical moments of the distribution of one's affect (including standard deviation, skew, and kurtosis) may approximate these processes. Overall, the relevance of these or other distributional features of emotion to psychiatric spectra, subfactors, or syndromes must be validated by controlling for simpler metrics.

Moreover, extant research linking EMA to psychiatric symptoms is limited by examining relations with single disorders, despite aforementioned evidence that symptom comorbidity is the norm. To date, only one study has examined associations between the distribution of one's daily affect via EMA with internalizing and externalizing spectra (Scott et al., 2020; see Wright et al., 2015 for a study using multilevel SEM to describe associations between spectra symptoms measured daily with SCID assessments). Applying dynamic structural equation modeling to a 21-day EMA protocol, Scott and colleagues found surprising dissociations between NA and PA and internalizing and externalizing spectra: NA mean and variability were uniquely and positively associated with internalizing spectra, whereas PA inertia was inversely and uniquely associated with externalizing. Narrower subfactors or syndromes were not explored. This finding is in contrast to the bulk of the EMA psychopathology literature indicating increases in mean NA across internalizing and externalizing spectra. Further research linking EMA to multiple levels of HiTOP would shed light on whether putatively distinct spectra, subfactors, or syndromes manifest similarly or dissimilarly in the distribution of day-to-day affect (Wright & Woods, 2020). This may be particularly important as symptoms of certain syndromes are more situationally dependent (e.g., social cues in social anxiety, contamination cues in OCD), whereas others are defined by more context-independent processes (e.g., sad mood in depression, worry in generalized anxiety).

Using a hierarchical approach to modeling psychiatric comorbidity, this study explored the associations between daily affect and internalizing and externalizing spectra and narrower syndromes. In a sample of 462 young adults, we measured NA and PA every other day over a 3–4-month period. We selected an undergraduate sample given that many psychiatric difficulties emerge during this developmental period (De Girolamo et al., 2018), and because the distribution of psychiatric symptoms among college students is similar to those of large, representative epidemiological studies (Auerbach et al., 2016). Following prescreening, approximately 22% of the sample was invited to participate because of elevated levels of repetitive negative thinking (RNT). RNT was selected as a transdiagnostic cognitive risk factor linked with elevated psychopathology symptoms (Ehring et al., 2011; McEvoy et al., 2013). Our sample therefore reflected a true continuous distribution, including clinically significant levels of symptomatology.

Our primary aim tested associations between psychiatric spectra and syndromes with the standard EMA affective metrics of mean and standard deviation. These metrics reflect the first and second statistical distribution moments of day-to-day affect, respectively. Given comorbidity between internalizing and externalizing disorders, we hypothesized that individuals with higher levels of internalizing or externalizing spectra would report heightened mean NA. For mean PA, we hypothesized that higher depression levels would be associated with lower mean PA. Given the classic distinctions between depression and anxiety on anhedonia (Clark & Watson, 1991), we also hypothesized that attenuated mean PA might also be linked to heightened internalizing levels overall but would not be associated with the externalizing spectrum. For standard deviation, given the bulk of the extant literature, we hypothesized that heightened NA and PA standard deviation would be associated with more global (context nonspecific) affective dysregulation and would be linked to both internalizing (specifically depression and generalized anxiety syndromes) and externalizing spectra.

In addition, we tested whether the third and fourth distribution moments, the skew and kurtosis, explained unique symptom variance. Whether skew and kurtosis account for unique variance in psychiatric symptoms remains unexplored. Thus, we selected these distributional moments in lieu of more typical complex EMA metrics (inertia, *MSSD*, emo-diversity) because skew and kurtosis are not mathematically related by definition to mean and standard deviation, whereas some complex affective metrics are (i.e., inertia and *MSSD*). We hypothesized that greater skew would characterize a more jagged or reactive emotional profile in the absence of specific contextual information. Affective skew may indicate the presence of contextually specific symptoms, such as in social anxiety or specific phobia. This would not be captured by the mean or standard deviation. High kurtosis, on the other hand, by capturing the "heaviness of the tails" of one's affect distribution, may reflect a tendency to utilize extreme affect ratings more

frequently, though our hypotheses regarding kurtosis was more exploratory.

In accordance with HiTOP guidelines (Conway et al., 2019; Ruggero et al., 2019), we used a hierarchical, confirmatory factor approach to model symptoms. Then we built multivariate path models to test whether features of the first–fourth moments of NA and PA predicted psychiatric spectra and syndromes. This approach allowed us to consider internalizing and externalizing spectra and more specific syndromes, including depression, generalized anxiety, social anxiety, obsessive–compulsive, hoarding, mania, and substance and alcohol use symptoms.

Method

Participants

The sample comprised 966 university students who participated in exchange for research familiarization credits. Participants completed symptom assessments; all data were used in constructing the psychiatric symptom models (for demographic information, see Table S1 in the online supplemental materials). Of the 966 students, 462 also participated in an EMA study. There were no differences in any demographic variables between the symptom-only and the symptom + EMA samples. Students in the EMA study were offered course credit or a cash bonus as compensation. The sample was recruited across four semesters and multiple courses, resulting in seven distinct EMA cohorts, which were combined for the current study. There were no eligibility restrictions; however, a subset of the sample was invited following a screening procedure at the start of each semester. Specifically, we used the Perseverative Thinking Questionnaire (Ehring et al., 2011) to identify individuals with elevated levels of repetitive negative thinking, a transdiagnostic cognitive risk factor for psychopathology (McEvoy et al., 2013). Heightened RNT was defined as scores above the mean (M = 23). Within the EMA sample, 101 students (22%), had scores greater than 23. Sample size was not determined a priori; sample size was the maximum number of participants recruited over this time-frame.

Psychiatric Symptom Measures

Participants completed a range of well-validated self-report, symptom assessments at the start of each semester, with a greater number of internalizing spectrum symptom measures:

Generalized Anxiety Disorder (GAD-7)

Items assessed the frequency of seven primary generalized anxiety symptoms across the last 2 weeks (Spitzer et al., 2006). Item responses range on a scale from 0 (*not at all*) to 3 (*nearly every day*). In our sample, Cronbach's alpha = .91.

Patient Health Questionnaire (PHQ-9)

Nine items assessed the frequency of depression symptoms over the last 2 weeks using a scale from 0 (*not at all*) to 3 (*nearly every day*; Spitzer et al., 1999). In our sample, Cronbach's alpha = .86.

Social Interaction Anxiety Scale (SIAS)

The SIAS captured levels of fear in social interactions. Nineteen items are rated on a scale from 0 (*not at all characteristic or true*) to 4 (*extremely characteristic or true*; Mattick & Clarke, 1998). In our sample, Cronbach's alpha = .93.

Obsessive Compulsive Inventory Revised (OCIR)

A modified version of the OCIR was used in the current study, and included twelve items that assess levels of obsessions, contamination/washing symptoms, symmetry concerns, and checking behaviors (Abramowitz & Deacon, 2006). The neutralizing and hoarding subscales included in the original OCIR were not used in the present report. Instead, we measured hoarding symptoms using a well-validated hoarding-specific measure (Timpano et al., 2014; see below). We excluded the OCIR neutralizing items in light of evidence indicating poor psychometric performance of this subscale (Huppert et al., 2007; Wu & Watson, 2003). Items are rated on a scale from 0 (*not at all*) to 4 (*extremely*). In our sample, Cronbach's alpha = .89.

Saving Inventory Revised (SIR)

A modified SIR total assessing hoarding symptoms was used in the current study and included 14 items that assess levels of difficulty discarding, the core symptom of hoarding, along with acquiring behaviors (Frost et al., 2004). The clutter subscale was not used given our focus on college students and that clutter is less relevant to this age-group. Item responses range on a scale from 0 (*not at all*) to 4 (*extremely*). In our sample, Cronbach's alpha = .87.

The Altman Self-Rating Mania Scale (ASRM)

Manic symptoms were assessed via the ASRM (Altman et al., 1997). Five items are rated on a scale from 0 (*not applicable*) to 4 (*extremely applicable*). In the current sample the ASRM items had a Cronbach's alpha = .68.

NIDA Alcohol and Substance Use Screen

Alcohol and substance use symptoms were assessed using four specific items from the National Institute on Drug Abuse (NIDA) Substance Use and Alcohol Use Quick Screen and Modified ASSIST (National Institute on Drug Abuse, 2012). Participants rated past-year and past 3-month use frequency; frequency of desire to use; frequency their use led to health, social, legal or financial problems; and how often they failed to fulfill responsibilities because of use. Items were rated on a 0–4 scale. For the alcohol use items, Cronbach's alpha = .60. For the substance use items, Cronbach's alpha = .73

Procedure

For the sample completing EMAs, participants provided written consent, completed a battery of demographic questions and symptom severity measures and received detailed instructions for completing the EMA protocol. Participants then completed EMA surveys for the remainder of the academic semester. The EMA phase ended approximately 10 weeks after the lab session. A subset of these subjects were also analyzed in an unrelated analysis (Villano et al., 2020).

SMS messages were sent to participants' mobile phones through FileMaker Pro with a URL to the EMA survey created in Qualtrics.

Participants received the same survey once every other day at a random time between 10 am and 8 pm. The survey assessed the participant's current affective experience. While some items varied slightly by cohort, we analyzed only items common across all cohorts. Participants were prompted by "How much do you feel _____ right now," in which the blank was populated by one of nine different affect items (happy, content, attentive, relaxed, excited, nervous, upset, anxious, and irritable). Ratings were made using visual analog scale ranging from 0–100. These nine affect items were selected, in part, from the PANAS (Watson & Clark, 1994; anxious is not part of the PANAS) to reflect a range of both positive and negative emotions to calculate summary NA and PA scores.

Participants were required to respond to all affect items for the survey to be submitted. Participants were instructed to respond to each survey as soon as possible. Over the course of the semester, participants received a total of between 23 and 44 surveys, depending on when they completed onboarding. On average, participants completed 31.20 surveys (SD = 10.68, range = 3–55), or 81.27% of surveys (SD = 22.74%, range = 7%-100%).

Modeling Psychiatric Symptoms

We fit measurement models to symptoms, testing a correlated factors model (see online supplemental materials), and three higher-order factor models. For all models, we specified eight symptom factors with items from each measure loading onto their respective symptom factor (e.g., PHQ items loading onto Depression factor). To arrive at a final higher-order factor model, we compared several alternative specifications: (a) a single super-spectra (so called "*p*-factor"; Caspi et al., 2014) model with all eight lower-order factors as loadings; (b) one higher-order factor representing an internalizing spectrum (Depression, Generalized Anxiety, Social Anxiety, OC, and Hoarding factors as loadings), and one higher-factor representing an externalizing spectrum (Alcohol Use, Substance Use, and Mania factors as loadings); and (c) one higher-order factor representing an internalizing spectrum (Depression, Generalized Anxiety, Social Anxiety, OC, and Hoarding factors as loadings), and one higher-factor representing an externalizing spectrum (Alcohol Use and Substance Use), with the Mania factor not loading onto either higher-order factor. To best account for the ordinal nature of the item-level data, we used Lavaan's (Version .6.5; Rosseel, 2012) diagonally weighted least squares (DWLS) estimation. Model fit was assessed according to standard criteria: nonsignificant chi-square, CFI $>$ .95, RMSEA $<$ .06, and SRMR $<$ .08 (Kline, 2015).

In line with prior literature (Carlson et al., 2011); we found that reverse-scored items (Items 2 and 4 on the SIR; Items 5, 7, and 9 on the SIAS) exhibited low reliability and high intercorrelations, suggesting that reverse-scored items performed distinctly and could be accounted for as a nuisance factor. In light of this, and in keeping with psychometric literature suggesting against reverse scored items (Suárez-Alvarez et al., 2018); these items were omitted from the models. When measurement models were initially tested, there was evidence of one potential Heywood case (Kline, 2015): one NIDA Substance Use item exhibited a small, negative residual variance (magnitude = −.003). This item was omitted from the models.

EMA

Calculation of Distribution of Daily Affect

Within each EMA, we averaged the negative and positive items to a separate NA and PA value. Then, we estimated the first–fourth moments of each participant's NA and PA affect distribution across the semester: the mean, standard deviation, skew, and kurtosis.

Removal of Plausibly Careless EMAs

We have found that individual EMAs may be completed carelessly and are implausible reflections of one's current affective state (Jaso et al., in press). Determinants of a careless EMA include: (a) an EMA completed in which the participant spent less than an average of 1 s per item; (b) any EMA in which the within-EMA standard deviation is less than 5 (when using a 0–100 scale); and (c) any EMA in which more than 60% of items are given the same modal score. Careless EMAs likely add unnecessary noise to statistical models. Therefore, in a second analysis, we first removed any EMAs flagged as careless using these three determinants (https://github.com/manateelab/EMAeval-R-Package) and report the results.

Linking EMA and Symptom Models

From measurement models, we extracted factor loadings for each participant. Factor loadings were outcomes in multivariate path models, with EMA metrics of each participant's affect distribution as simultaneous predictors. Thus, any significant relationships between EMA metrics (predictors) and symptoms (factor loadings as outcomes) are net of all other predictors. We assessed relationships of the symptom data with NA and PA separately. In all models, we controlled for cohort and EMA completion percentage. As models were saturated, fit was not assessed.

T-SNE Visualization of Extracted Effects

We used the t-Distributed Stochastic Neighbor Embedding (t-SNE) algorithm to reduce the dimensionality of the path models effects to provide a simpler visualization of the relation between syndromes and affect profiles. The rationale stemmed from the clear patterns of affective dynamics across certain syndrome groups (e.g., similarities for generalized anxiety and depression; for social anxiety and OCD). T-SNE was conducted using the *Rtsne* package (Krijthe, 2015); we specified a perplexity of 2, default theta of .5, and dimensionality of 2.

Results

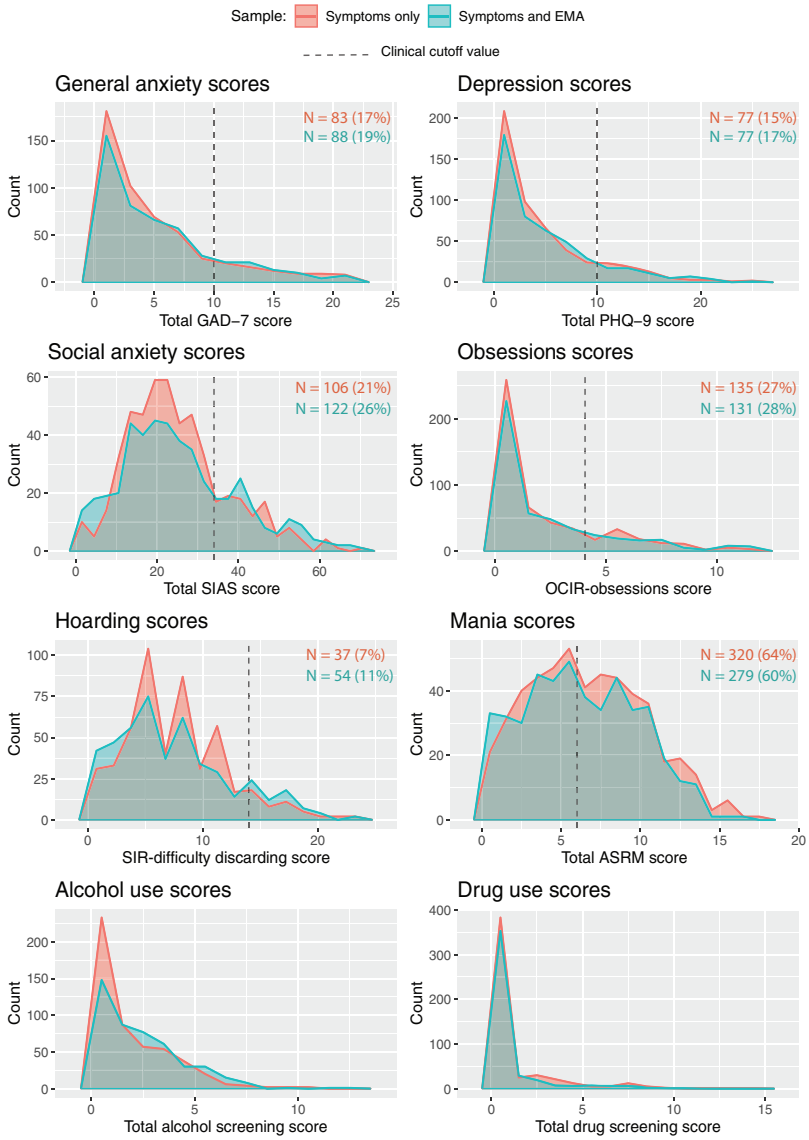
Distribution of Psychiatric Symptoms

Descriptives

Descriptive statistics for each symptom measure, relative to clinical cut-off values, for both the symptom-only and symptom-EMA groups are shown in Figure 1 and Table S2 in the online supplemental materials. For depression (PHQ-9), there were 77 students (15%) from the symptom-only sample and 77 students (17%) from the symptom and EMA sample that met clinical

Figure 1

Distribution of Symptoms, for the Symptoms-Only Cohort (Red [Light Gray]), and Separately for Those Participating in EMA (Blue [Dark Gray])



Note. EMA = ecological momentary assessment. See the online article for the color version of this figure.

thresholds (≥10) (Kroenke et al., 2001). For anxiety (GAD-7), there were 83 students (17%) and 88 students (19%) from the symptom and EMA samples, respectively that met the clinical threshold (≥10) (Spitzer et al., 2006). For social anxiety (SIAS), there were 106 students (21%) in the symptom-only sample and 122 students (26%) in the symptom and EMA sample that met the clinical threshold (≥34) (Brown et al., 1997; Heimberg et al., 1992). For OCD (OCIR–obsessions subscale), there were 135 students (27%) from the symptom-only sample and 131 students (28%) from the symptom and EMA sample that met the clinical threshold (≥4) (Foa et al., 2002). For hoarding (SIR–difficulty discarding subscale), 37 students (7%) in the symptom-only sample and 54 students (11%) in the symptom and EMA sample endorsed clinically elevated symptoms (≥15) (Frost et al., 2004). For mania (ASRM), 320 students (64%) in the symptom-only and 279 students (60%) in the symptom and EMA sample met the clinical threshold (≧6) (Altman et al., 1997). Because only select items from the NIDA alcohol and substance use screener were used, there are no clinical thresholds with which to compare.

To explore whether our sampling strategy of overrecruiting individuals at heightened psychopathology risk was successful, we compared the mean and max for each symptom scale (syndrome) in the current sample to previously published nonclinical and clinical means (Figure S1 in the online supplemental materials). For each syndrome,

the mean is between nonclinical and clinical means, while the max falls above clinical means. This indicates that our oversampling strategy was successful, leading to mean symptom levels being higher than those typically found in nonclinical samples.

Correlations Between Symptoms

We calculated zero-order correlations between raw symptom scores (see Table 1). Nearly all symptom measures were significantly associated with one another with the exceptions of, alcohol use with social anxiety ($r = -.03$, $p = .40$), OC symptoms ($r = .02$, $p = .51$), and mania ($r = .05$, $p = .14$), as well as substance use with social anxiety ($r = .04$, $p = .27$) and mania ($r = .00$, $p = .90$). Additionally, mania and hoarding symptoms were not significantly correlated ($r = .01$, $p = .63$).

In addition, some symptoms were associated with EMA compliance (see Table 1). There were significant associations between EMA completion percentage and depression symptoms ($r = -.11$, $p = .02$), generalized anxiety symptoms ($r = -.12$, $p = .01$), and alcohol use ($r = -.11$, $p = .02$). In contrast, the proportion of EMAs designated as "careless" was not related to any symptoms.

Distribution of Affect

The distribution of daily affect assessed via EMA, both of the entire sample and after having removed careless responses, is presented in Figure 2. Kurtosis is the only distributional EMA metric that appeared to shift after removing the 478 (2.93%) plausibly careless responses (Jaso et al., in press; defined as: <1 s time per item, within EMA $SD \leq 5$, proportion of modal items $\leq 60\%$), leaving 15,834 total EMAs. Correlations between EMA metrics are displayed in Table 2.

Higher-Order Factor Measurement Model

The first higher-order model containing a single higher-order factor exhibited mixed fit to the data, ($\chi^2(2336) = 11255.951$, $p < .001$; CFI = .969; RMSEA = .065; SRMR = .080). There were several negative variances (Alcohol Use item #3: −.057, Substance Use item #3: −.149), and indicators of the higher-order factor did not appear to capture a unitary construct. All internalizing symptom factors loaded strongly and positively (loadings > .550, $ps < .001$) onto the higher-order factor. The Mania factor loaded negatively onto the higher-order factor (−.407, $p < .001$), and the Alcohol and Substance Use factors had relatively low loadings onto the higher-order factor (Alcohol Use: .243, $p < .001$; Substance Use: .335, $p < .001$).

The second higher-order model contained two higher-order factors (Factor 1: Depression, Generalized Anxiety, Social Anxiety, OC, Hoarding; Factor 2: Mania, Alcohol Use, Substance Use). This model exhibited slightly better fit to the data, ($\chi^2(2268) = 11203.675$, $p < .001$; CFI = .969; RMSEA = .065; SRMR = .079). Again, there were several negative variances (Alcohol Use item #3: −.057, Substance Use item #3: −.149), and indicators of the externalizing higher-order factor did not appear to be unitary. Specifically, the Mania factor loaded positively onto the higher-order externalizing factor (.573, $p < .001$), whereas the Alcohol and Substance Use factors loaded negatively onto the externalizing higher-order factor (Alcohol: −.358, $p < .001$; Substance Use: −.495, $p < .001$).

The third higher-order model was identical to the previous model except we removed the Mania factor from the externalizing higher-order factor. This model exhibited the best fit to the data, ($\chi^2(2267) = 10497.512$, $p < .001$; CFI = .971; RMSEA = .062; SRMR = .075), containing no negative residual variances. Item loadings were generally strong onto each respective symptom factor (>.400), with the exception of one item (ASRM3: .136). Loadings onto each of the higher-order factors were strong for both the internalizing (Depression: .870; Generalized Anxiety: .836; Social Anxiety: .661; OC: .659; Hoarding: .565; all $ps < .001$) and externalizing (Alcohol Use: .749; Substance Use: .987; $ps < .001$) factors. Mania did not load onto either higher-order factor. Consequently, this model was retained as the higher-order factor model used in analyses linking to metrics of EMA distribution.

Linking Distribution of Affect With Symptoms: Path Models

Results linking NA and PA metrics with factor scores from the higher-order factor model are depicted in Figure 3 and Figure 4 and reported in Table 3. We also performed identical multivariate

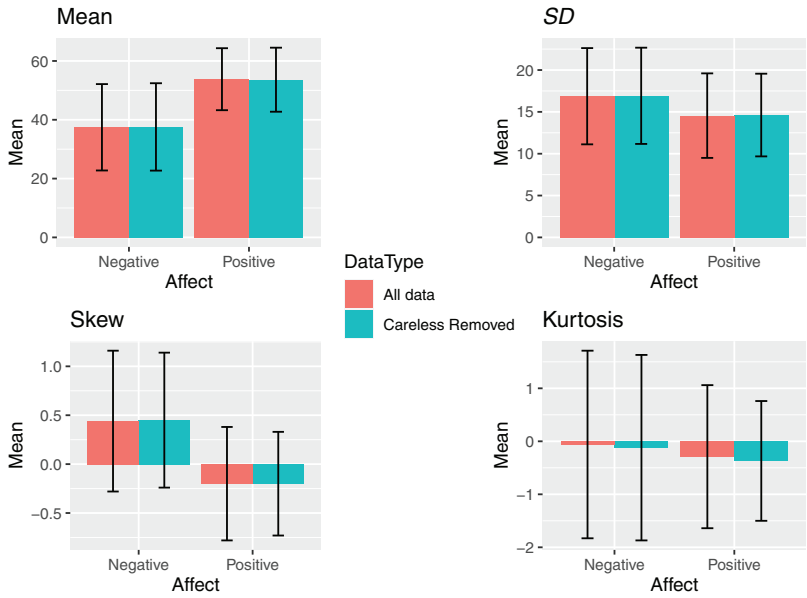
Table 1
Correlations of Symptom Measures

Variable	1	2	3	4	5	6	7	8	9
1. DEP									
2. GAS	0.71***								
3. SAS	0.51***	0.46***							
4. OCS	0.41***	0.53***	0.38***						
5. Hoard	0.38***	0.40***	0.35***	0.44***					
6. Mania	−0.27***	−0.24***	−0.27***	−0.11**	0.01				
7. ALC	0.13***	0.13***	−0.03	0.02	0.11***	0.05			
8. SUB	0.17***	0.15***	0.04	0.08*	0.09**	0	0.47***		
9. CompPct	−0.11*	−0.12**	−0.04	−0.09	−0.03	0.02	−0.11*	−0.09	
10. RmvPct	−0.06	−0.03	−0.04	−0.01	0.05	0.04	0.03	0.06	0.05

Note. DEP = Depression; GAS = Generalized Anxiety; SAS = Social Anxiety; OCS = Obsessive Compulsive; Hoard = Hoarding; Mania = Mania; ALC = Alcohol Use; SUB = Other Substance Use; CompPct = EMA Completion Percentage; RmvPct = Percentage of Careless EMAs Removed. Correlations between variables 1–8 are derived from both the EMA and symptom-only samples. Correlations involving variables 9 and 10 are derived only from the EMA sample.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Figure 2

Distribution of EMA Responses, Both Using the Entirety of EMA Data, and After Having Removed the 478 (2.93%) Plausibly Careless Responses (<1 s Time per Item, Within EMA SD ≤ 5, or Proportion of Items ≤ 60%)



Note. EMA = ecological momentary assessment. Error bars reflect 1 *SD*. See the online article for the color version of this figure.

path models using the factor scores as outcomes except with the NA and PA distributional metrics after removing plausibly careless EMAs. Results across these two analyses were similar (Table S4). Further, EMA-symptom associations from a correlated factor model also demonstrated similar results (see the online supplemental materials).

Discussion

There is increasing use of dimensional systems to improve the reliability and validity of psychiatric nosology (Caspi et al., 2014; Kotov et al., 2017; Lahey et al., 2012). Despite evidence for the clinical utility and construct validity of these classification systems (Ruggero et al., 2019), how this nosology manifests in day-to-day emotional life remains unknown. Using a HiTOP approach, we demonstrate that the idiographic distribution of daily NA and PA differ across psychiatric symptoms.

Our symptom structure generally mirrored the taxonomy identified by HiTOP and others (Kotov et al., 2017). We found support for an internalizing spectrum, made up of depression, generalized anxiety, social anxiety, obsessive–compulsive and hoarding syndromes (Achenbach, 1966). Additionally, our data supported an externalizing factor that included symptoms of substance use. The one symptom not loading onto either spectrum was that of mania, which often cross-loads with thought disorder (Keyes et al., 2013)—not modeled here.

This symptom taxonomy was linked to metrics of the distribution of daily affect (see Figure 3). Mean NA was consistently (i.e., regardless of using the entire EMA sample or removing plausibly careless responses) associated with endorsement of all symptoms

Table 2

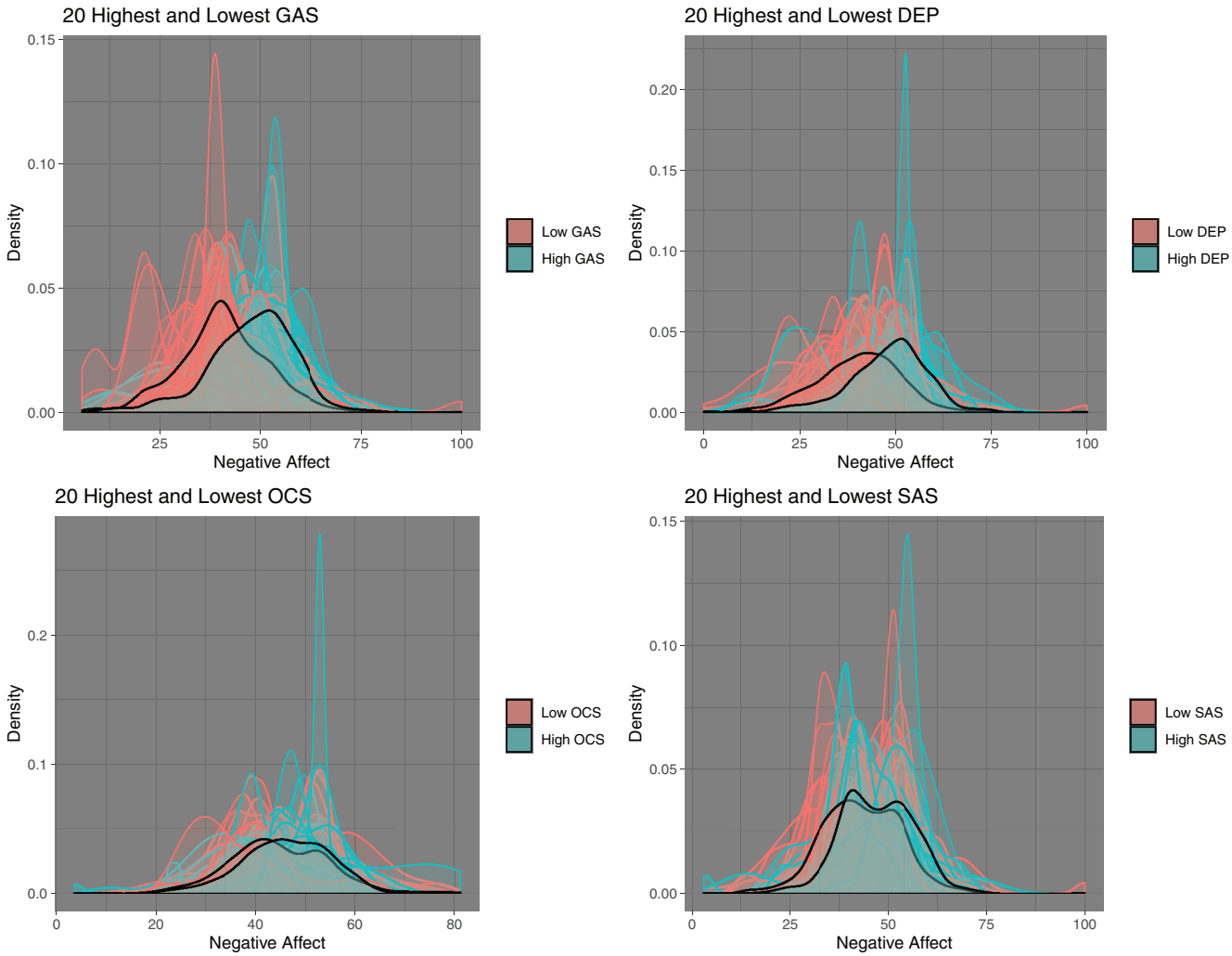
Correlations of Distribution of Daily NA and PA

Variable	1	2	3	4	5	6	7	8
1. NA *M*		−0.56***	0.14**	−0.01	−0.67***	0.2***	−0.36***	−0.06
2. PA *M*	−.53**		−0.14**	−0.02	0.32***	−0.49***	0.12**	0.22***
3. NA *SD*	0.09	−.10*		0.75***	−0.04	0.01	−0.21***	−0.16***
4. PA *SD*	−0.05	0.00	.76**		0.07	−0.04	−0.09*	−0.19***
5. NA skew	−.65**	.26**	0.02	.13**		−0.28***	0.68***	0.14**
6. PA skew	.15**	−.41**	0.03	0	−.23**		−0.17***	−0.49***
7. NA kurtosis	−.30**	0.06	−.22**	−.16**	.53**	−.11*		0.32***
8. PA kurtosis	0.04	.15**	−.21**	−.25**	0.04	−.47**	.38**	

Note. PA = positive affective; NA = negative affective. Below diagonal are associations for the entire EMA sample; above diagonal correlations reflect associations after removing plausibly careless responses.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Figure 3

Density Plots of Negative Affect for Individuals High and Low on Generalized Anxiety, Depression, Obsessive Compulsive, and Social Anxiety Symptoms. Black Lines Represent the Density Across NA Observations Separately for the High and Low Symptom Groups



Note. An individual may be in multiple panels. DEP = Depression; GAS = Generalized Anxiety; SAS = Social Anxiety; OCS = Obsessive Compulsive. See the online article for the color version of this figure.

with the exception of mania, for which the association was inverse. The effect sizes for the mean NA-internalizing spectra association (.49) was more than double that of the externalizing spectra (.20). Moreover, the confidence intervals for mean NA were substantially narrower for the internalizing than externalizing spectrum. These effect size and precision differences notwithstanding, links between heightened levels of mean NA to nearly all syndromes is consistent with evidence that negative affectivity/neuroticism/emotional instability might represent the so-called P-factor (Caspi et al., 2014; Kalokerinos et al., 2020; Watson & Clark, 1984).

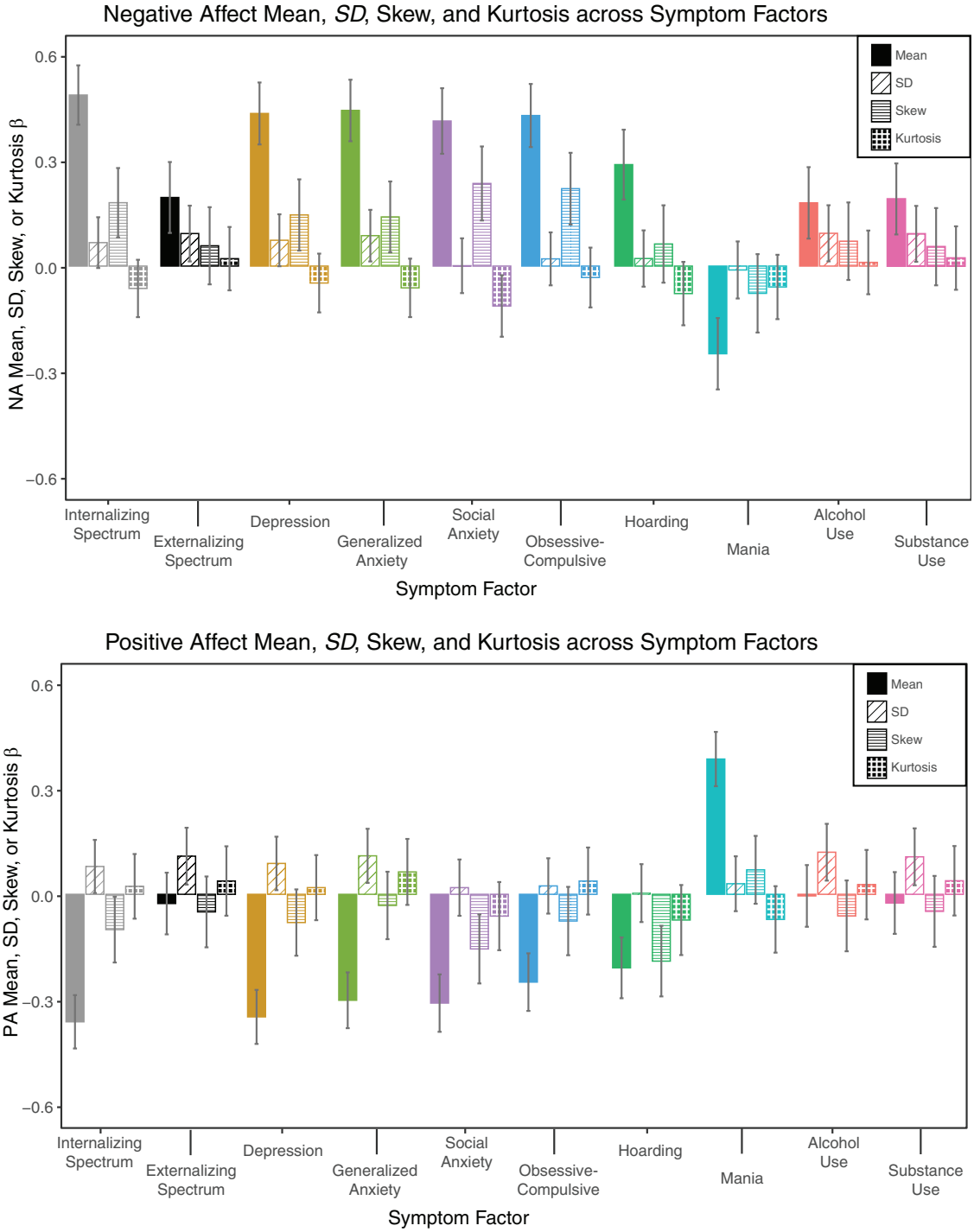
Despite the inverse correlation between mean PA and mean NA ($r = -.54$), mean PA demonstrated more divergent effects across spectra and syndromes. Higher internalizing syndromes were consistently associated with lower mean PA, with slightly smaller effect sizes (−.21 to −.35) than associations with mean NA (effect sizes: .29 to .44). In contrast, only mania was associated with elevated mean PA. Considered jointly, the results for mean affect indicate that daily NA and PA are associated with distinct association patterns across internalizing and externalizing spectra.

Variability in NA and PA further distinguished spectra and syndromes. As has been found previously (Houben et al., 2015); NA and PA standard deviation shared substantial variance ($r = .76$), suggesting that affective variability is a general property of one's emotional experience independent of valence. On the externalizing side, PA variability was associated with the externalizing spectrum, alcohol use and substance use syndromes. Effects were present, although weaker and less consistent, with NA variability.

On the internalizing side for affective variability, the most consistent, albeit relatively weak, effect was a positive association between both NA and PA variability and generalized

Figure 4

Effect Sizes Linking the Symptom Factors With EMA Metrics



Note. Error bars reflect 95% CI. EMA = ecological momentary assessment. See the online article for the color version of this figure.

anxiety symptoms, indicating that individuals with higher generalized (noncontext specific) anxiety displayed greater variation in day-to-day affect. Moreover, patterns of associations between affective variability and internalizing syndromes belonging to the so-called fear (obsessive–compulsive, social anxiety) and distress (depression and generalized anxiety) subfactors were strikingly different. While parameter estimates between syndromes of the distress subfactor and PA variability were between .07 and .11, parameter estimates between syndromes of the fear subfactor and PA variability were an order

Table 3
Results of Path Models Linking Symptom Factors With EMA Metrics

Symptom factor	EMA metric	Negative affect β [95% CI]	Positive affect β [95% CI]
Internalizing Spectrum	Mean	.49*** [.39, .59]	−.36*** [−.45, −.27]
Externalizing Spectrum		.20*** [.08, .32]	−.03 [−.13, .08]
Depression		.43*** [.33, .54]	−.35*** [−.44, −.26]
Generalized Anxiety		.44*** [.34, .55]	−.30*** [−.40, −.21]
Social Anxiety		.41*** [.30, .52]	−.31*** [−.41, −.21]
Obsessive-Compulsive		.43*** [.32, .54]	−.25*** [−.35, −.15]
Hoarding		.29*** [.17, .41]	−.21*** [−.31, −.11]
Mania		−.25*** [−.37, −.13]	.39*** [.29, .48]
Alcohol Use		.18** [.06, .30]	−.01 [−.11, .10]
Substance Use		.19** [.07, .31]	−.03 [−.13, .08]
Internalizing Spectrum	Standard Deviation	.07 [−.02, .15]	.08^{+} [−.01, .17]
Externalizing Spectrum		.09^{+} [.00, .19]	.11* [.01, .21]
Depression		.07 [−.02, .16]	.09^{+} [.00, .18]
Generalized Anxiety		.09^{+} [.00, .17]	.11* [.02, .20]
Social Anxiety		.00 [−.09, .09]	.02 [−.08, .11]
Obsessive-Compulsive		.02 [−.07, .11]	.02 [−.07, .12]
Hoarding		.02 [−.07, .12]	.00 [−.10, .10]
Mania		−.01 [−.11, .09]	.03 [−.06, .12]
Alcohol Use		.09^{+} [.00, .19]	.12* [.02, .22]
Substance Use		.09^{+} [.00, .19]	.11* [.01, .20]
Internalizing Spectrum	Skew	.18** [.06, .30]	−.10^{+} [−.21, .01]
Externalizing Spectrum		.06 [−.07, .19]	−.05 [−.17, .07]
Depression		.15* [.03, .27]	−.08 [−.19, .03]
Generalized Anxiety		.14* [.02, .26]	−.03 [−.15, .08]
Social Anxiety		.24*** [.11, .36]	−.16** [−.27, −.04]
Obsessive-Compulsive		.22*** [.10, .34]	−.08 [−.19, .04]
Hoarding		.06 [−.07, .19]	−.19** [−.31, −.07]
Mania		−.08 [−.21, .06]	.07 [−.05, .19]
Alcohol Use		.07 [−.06, .20]	−.06 [−.18, .06]
Substance Use		.06 [−.08, .19]	−.05 [−.17, .07]
Internalizing Spectrum	Kurtosis	−.06 [−.16, .03]	.02 [−.09, .13]
Externalizing Spectrum		.02 [−.09, .13]	.04 [−.08, .16]
Depression		−.05 [−.15, .05]	.02 [−.09, .13]
Generalized Anxiety		−.06 [−.16, .04]	.06 [−.05, .18]
Social Anxiety		−.11* [−.22, −.01]	−.06 [−.18, .05]
Obsessive-Compulsive		−.03 [−.13, .07]	.04 [−.08, .15]
Hoarding		−.08 [−.19, .03]	−.07 [−.19, .05]
Mania		−.06 [−.17, .05]	−.07 [−.18, .04]
Alcohol Use		.01 [−.10, .12]	.03 [−.09, .15]
Substance Use		.02 [−.09, .13]	.04 [−.08, .16]

Note. Standardized estimates in *SEM* approximate effect sizes (Hoyle, 1995). EMA = ecological momentary assessment.
$^{+}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

of magnitude lower (.00–.02). One explanation for this pattern is that those with heightened symptoms within the fear subfactor primarily experience situationally contingent affective reactions–responses dependent on exposure to specific social or contamination related triggers. In contrast, affective variation in individuals with heightened depression or generalized anxiety symptoms may be global and situationally independent. These findings provide the intriguing hypothesis that affective variability may dissociate syndromes that load onto fear and distress subfactors net of mean affect.

There were also syndrome-specific patterns for affective skew. First, affective skew was the metric with the least shared variance across valence ($r = -.23$). NA skew was robustly associated with internalizing spectra, such that higher internalizing symptoms were associated with a more positively skewed NA distribution, with a modest effect size (.18). NA skew was more strongly associated with syndromes linked to the fear (medium effect sizes of .22 to .24) than distress (small effect sizes of .14 to .15) subfactor, although these differences were not significant. Lastly, removing plausibly careless EMA responses increased the strength of associations with the internalizing spectrum and its syndromes and also revealed associations with alcohol and substance use. Broadly, this pattern of findings indicates that syndromes linked to the fear subfactor are most robustly associated with NA skew (beyond the effects of mean and standard deviation) and may reflect a more jagged or reactive emotional profile in response to specific situational triggers. This suggests that psychiatric symptoms that are situationally dependent and situationally independent produce distinct patterns of affective profiles in daily life.

Epidemiological evidence suggests that symptoms linked the fear subfactor (e.g., behavioral inhibition and social anxiety) emerge prior to symptoms of the distress subfactor (Hankin et al., 2016; Kagan & Snidman, 1999). From this, we hypothesize that

internalizing pathology may initially emerge via contextually specific aversive experiences. This would result in a skewed affective profile, perhaps due to epigenetic or genetic predispositions toward temperamentally heightened affective reactivity. Depending on the types of experiences one has through adolescence, this skewed affective profile may shift toward a more context-independent "rolling" affective variation, captured here by heightened standard deviation. Over time, and in response to stressful life events, we hypothesize that this shift may be accompanied by more habitual and ubiquitous cognitive processes of worry and rumination, linked to generalized anxiety and depression. In terms of daily affect, this would be captured by greater affective variability and, perhaps eventually, a qualitative shift into a state of maximally heightened negative affect. This hypothesis is supported by emerging evidence from dynamical systems models indicating that increases in the variance, kurtosis, and skewness of one's states are warning signs for "critical transitions" to a new equilibrium (that is, a depressive episode; Dablander et al., 2020; Guttal & Jayaprakash, 2008; Scheffer et al., 2012).

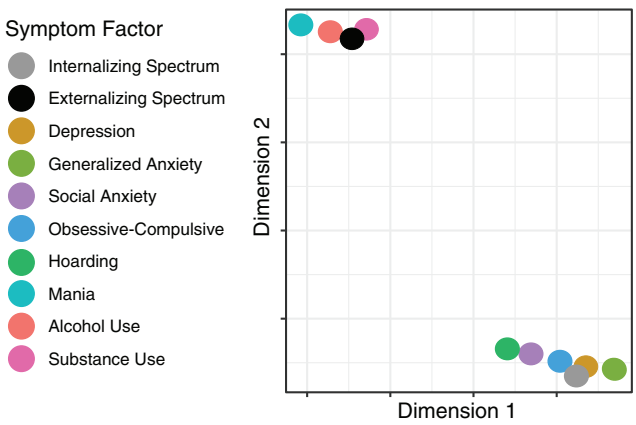
We performed our analyses using both full EMA data as well as EMA data after having removed plausibly careless responses. We have found (Jaso et al., in press) that an individual EMA may be careless if it is completed too quickly (≤1 s taken per item), if there is too little variance across item responses ($SD \leq 5$ if items are on a 100-point scale), or if a substantial proportion of items are rated at the modal response (≥60% items rated at the mode). While there were few EMAs removed in total (<3% of EMAs), and the distribution of EMA data did not change dramatically, removing careless responses altered some associations with psychiatric spectra and syndromes. In particular, removing careless responses (a) increased the effect size of associations between NA skew and syndromes associated with the fear subfactor (social anxiety and OC) and alcohol/substance use; and (b) revealed several associations between symptom and NA kurtosis, particularly one in which higher levels of social anxiety were associated with lower kurtosis (more data-points in the tails). This flagging protocol tends to remove EMAs clustered at the midpoint of the 0–100 scale, which occurs when participants quickly and capriciously tap the midpoint of the scale. Removal of these responses revealed additional associations with both skewness and kurtosis. Overall, we strongly recommend future work carefully consider the quality of each individual EMA data-point and remove plausibly careless responses prior to performing any individual differences analyses.

These findings should be interpreted in light of limitations. While our battery assessed a range of internalizing and externalizing symptoms, there are syndromes and subfactors reflected in HiTOP that we did not capture. For example, we relied on social anxiety and OC symptoms to describe the fear subfactor, but we did not assess panic, specific phobias, or agoraphobia symptoms. Similarly, we did not assess eating or dissociative symptoms, and we did not measure the full range of externalizing symptoms. At the spectra level, our measures more extensively sampled the internalizing space relative to externalizing space (which was limited to alcohol and substance use). A second limitation is that our EMA procedure did not incorporate assessments of context. Thus, despite the evidence that fear and distress subfactors may be distinguishable via context-dependent and context-independent negative via skew and variability, respectively, our sampling procedure cannot determine whether and when affective triggers were encountered because assessments were not yoked to triggers (Villano et al., 2020). A third limitation is that our sampling rate was somewhat unique. We chose a once every other day assessment schedule. This slightly more infrequent sampling rate permitted us to assess affect over a much longer period of time than is typically done (i.e., 3–4 months as opposed to the more typical 5–10 times per day for 2–3 weeks). We believe this allows ascertainment of trait-like levels of the distribution of one's affect. It is more likely that idiosyncratic events impact the distribution of one's affect during a 2-week period than a 3–4-month period. Nonetheless, it is unknown whether associations between psychiatric symptoms and the distribution of daily affect is dependent on sampling rate. Lastly, while a fourth limitation is our use of a nonclinical sample of young adults, symptom severity distribution in this sample is similar to that of epidemiological studies (Alonso et al. 2018; Kessler et al., 2005), and one-quarter of the sample was targeted to be at elevated risk for psychopathology. Further, young adult samples are critical to fully characterize psychopathology (Auerbach et al., 2018) and many psychiatric difficulties emerge during early adulthood (De Girolamo et al., 2018). Thus, while our sample is not a traditional case-control design, we are able to characterize distributions that match population distributions.

Our findings indicate that the distribution of affective experiences in daily life differs across psychiatric spectra, subfactors, and syndromes (Figure 5). This approach builds on recommendations by Conway et al. (2019) and serves as an exemplar of linking levels of HiTOP to psychiatrically relevant correlates. Because the daily manifestations of internalizing subfactors are distinguishable via one's affective distribution, we suggest that ambulatory monitoring systems and intervention protocols may integrate these measures into procedures. The lack of specificity with which heightened mean negative affect was present across internalizing spectra and syndromes underscores the utility of the second and third distributional moments in delineating internalizing subfactors. Modeling of the within- and between-person effects using

Figure 5

T-SNE Collapsing the Parameter Estimates for All 8 EMA Effect Sizes (PA, NA, Mean, Standard Deviation, Skew, Kurtosis) for Each Spectra/Syndrome to Two Dimensions



Note. T-SNE = t-Distributed Stochastic Neighbor Embedding; EMA = ecological momentary assessment; PA = positive affective; NA = negative affective. See the online article for the color version of this figure.

idiographic models is necessary. However, better understanding the ways in which psychiatric symptoms manifest in day-to-day life can refine nosological models and our understanding of the co-occurrence of psychiatric phenomena.

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Received May 26, 2020
Revision received December 11, 2020
Accepted December 30, 2020 ■