Emotion

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Identifying Real-World Affective Correlates of Cognitive Risk Factors for Internalizing Disorders

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Cognitive risk factors are key in the vulnerability for internalizing disorders. Cognitive risk factors modulate the way individuals process information from the environment which in turn impacts the day-to-day affective experience. In 296 young adults, we assessed two transdiagnostic, general risk factors—repetitive negative thinking (RNT) and anxiety sensitivity in a high-RNT subsample (N = 119). We also assessed disorderand content-specific risk factors including worry, rumination, and three facets of anxiety sensitivity (cognitive, social, physical). To determine the day-to-day affective experience, we used cellphone-based ecological momentary assessment to assess the mean and variability of positive and negative affect (PA; NA) over 3–4 months. Two multilevel multivariate Bayesian models were used to predict PA and NA mean and variability from (1) general and (2) specific cognitive risk factors. Mean NA was a nonspecific correlate of cognitive risk across both models, while mean PA was most strongly related to RNT and rumination. NA variability was most strongly related to RNT, rumination, and the physiological facet of anxiety sensitivity. PA variability was a specific correlate of RNT. Results highlight that cognitive risk factors for internalizing disorders manifest in unique patterns of day-to-day emotional experience.

Keywords: cognitive risk, ecological momentary assessment, internalizing disorders, repetitive negative thinking, anxiety sensitivity

Supplemental materials: https://doi.org/10.1037/emo0001117.supp

Cognitive risk factors (e.g., rumination, worry, and anxiety sensitivity) are trait-like patterns of thinking that are harmful, unpleasant, or result in maladaptive behavior (Alloy et al., 2000). Cognitive risk factors increase vulnerability for internalizing disorders, such as depression and anxiety disorders (Allan et al., 2018; Alloy et al., 2006; LeMoult & Gotlib, 2019; Naragon-Gainey & Watson, 2018). Critically, cognitive risk factors modulate the way individuals process information from the environment and therefore influence their affective and behavioral responses (Caudek & Monni, 2013; Haeffel et al., 2012). Over time, these responses can become reinforced and cemented, emerging as symptoms of mental disorders.

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Several cognitive risk factors have been identified that are specific to single disorders/syndromes; these risk factors are often content-specific in that they manifest as unhelpful patterns of thought related to concerns of a particular disorder (e.g., rumination in depression). Recently, there has also been an interest in identifying cognitive risk factors that predict psychiatric symptoms that cut across diagnoses (so-called 'transdiagnostic' risk factors, e.g., repetitive negative thinking for internalizing psychopathology; Ehring & Watkins, 2008). These cognitive risk factors, which tend to be more general, agnostic to, or devoid of disorder-specific content, may shed light on the common processes among disorders that are highly comorbid (e.g., depression and generalized anxiety). These more 'general' cognitive risk factors are thought to be useful for identifying the shared, transdiagnostic risk mechanisms that explain high levels of comorbidity among internalizing disorders. In contrast, content-specific cognitive risk factors may help to determine how cognitive pathways might diverge for individual internalizing disorders (McEvoy et al., 2013). Enhancing our understanding of both general and specific cognitive risk factors is key to understanding the pathophysiological mechanisms and etiology of internalizing disorders broadly, as well as specific disorders including anxiety, depression, and others.

One general (i.e., transdiagnostic) cognitive factor, repetitive negative thinking (RNT), captures the process by which negative thoughts are experienced. RNT is characterized by repetitious, uncontrollable thoughts focused on negative topics (Ehring & Watkins, 2008; McEvoy & Brans, 2013). RNT is one facet under the broader umbrella

of perseverative cognition that focuses on negatively valenced cognitions (Brosschot et al., 2006; Ottaviani et al., 2016). RNT is reliably associated with risk for depression, generalized anxiety disorder, social anxiety disorder, as well as panic disorder and obsessive–compulsive spectrum disorders (Ehring & Watkins, 2008; Arditte et al., 2016). RNT can be conceptualized as a latent factor that subsumes content-specific cognitive risk factors such as rumination, worry, and postevent processing (McEvoy et al., 2010), which we briefly describe here. Rumination is a pattern of negative thinking focused on past mistakes or perceived shortcomings (Nolen-Hoeksema et al., 2008). Rumination confers risk specifically for depression, but it is also associated with other internalizing disorders, though to a lesser degree (Spasojević & Alloy, 2001). Worry is defined by catastrophic, future-oriented thinking, and it is a core feature of generalized anxiety disorder (Hong, 2007). Lastly, postevent processing is repeated and prolonged thoughts focused on social situations and is specifically associated with risk for social anxiety disorder (Brozovich & Heimberg, 2008). While worry, rumination, and postevent processing all capture different content domains by virtue of focusing on future, past, or event-specific repetitive thoughts, they all share the core features of RNT.

In addition to RNT, another 'general' transdiagnostic cognitive risk factor is anxiety sensitivity, a higher-order latent construct that reflects the tendency to interpret physiological arousal as having catastrophic consequences (Reiss, 1991). Anxiety sensitivity is critical in predicting the development and maintenance of a range of disorders, including panic disorder (Rodriguez et al., 2004), social anxiety disorder (Ball et al., 1995; Norton et al., 1997), generalized anxiety disorder (Deacon & Abramowitz, 2006), eating disorders (Anestis et al., 2008), depression (Olthuis et al., 2014), and suicidality (Stanley et al., 2018). Like RNT, anxiety sensitivity manifests in three unique content-specific subdomains or facets (Rodriguez et al., 2004). The first facet is physiological anxiety sensitivity, which captures fears about the health consequences of arousal and is specifically linked with risk for panic disorder (Zinbarg et al., 2001). The second facet of anxiety sensitivity is social, which is characterized by recurrent fears about embarrassment and social rejection related to physiological arousal (e.g., sweating) and predicts social anxiety disorder (Zinbarg & Barlow, 1996). The third facet of anxiety sensitivity is cognitive, which is defined by recurrent concerns about "going crazy" or becoming mentally incapacitated by physiological arousal (Taylor et al., 2007). Cognitive anxiety sensitivity is most strongly associated with disorders marked by difficulties with thought control (Rector et al., 2007) including generalized anxiety disorder (Zinbarg & Barlow, 1996) and obsessive–compulsive symptoms (Robinson & Freeston, 2014), as well as suicidality (Capron et al., 2012; Oglesby et al., 2015). Similar to how RNT encapsulates aspects of worry, rumination, and postevent processing, anxiety sensitivity is a multifaceted construct that subsumes multiple domains based on content.

While a considerable body of research has linked cognitive risk factors to internalizing disorders (Hankin et al., 2004), work relating cognitive risk factors to day-to-day emotion has emerged only more recently with the growing popularity of intensive longitudinal studies using ecological momentary assessment (EMA). Broadly, EMA is a set of methods for collecting data (e.g., self-reported affect) from participants in real-time as they go about their daily life (Hormuth, 1986), often using cell phones. EMA has three major benefits over cross-sectional methods: it minimizes "peak" and "end" biases from retrospective recall, maximizes ecological validity by sampling across many contexts in the real world, allows for the study of transitory, dynamic processes such as affect and behavior (Shiffman et al., 2008), and protects against overgeneralized negative memory biases (aan het Rot et al., 2012). These methodological considerations make EMA ideally suited to investigating the ways cognitive risk factors manifest in an individual's day-to-day emotional life. Given the key role cognitive risk factors are thought to play in shaping daily affective experiences, EMA provides a granular and powerful method to examine the specific ways cognitive risk factors influence daily emotion and may eventually result in internalizing disorders.

While research examining the day-to-day affective correlates of cognitive risk is in its infancy, work relating emotion dynamics to internalizing symptoms has enhanced our understanding of their phenomenology and underlying affective processes. This is because an individual's patterns of daily affect accumulate into more stable emotional states that in turn reflect psychological syndromes (Cunningham et al., 2013). For example, high mean negative affect (NA) and low mean positive affect (PA) have emerged as hallmark features of depression (Peeters et al., 2006). Newer evidence also suggests that affect variability may be a feature of depression that reflects a deficit in emotion regulation, although this finding has not reliably replicated (Heller et al., 2019 but see Houben et al., 2015). One recent study found that mean PA distinguished internalizing and externalizing disorders generally as well as individual disorders within these broad categories, while mean NA was consistently related to psychopathology (Heller et al., 2021). This same study found that affect variability was specific to disorders with situationally independent symptoms such as depression and general anxiety in contrast to context-specific disorders such as social anxiety. Together, this work supports the idea that affective dynamics are useful for untangling the common and specific processes underlying internalizing disorders.

To date, a limited number of studies have linked cognitive risk factors to affective dynamics, yet day-to-day affective functioning may be key to understanding the processes by which cognitive risk contributes to the development of internalizing disorders. In one study, moment-to-moment rumination was associated with concurrent NA (Takano & Tanno, 2011), as well as increased NA in response to negative events (Moberly & Watkins, 2008; Selby et al., 2016). Furthermore, Takano and Tanno (2011) found that trait rumination was associated with higher levels of momentary NA. Trait anxiety, a construct that reflects the tendency to worry, has been found to be associated with greater instability of NA (Heller et al., 2019). These studies are promising, in that they suggest that there may be features of an individual's affective experience that differentiate risk for depression (e.g., mean NA) and anxiety (e.g., NA instability), but the extant literature is limited.

There are three critical ways to extend this nascent literature connecting cognitive risk to daily affect. First, considering *both* general and specific cognitive risk factors is necessary for a complete picture of the etiological trajectories of internalizing disorders. Linking daily affect to both general and specific cognitive risk is important because it is unknown if features of day-to-day emotional experiences predict unique internalizing disorders or are nonspecific markers of risk. In the longer term, this work also may help to predict and identify the onset of internalizing disorders on the basis of individuals' day-to-day affective characteristics. Second, the duration of the sampling period in the extant literature is generally on the order of days or weeks, which

might not capture stable affective signatures related to trait-like cognitive risk factors. Third, prior work has largely used frequentist analyses, where a Bayesian approach confers some important benefits. For example, Bayesian inference incorporates prior knowledge based on theory and research and allows for the simultaneous estimation of affective dynamics such as mean and variability as outcome variables in a multilevel framework. This type of model is ideal for exploring the affective correlates of cognitive risk factors.

As such, the overarching goal of this study was to address these limitations and explore links between affective patterns, RNT, and anxiety sensitivity, two broad cognitive factors that reliably convey transdiagnostic risk for internalizing disorders, in a Bayesian modeling framework. Our first aim was to systematically investigate how the more general cognitive risk factors of RNT and anxiety sensitivity are related to one's mean and variability of daily positive and negative affect. The second aim was to model content-specific components of RNT (worry and rumination) and facets of anxiety sensitivity (physical, cognitive, and social) as predictors of these same affective dynamics, and to determine whether the associations between risk factors and affective dynamics differ when general versus specific factors are examined. Results from this exploratory study will help us to understand how general versus specific risk factors explain day-to-day affective processes and ultimately result in internalizing disorders.

Method

Participants and Procedures

This study is a secondary analysis of data collected over three years. Participants (N = 296) were recruited from University of Miami psychology and chemistry courses from 11 cohorts between 2016 and 2019 as part of the *Measuring Daily Life* and *Health U* studies. These studies were approved by the Institutional Review Board of the University of Miami, and signed informed consent was obtained from all study participants. All participants were enrolled at the start of the semester when they completed a battery of demographic and self-report measures of cognitive risk including RNT and anxiety sensitivity. *Healthy U* participants (N = 119) were specifically recruited on the basis of high RNT scores (Perseverative Thinking Questionnaire total score $>$ 23 which was the mean of the entire undergraduate subject pool), and completed additional questionnaires assaying specific types of RNT, including rumination and worry. We collected these additional measures in order to capture a wider range of risk profiles in a subset of individuals.

After the baseline assessment, all participants received one SMS text message every other day at pseudorandomly determined times between 10:00 a.m. and 8:00 p.m. with a hyperlink to a brief one-minute survey. Participants received text messages every other day for approximately 3 months. The strategy to sample every other day was selected to get a trait-like estimate of an individual's emotional experience over the course of a relatively long time in order to examine the longer-term, overall emotional experience of our participants' in daily life. This sampling approach also mitigates some bias present in short-term sampling (e.g., if someone is sampled intensively for 1 week, they may be having a particularly good/bad week that is not representative of their normal emotional functioning). Participants were included in the analysis if they responded to at least 15 assessments throughout the semester; this retained 90% of the original sample. The maximum number of responses was 41 surveys over 88 days. EMA compliance was acceptable (90.5% on average).

Measures

Repetitive Negative Thinking (RNT)

RNT was measured using the Perseverative Thinking Questionnaire (PTQ; Ehring et al., 2011). This scale consists of 15 items (e.g., "*The same thoughts keep going through my mind again and again*," and, "*I get stuck on certain issues and cannot move on*"), rated on a 5-point scale from '0' (*never*) to '4' (*almost always*). Sum-scores were calculated. Cronbach's alpha in the current study was .96.

Anxiety Sensitivity Index—Short (ASI-S)

The Anxiety Sensitivity Index-3 (ASI-3; Taylor et al., 2007) captures levels of AS, defined as the intensity of distress one feels when experiencing symptoms of anxiety (e.g., "When I notice that my heart is beating rapidly, I worry that I might have a heart attack"). Participants rate each item on a 5-point Likert scale from '0' (*very little*) to '4' (*very much*). For the purposes of the current study and due to survey-length restrictions, we reduced the number of items to 9 by selecting the highest item-total score correlations from each subscale in three separate large ($n1$ = 450; $n2$ = 256; $n3$ = 290) general community samples and by conferring with the originally published ASI-3 factor loadings. A total score was calculated by summing all 9 items, along with three subscale scores to capture physical (e.g., "*It scares me when my heart beats rapidly*"), cognitive (e.g., "*When I cannot keep my mind on a task, I worry that I might be going crazy*"), and social (e.g., "*When I tremble in the presence of others, I fear what people might think of me*") facets of AS. Cronbach's alpha for the total score was .89, with alphas of .81, .80, and .81 for the physical, cognitive, and social subscales, respectively.

Rumination

Rumination was measured using the Ruminative Response Scale (RRS) from the Response Style Questionnaire (Nolen-Hoeksema & Morrow, 1991). This scale consists of 22 items (e.g., "*do you think about all your shortcomings, failings, faults, mistakes*?," and "*do you go away by yourself and think about why you feel this way?*"), rated on a 4-point Likert scale from 1 (*almost never*) to 4 (*almost always*). Sum-scores were calculated for each participant, and the Cronbach's alpha was .95 in the present study.

Worry

Worry was measured using the Penn State Worry Questionnaire (PSWQ; Meyer et al., 1990). This scale contains 16 items (e.g., "*Once I start worrying, I cannot stop*" and "*As soon as I finish one task, I start to worry about everything else I have to do*"), rated on a 5-point Likert scale from 1 (*not at all typical*) to 5 + (*very typical*). Sum scores were calculated for each participant. Cronbach's alpha was .90 in this sample.

Ecological Momentary Assessment Survey

EMA surveys consisted of 5 PA items (*attentive, content, happy, excited, relaxed*) and 3 NA items (*anxious, irritable, upset*)

from the Positive and Negative Affect Schedule (Watson et al., 1988). Each item was rated on a visual analog scale (range 0–100). Composite PA and NA scores were computed by taking the average of the PA and NA items endorsed at each survey prompt. Multilevel reliabilities were estimated for PA and NA using the lavaan (Rosseel et al., 2019) and semTools (Jorgensen et al., 2022) packages in R. Cronbach's alpha was computed at the within- and between-person levels separately. We found that within-person reliability for PA and NA were acceptable (αPA = .70; αNA = .76), and between-person reliability for PA and NA was very good (αPA = 93; αNA = .88).

Statistical Analysis

Descriptive Statistics

Data and analysis code can be found on the Open Science Framework (Baez, 2022). Descriptive statistics of participant demographic characteristics such as age, gender, race and ethnicity, as well as all predictor and outcome variables were calculated. Welch's two-sample t-tests were used to check for differences in predictors and outcomes between the total sample and the subsample (see online supplemental materials). Pearson's correlation coefficients were also calculated between all predictor and outcome variables in each model.

Bayesian Multilevel Multivariate Models

Bayesian multilevel multivariate models were used to test the relationship between cognitive risk factors and day-to-day affective dynamics as this flexible approach confers several advantages over frequentist methods. First, the Bayesian approach is suitable for our relatively small sample size. Second, we were able to incorporate some prior knowledge about the size of the parameter estimates into the analysis. Third, the Bayesian framework allowed us to model positive and negative affect mean and variability simultaneously as outcomes in a multilevel framework. Finally, the Bayesian multilevel framework does not assume an equal number of observations or fixed time points, so all cases can be used in the analysis.

All models were estimated using the brms package (Bürkner et al., 2021) in R (Version 4.2, R Core Team, 2020). First, a general risk factor model was estimated, followed by a second model that examined specific risk factors in the subsample of participants with those data. Participants in the specific risk subsample were also included in the main model. Multivariate maximum-likelihood functions were used in general risk factor and specific risk factor models. The predictor variables of interest in model 1, the general risk model, included repetitive negative thinking (PTQ) and anxiety sensitivity (ASI-S total). The predictor variables in model 2, the specific risk model, included the sum-total scores for rumination (RRS), worry (PSWQ), and the social, physical, and cognitive ASI-S subscales. The outcome variables were repeated measures of PA and NA within each participant. Specifically, in both model 1 and model 2, we used the cognitive risk variables to predict both the between-person mean (beta), and the between-person standard deviation (*sigma*; here referred to as variability), of PA and NA. This allowed us to model the association between cognitive risk and affect mean and variability within a single multivariate, multilevel model. We focused on mean and variability because prior work suggests that more complex dynamics (e.g., inertia) are redundant with mean and variability, and they may not be meaningfully related to psychological variables (Dejonckheere et al., 2019).

Weakly informative prior distributions for each parameter were set based on previous work from our research group suggesting that the parameters linking affective dynamics to psychological variables are relatively small (Heller et al., 2021). As such, we expected parameters to have small absolute values but did not want to make assumptions about the signs of each parameter due to the exploratory nature of these analyses. Therefore, priors were set to be Normal with a mean of 0 and variance of 2. Samples were derived by the Markov Chain Monte Carlo (MCMC) algorithm with 2 chains, 2,000 iterations, 2,000 warmup iterations, and 8,000 postwarmup samples.

In these models, the parameter estimates from the population-level effects represent the unique associations across the sample between the cognitive risk factor and affective metric. Bayesian inferences returns a distribution of possible values for each parameter, called the posterior. In Bayesian models, the credible interval (akin to the frequentist confidence interval) is the range containing a particular percentage of probable posterior values for the parameter. In our analyses, we selected the 95% credible interval, which is an arbitrary but commonly used threshold (McElreath, 2020). Otherwise said, when the 95% credible interval does not include zero, we can be fairly confident that the estimated parameter is not zero, given the data. Because the 95% cutoff is arbitrary, it can be useful to calculate the percent of the posterior that is greater than zero for each parameter. This allows us to compare the relative probability that the parameter estimate is not zero, given the data —this is similar to comparing effect sizes in a frequentist approach. The interpretation of the percent of the posterior greater than zero is dependent upon the sign of the parameter—values close to 100 indicate greater certainty for positive parameters and values close to 0 indicate greater certainty for negative parameters. We also reported the potential scale reduction factor on split chains (Rhat). Rhat values close to 1 indicate that the chains converged, suggesting that the number of iterations was sufficient. The multivariate maximum-likelihood functions used in both models handle missing outcome data (Enders, 2001).

For completeness, we also modeled PA mean/variability and NA mean/variability separately as outcomes in 4 additional Bayesian models—two for the general risk factor model, and two for the specific risk factor model. Results, presented in the online supplemental materials, did not differ meaningfully from the multivariate multilevel models described above (Tables S3 and S4). Therefore, we retained the more parsimonious models that combine PA and NA outcomes together in the same model.

Results

Demographic statistics for the total sample (N = 296) and the specific risk factor subsample (N = 119) are presented in Table 1. Both samples were predominantly female, and over 40% in the total sample self-described as being Black, Indigenous, or a person of color. No meaningful differences were observed between the total sample and specific risk factor subsample (see Table S1).

Descriptive statistics for the variables of interest are displayed in Table 2. The average within-person correlation between EMA-derived PA and NA was −.632 (95% CI [−.644, −.62], $p < .0001$), and the between-person correlation between PA mean and NA mean was −.46 (95% CI [−.54, −.36]; $p < .0001$). The correlation

Table 1
Demographics of the Total Sample (N = 296) and Subsample of Participants With Specific Risk Factor Scores (N = 119)

	Total sample		Specific risk factor subsample	
Sample	*M*	*SD*	*M*	*SD*
Age	18.8	1.59	18.45	1.13
	N	%	*N*	%
Female Gender	202	68	82	69
Ethnicity				
Hispanic	72	24	26	22
Race				
African American/Black	30	10	10	9
Asian/Asian-American	46	16	29	24
Caucasian/White	173	58	59	50
Mixed	28	9	11	9
Native American	1	.3	0	0
Other	16	5	9	8
No Response	2	.6	0	0

Note. *M* = mean; *SD* = standard deviation. *N* = 296 (*N* = 296 in Total Sample; *N* = 119 in Specific Risk Factor Subsample).

between the general cognitive risk factors, PTQ and ASI-S total score was .48 (95% CI [.39, .57], $p < .0001$). Correlations among predictors in the specific risk factor model were generally moderate and significant (see Table 3). The total sample and specific risk factor subsample differed on PTQ scores but did not differ on any other predictor variables. This was not surprising given that the subsample was selected on the basis of high PTQ (see Supplemental Table S2).

Results from the general risk factor model (see Figure 1, model 1 and Table 4) suggested that PTQ was associated with greater mean NA and lower mean PA. On the other hand, ASI-S was only predictive of greater mean NA but not lower mean PA. Furthermore, although the credible intervals included zero, the proportion of the credible interval greater than zero was larger for the associations between PTQ and NA variability (97%) and PA variability (96%) compared to the associations between ASI and NA variability (78%) and PA variability (19%), (see Table 4). This suggests that both PA and NA variability are more related to PTQ than ASI.

Results from the specific risk factor model (see Figure 1, model 2 and Table 5) suggested that higher scores on the ASI-S cognitive, RRS, and PSWQ were significantly associated with greater mean NA. The RRS was also significantly associated with lower mean PA scores. The percentage of the credible interval that was less than zero was much larger for the effect of PSWQ on mean PA (98%), than any of the ASI subscales (all <80%), (Table 5; Figure 1). The percentage of the credible interval that was greater than zero was much greater for the effects of ASI-S physical on NA variability (91%) and the RRS on NA variability (95%) than other specific risk factors. Lastly, PA variability was not associated with any of the specific risk factors as indicated by the small percentage of the credible intervals above zero for associations with specific risk factors (all < 90%).

Table 2
Descriptive Statistics of the Cognitive Risk Factors of Interest in the Total Sample (N = 296) and Subsample of Participants With Specific Risk Factor Scores (N = 119)

	Total sample		Specific risk factor subsample	
Sample	*M*	*SD*	*M*	*SD*
PTQ	22.85	12.92	27.03	11.34
ASI-S	10.72	7.71	11.06	7.40
RRS	—	—	44.85	15.30
PSWQ	—	—	49.04	12.60
ASI-S cognitive	2.85	2.72	3.13	2.97
ASI-S physical	3.12	2.85	3.08	2.94
ASI-S social	4.44	3.27	4.53	2.88

Note. *M* = mean; *SD* = standard deviation; PTQ = Perseverative Thinking Questionnaire; ASI-S = Anxiety Sensitivity Index – Short; RRS = Ruminative Response Scale; PSWQ = Penn State Worry Questionnaire. *N* = 296 (*N* = 296 in Total Sample; *N* = 119 in Specific Risk Factor Subsample).

Table 3
Correlations Between Specific Risk Factors With Confidence Intervals

Variable	1	2	3	4
1. ASI-S social				
2. ASI-S physical	.55** [.47, .63]			
3. ASI-S cognitive	.57** [.49, .64]	.59** [.51, .66]		
4. RRS	.25** [.07, .41]	.26** [.08, .42]	.29** [.11, .44]	
5. PSWQ	.30** [.12, .45]	.27** [.10, .43]	.29** [.11, .44]	.30** [.13, .46]

Note. ASI-S = Anxiety Sensitivity Index – Short; RRS = Ruminative Response Scale; PSWQ = Penn State Worry Questionnaire. Values in square brackets indicate the 95% confidence interval for each correlation. The confidence interval is a plausible range of population correlations that could have caused the sample correlation.
** $p < .01$.

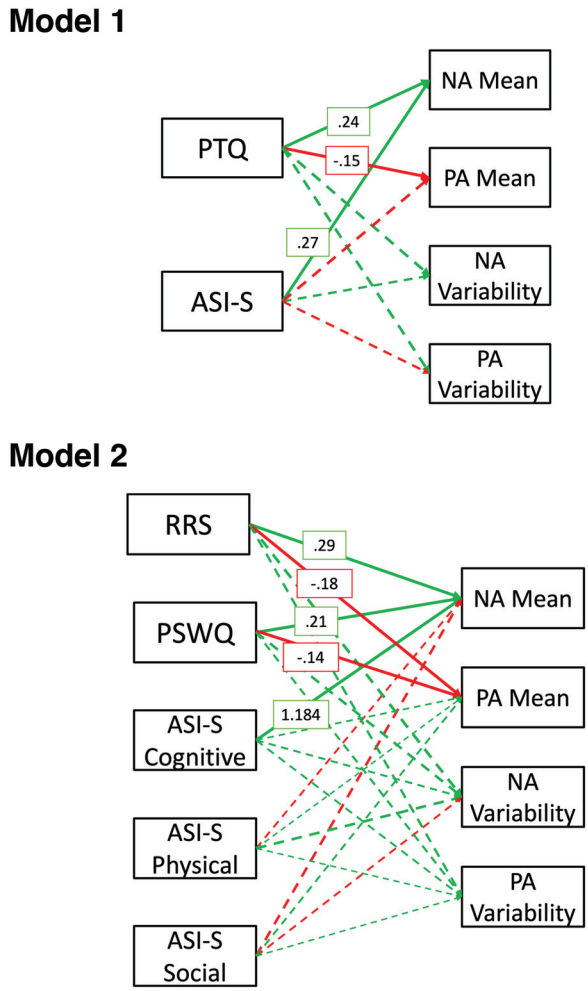
Discussion

This study aimed to examine how cognitive risk factors are related to day-to-day affective functioning. We investigated associations between general risk factors such as RNT and anxiety sensitivity, and content-specific cognitive risk factors, such as worry, rumination, and anxiety sensitivity subdomains and day-to-day affective dynamics in a sample of undergraduates using multilevel multivariate Bayesian models. Results across both general and specific cognitive risk models suggested that mean NA is largely a nonspecific correlate of cognitive risk: RNT, anxiety sensitivity, rumination, worry and the cognitive subdomain of anxiety sensitivity were all significantly associated with mean NA across the semester. Conversely, mean PA and NA variability were most strongly related to RNT and rumination. Interestingly, NA variability was most strongly related to physiological anxiety sensitivity, compared to other anxiety subdomains. PA variability emerged as a correlate of RNT, but no specific cognitive risk factor. These findings can be interpreted in the context of well-established psychological theories.

One of the primary findings was that greater mean NA was associated with the vast majority of both general and specific cognitive risk factors we examined, regardless of whether they are typically more strongly linked with depressive or anxious symptomatology. These effects can be considered in the context of the tripartite model of anxiety and depression (Clark & Watson, 1991), along with research on neuroticism (Jylhä & Isometsä,

Figure 1

Path Diagrams Depicting Results From the Bayesian Multilevel Multivariate Models



Note. Model 1: General cognitive risk factor model (N = 296). Model 2: Specific cognitive risk factor model (N = 119). Green paths represent positive regression coefficient estimates, and red paths represent negative regression coefficient estimates. Solid lines represent estimates for which the 95% credible interval does not include zero. Only the estimates for which the 95% credible interval does not include zero are included in the figure for clarity. Dashed lines represent estimates for which the 95% credible interval includes zero. The thickness of the lines is proportional to the percentage of the credible interval greater than zero. Mean NA is a nonspecific correlate of cognitive risk (% CI > 0 above 99% in general risk model and above 98%in specific risk model). Mean PA and NA variability are correlates of rumination and RNT (% CI > 0 above 95% for all parameters). The physical facet of anxiety sensitivity was more related to NA variability (91% CI > 0) than other facets of anxiety sensitivity (% CI > 0 below 70% for social and cognitive). PTQ = Perseverative Thinking Questionnaire; ASI-S = Anxiety Sensitivity Index – Short; RSQ = Response Style Questionnaire; PSWQ = Penn State Worry Questionnaire; PA = positive affect; NA = negative affect. See the online article for the color version of this figure.

2006; Kalokerinos et al., 2020; Shackman et al., 2018). The tripartite model suggests that elevated levels of NA is a shared feature of internalizing disorders and may explain their comorbidity. This may be because of the tight link between trait (or average) NA and neuroticism, which underlies vulnerability for generalized anxiety and depression (Hettema et al., 2006). We found that elevated levels of NA in daily life, assessed via EMA across months, were associated with a number of cognitive risk factors, both specific and general. Our results thus provide ecological support for the tripartite theory and extend the current literature by suggesting that elevated NA so often seen across anxiety and depressive disorders may be traced back to shared cognitive risk factors.

M PA in our study was more specific than mean NA, with mean PA exhibiting differential associations to content-specific RNT domains. Rumination and worry were both negative predictors of mean PA, however the effect was larger for rumination compared to worry. Anxiety sensitivity was less related to mean PA in the general model than RNT, and no specific subscale of the ASI-S was meaningfully related to mean PA in the content-specific cognitive risk factor model. The findings for mean PA were generally consistent with the tripartite model (Clark & Watson, 1991), which suggests that lower levels of PA may be specific to risk for depression. Our findings support the application of the tripartite theory to cognitive risk for depression in RNT and rumination manifesting in specifically lower levels of day-to-day PA compared to worry and anxiety sensitivity. Additionally, one recent study that measured perseverative cognition, a construct encompassing both negatively and positively valenced repetitive thought, and reward processing in daily life found that momentary RNT predicted reduced reward satisfaction (a construct tied to diminished PA) after consuming the reward (Schettino et al., 2021). While Schettino et al., did not explicitly measure momentary PA, their study lends further ecological validity to the relationship between RNT and positive emotion found here.

The role of NA variability in the day-to-day expression of internalizing disorders has been inconsistent in the literature. Some work, for example, suggests that individuals with depression are characterized by more variable/more unstable emotions (Koval et al., 2013; Peeters et al., 2006). Other work, however, has demonstrated that depression is associated with less variability/more rigid emotions—particularly negative emotions (Bos et al., 2019; Pe et al., 2015). This may be because of the dependency between mean affect and affective variability, such that at low (or high) mean levels of PA or NA, it is statistically impossible to see high affect variability (Dejonckheere et al., 2019). A recent meta-analysis of 11 studies found that, indeed, the relationship between neuroticism (another risk factor for internalizing disorders) and affect variability was entirely dependent on the mean (Kalokerinos et al., 2020). However, in our sample, mean levels of NA were higher than those observed by Kalokerinos et al. (2020). This suggests that the mean-variability dependency observed in their paper is less likely to be an issue in the present study. In particular, we found that greater PA and NA variability were related to RNT in the general risk factor model. We also found that rumination was far more related to NA compared to PA variability. Given affect variability may reflect deficits in emotion regulation (Wenzel et al., 2021), this suggests that people at-risk for comorbid emotional disorders may have deficits in emotion regulation broadly (Joormann & Gotlib, 2010), while people specifically at-risk for depression do not share the same difficulty with positive emotion regulation (Vanderlind et al., 2020).

An interesting discrepancy emerged among the anxiogenic risk factors in the specific risk factor model that can be interpreted in

Table 4

Bayesian Multilevel Multivariate Model: EMA-Derived Affect Regressed on General Cognitive Risk Factors

Parameter	Estimate	EE	95% CI LL	95% CI UL	Rhat	% CI > 0
Intercepts						
NA mean	34.55	0.81	32.97	36.18	1.01	
NA variability	2.76	0.01	2.72	2.80	1.00	
PA mean	55.62	0.60	54.42	56.79	1.00	
PA variability	2.63	0.01	2.59	2.67	1.00	
Regressions						
NA mean on PTQ	0.24	0.072	0.10	0.39	1.00	100
NA mean on ASI-S	0.27	0.12	0.04	0.51	1.00	99
NA variability on PTQ	0.0,030	0.0,017	−0.00,030	0.0,064	1.00	97
NA variability on ASI-S	0.0,021	0.0,028	−0.0,033	0.0,076	1.00	78
PA mean on PTQ	−0.15	0.052	−0.25	−0.044	1.00	.4
PA mean on ASI-S	−0.16	0.090	−0.35	0.0,088	1.00	3
PA variability on PTQ	0.0,028	0.0,017	−0.00,041	0.0,064	1.00	96
PA variability on ASI-S	−0.0,025	0.0,028	−0.0,079	0.0,028	1.00	19

Note. $N = 296$. EE = estimate error (standard deviation of the posterior); CI = credible interval; LL = lower limit; UL = upper limit; Rhat = convergence of the MCMC algorithm (values of 1 indicate good convergence); % CI > 0 = percent of the credible interval greater than zero; NA = negative affect, PA = positive affect; PTQ = Perseverative Thinking Questionnaire; ASI-S = Anxiety Sensitivity Index – Short.

the context of the contrast avoidance model of worry and generalized anxiety (Newman & Llera, 2011). This model hypothesizes that people at-risk for pathological worry avoid the discomfort that comes with large shifts in emotion (both positive and negative), which implies lower day-to-day PA and NA variability. Indeed, we found that PA variability was not related to any specific risk factors, and that worry, the cognitive facet of anxiety sensitivity, and the social facet of anxiety sensitivity were less related to NA variability than the physical facet of anxiety sensitivity. These findings suggest that people at-risk for generalized anxiety (e.g.,

Table 5

Bayesian Multilevel Multivariate Model: EMA-Derived Affect Regressed on Specific Cognitive Risk Factors

Parameter	Estimate	EE	95% CI LL	95% CI UL	Rhat	% CI > 0
Intercepts						
NA mean	34.73	1.18	32.38	37.073	1.00	
NA variability	2.79	0.03	2.73	2.85	1.00	
PA mean	54.02	0.85	52.34	55.73	1.00	
PA variability	2.64	0.031	2.57	2.70	1.00	
Regressions						
NA mean on ASI-S cognitive	1.184	0.48	0.25	2.15	1.00	99
NA mean on ASI-S physical	−0.20	0.48	−1.13	0.77	1.00	33
NA mean on ASI-S social	−0.69	0.51	−1.69	0.35	1.01	9
NA mean on RRS	0.29	0.086	0.12	0.46	1.00	100
NA mean on PSWQ	0.21	0.12	0.0,087	0.41	1.01	98
NA variability on ASI-S cognitive	0.0,052	0.012	−0.019	0.030	1.00	66
NA variability on ASI-S physical	0.017	0.012	−0.0,069	0.041	1.00	91
NA variability on ASI-S social	−0.0,061	0.012	−0.031	0.018	1.00	31
NA variability on RRS	0.0,035	0.0,020	−0.00,060	0.0,075	1.00	95
NA variability on PSWQ	0.0,029	0.0,025	−0.0,021	0.0,078	1.00	87
PA mean on ASI-S cognitive	0.077	0.34	−0.60	0.73	1.00	59
PA mean on ASI-S physical	−0.011	0.35	−0.71	0.68	1.00	48
PA mean on ASI-S social	−0.16	0.35	−0.85	0.53	1.00	32
PA mean on RRS	−0.18	0.06	−0.30	−0.065	1.00	.2
PA mean on PSWQ	−0.14	0.072	−0.28	−0.0,075	1.00	2
PA variability on ASI-S cognitive	0.0,062	0.012	−0.019	0.031	1.00	69
PA variability on ASI-S physical	0.0,019	0.012	−0.023	0.027	1.00	56
PA variability on ASI-S social	0.0,013	0.013	−0.025	0.026	1.00	56
PA variability on RRS	0.0,022	0.0,021	−0.0,021	0.0,063	1.00	85
PA variability on PSWQ	0.0,013	0.0,027	−0.0,039	0.0,067	1.00	70

Note. $N = 119$. EE = estimate error (standard deviation of the posterior); CI = credible interval; LL = lower limit; UL = upper limit; Rhat = convergence of the MCMC algorithm (values of 1 indicate good convergence); % CI > 0 = percent of the credible interval greater than zero; NA = negative affect, PA = positive affect; ASI-S = Anxiety Sensitivity Index – Short; RRS = Ruminative Response Scale; PSWQ = Penn State Worry Questionnaire. The interpretation of the percent of the posterior greater than zero is dependent upon the sign of the parameter—values close to 100 indicate greater certainty for positive parameters and values close to 0 indicate greater certainty for negative parameters.

people high in worry and the cognitive facet of anxiety sensitivity) experience less drastic changes in positive and negative emotion in their day-to-day lives, which may be a consequence of contrast avoidance. Interestingly, people at-risk for panic disorder (high in the physical facet of anxiety sensitivity) did experience larger shifts in emotion—specifically NA. To our knowledge, no studies have examined the role of day-to-day NA in panic attacks or panic disorder, but our findings suggest that people at-risk for panic tend to experience a wider range of negatively valenced emotions across months than those typically at risk for other anxiety disorders such as GAD. Given that intense shifts in emotion and physiology are central to the phenomenology of panic disorder, our results highlight that such shifts may be captured in the daily affective experiences of individuals at-risk for panic disorder.

This study was not without limitations. As noted throughout the discussion, the every-other-day sampling strategy was useful in characterizing peoples' emotional lives in broad strokes, but it did not allow for an investigation of dynamics within days. The differential effects of measurement timescale on the application and interpretation of affective dynamics in psychopathology is a budding area of research (Heller et al., 2021). Second, the sampling was random, and therefore not tied to any particularly stressful event, context, or cognitive state. Future work might tie data collection to idiographic stressors, in-the-moment avoidance behaviors, and EMA of cognitive processes. Third, this study captured only a subset of the possible cognitive vulnerabilities that may have specific links to day-to-day emotion. Incorporating additional transdiagnostic and disorder-specific measures of risk such as negative cognitive biases (Mathews & MacLeod, 2005) and early maladaptive schemas (Young et al., 2006) is an important area of further investigation. Finally, this study was focused on cognitive risk factors for internalizing disorders, but it did not include longitudinal measures of depression/anxiety symptoms; thus, we were not able to explicitly test whether these suggested affective mechanisms result in increased or decreased levels of psychopathology.

In summary, this study demonstrated that cognitive risk factors for internalizing disorders manifest in unique patterns of day-to-day emotional experience. Our findings were largely in line with the tripartite model: mean NA was as a critical marker for both depressive and anxiogenic cognitive risk factors, whereas mean PA was particularly important for depressogenic risk factors. We also found affect variability to be an important marker of risk factors associated with depression and panic disorder. Our results extend the literature examining affective dynamics and affective disorders (Heller et al., 2021) by tying daily affect metrics to more proximal cognitive risk factors. Uncovering the specific mechanisms by which patterns of affective dynamics result in mental disorders is an exciting avenue for future research.

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