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Examining the clinical utility of using affective dynamics to characterize and predict depression symptoms within a comorbid sample

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Abstract

Background: Dynamic indices calculated from ecological momentary assessment (EMA) data can model individual-level symptom fluctuations over time. However, the clinical utility for using these complex metrics to characterize comorbid symptomatology and to predict future symptom changes has not been adequately examined.

Methods: Women ($N = 35$) with social anxiety disorder and a history of major depression completed a clinical diagnostic interview and self-report measures at baseline and approximately two months later. In between these assessments, participants completed EMA surveys on mood and anxiety symptoms five times a day for approximately 30 days ($T = 5,250$). Symptom severity and dynamic indices (i.e., variance, inertia) during EMA were calculated. The relative predictive value of these indices for characterizing baseline symptomatology, as well as the relative prospective predictive value of dynamic indices predicting future depressive symptomatology was assessed.

Results: Baseline depressive symptoms were associated with mean levels of anxiety ($b = .38, p = .001$); whereas, baseline social anxiety symptoms were associated with mean levels of depression during EMA ($b = -.38, p = .013$). Moment-to-moment variance in anxiety during EMA ($b = .22, p = .020$) and baseline self-report measures of depression ($b = .50, p < .001$) predicted future depressive symptoms.

Conclusions: Moment-to-moment fluctuations in *anxiety* may constitute a unique early warning sign of future increases in *depression* for individuals with mood and anxiety comorbidity.

Keywords: Ecological momentary assessment; depression; anxiety

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Introduction

Social anxiety and mood disorders are the most common psychological conditions for adults (Kessler et al., 2005) and these disorders commonly co-occur. As many as 41% of individuals with primary major depressive disorder (MDD) also meet criteria for social anxiety disorder (SAD; Brown et al., 2001). Despite high co-occurrence, the reasons for high comorbidity are not immediately clear. The phenomenology of these disorders has often been studied separately using cross-sectional designs or longitudinal designs with low temporal density, limiting our ability to evaluate dynamic changes in comorbid symptoms both between and within people. Consequently, the mechanisms by which social anxiety and depression perpetuate one another remain poorly understood (Jacobson, 2015; Naragon-Gainey, 2019).

Affect or symptom dynamics refers to the measurement of individual-level fluctuations of emotions or symptoms (see Jahng et al., 2008). This type of measurement offers a potential avenue for understanding comorbidity by examining the stability and instability of multiple symptoms over time. These metrics are calculated from repeated measurements typically collected via ecological momentary assessment (EMA), wherein participants respond to brief self-report questionnaires using smartphones. Dynamic indices include *mean levels* (e.g., average symptom intensity), *variability* (e.g., overall variation in the symptom), *instability* (e.g., moment-to-moment symptom fluctuation), and *inertia* (e.g., the degree to which an symptom predicts itself from one time point to the next) (see Jahng et al., 2008 for a full review of dynamic indices).

Reviews of previous research on affective dynamics suggest that individuals with depression demonstrate higher affective inertia as compared to individuals without depression (Houben et al., 2015). Somewhat conversely, individuals with depression appear to exhibit higher affect variability compared to individuals without depression (Houben et al., 2015). This suggests that individuals who are currently depressed experience mood states that strongly predict themselves, albeit with higher variability overall and from moment-to-moment (e.g., higher highs and lower lows), compared to individuals that are not currently depressed.

These dynamic metrics may improve our understanding of the daily experience of individuals with comorbid symptomatology, offering additional information beyond what can be measured via retrospective self-report scales. For example, cross-sectional data has demonstrated that both social anxiety and depression are frequently reported in tandem; however, it may be that the dynamic indices of feeling *anxious* (in addition to dynamic indices of feeling *down*) predict increased depression for individuals with this comorbidity. For example, prior research has demonstrated that mean levels of anxiety and depression predict one another over the course of the day (Jacobson, 2015). However, the current literature does not disentangle how symptom dynamics of anxiety or depression relate to comorbid symptomatology. For example, it could be that the dynamics of depressed mood are redundant with self-report measures of depression; however, dynamics of anxiety may offer unique information about depressive symptoms.

Furthermore, few studies have compared these dynamic metrics to determine their relative contributions to characterizing symptomatology. Symptom dynamic research corresponds to measurement-based care initiatives that call for repeated symptom monitoring to increase standards of care (e.g., within national healthcare systems; Lemke et al., 2017). Although these dynamic metrics have appealing properties, they can be challenging to calculate

as they require high-density data not easily obtained from clinical samples. Recently, two studies have suggested that dynamic indices (i.e., mean, variance, and inertia) may provide redundant information, raising questions about the clinical utility of these indices (Bos et al., 2019; Dejonckheere et al., 2019). Thus, careful evaluation regarding whether more complicated dynamic indices (e.g., inertia) versus more accessible metrics, such as mean levels of intra-daily affect to understand symptomatology is needed (Dejonckheere et al., 2019).

Finally, there has been minimal research examining the extent to which any dynamic indices predict *prospective* symptomatology *above and beyond* standard self-report symptom measures. Some research has demonstrated that inertia predicts future depression (Elmer et al., 2020), even after accounting for depressogenic factors and baseline depression (Koval et al., 2012; Kuppens et al., 2012). Preliminary evidence has demonstrated that changes in emotional inertia may also precede transitions into major depressive episodes (van de Leemput et al., 2014; Wichers & Groot, 2016). However, additional research is needed to determine the relative contributions of dynamic indices in predicting future symptomatology, particularly in comorbid samples.

In this study, we first sought to determine the extent to which comorbid mood and anxiety symptomatology are associated with dynamic indices (mean, variance, RMSSD, and inertia) and the relative contributions of these indices in characterizing comorbid symptomatology. We then examined the relative contributions of dynamic indices in predicting future depressive symptomatology (assessed via a clinical interview) to evaluate the respective contributions of dynamic indices above and beyond a standard self-report symptom measure of depression. Finally, in a series of exploratory models, we examined how dynamic indices predicted the likelihood of a future depressive episode (assessed using the MINI diagnostic

interview; see supplementary material). In keeping with the previous literature, we predicted that individuals with higher levels of symptomatology would demonstrate more severe symptoms (i.e., higher mean during EMA) that were more variable (i.e., greater moment-to-moment fluctuations) and more inert (i.e., values at one time point significantly predicting values at the next time point), compared to individuals with lower levels of baseline symptomatology. Recent studies have highlighted the utility of measuring dynamic indices like mean and variability; thus, we hypothesized that these indices would be significantly associated with baseline symptomatology. Similarly, we hypothesized that mean and variability would predict future depressive symptoms, above and beyond a standard self-report depression symptom measure.

Materials and Methods

Participants

Participants ($N = 35$) were cis-gender women who were students and staff affiliated with a research university and who participated in a larger study examining cognitive-affective predictors of mood over time. Due to limited resources, only cis-gender women were recruited to complete the intensive EMA protocol, as we would be unable to study the effects of sex or gender due to the limited sample size. Women mostly identified as White (51.43%); however, 28.57% identified as East Asian, 17.14% identified as Black, and 5.71% identified as Hispanic or Latinx. The average age was 21.37 years (range 18-37).

Measures

A structured clinical interview (Mini International Neuropsychiatric Interview 6.0 (MINI; Lecrubier et al., 1997) was used to assess psychiatric symptoms for SAD and MDD at baseline. MDD was assessed again approximately two months later. The inter-rater reliability was assessed for MDD ($K = .83$) and SAD ($K = .73$).

Symptom-level measures were administered, including the Beck Depression Inventory, (BDI-II; Beck et al., 1996) and the Liebowitz Social Anxiety Scale (LSAS; Liebowitz, 1987). The BDI-II is a routinely used self-report measure with excellent internal reliability and good validity (Beck et al., 1996) that was used to assess depressive symptoms at baseline interview and approximately two months later. The LSAS is a clinician-rated interview with excellent internal reliability and good validity (Heimberg et al., 1999) that was used to assess social anxiety and avoidance of social interaction and performance situations at baseline.

Additionally, ecological momentary assessment (EMA) items were created for this study to correspond with symptoms of MDD and SAD. Participants rated the amount that they were experiencing symptoms such as low mood, positive affect, irritability, fatigue, and anxiety and avoidance of social situations in the present moment on a scale from 0 (*Not at all*) to 10 (*A lot*). For the present study, the EMA items of *feeling down* and *feeling anxious* were used to reflect ratings of the hallmark symptoms of depression and anxiety, respectively.

Procedure

Participants completed a brief phone screen to determine preliminary study eligibility, followed by a lab-based diagnostic interview. Women who met criteria for a current or past major depressive episode and current SAD were then invited to complete five EMA surveys during a self-selected 12-hour time for approximately 30 days ($T = 5,250$). On average, participants completed 78.13% of the 150 requested assessments ($M = 125$, range = 59 – 147). Participants returned to the laboratory for a second diagnostic interview approximately one month after completing EMA (approximately two months after completing the baseline interview).

Data Analytic Plan

We calculated four dynamic indices for each individual across EMA assessments using the two EMA items of interest – feeling down and feeling anxious. Dynamic indices included the (1) mean and (2) variance (i.e., within-person standard deviation). Variance has been criticized as it only provides an overall measure of variability across the time-series (Jahng et al., 2008). Thus, high variance could represent frequent changes or systematic improvement or decline over the observation period. Accordingly, we also calculated the (3) root mean squared successive difference (RMSSD), which provides a measure of moment-to-moment variability. To assess the amount that feeling down or feeling anxious predicted itself over time, we calculated the (4) first-order autocorrelation for feeling down and feeling anxious (i.e., inertia).

We accounted for the linear effect of time in each individual's time series data by regressing their time variables (i.e., day number, survey number) onto their EMA variables and using the residuals to calculate their person-specific value for each dynamics index (see Jahng et al., 2008). We also inserted a row of missingness at the end of each day when calculating RMSSD and inertia to ensure that we did not calculate symptom dynamics across night periods (i.e., an uneven time interval during which change in affect likely occurs) (see Bos et al., 2019). We grand-mean-centered symptom scores to assist with interpretation of output. Centered symptom scores represent the average depression or social anxiety symptom score for the group. Additionally, we imputed missing EMA observations using the missForest R package (Stekhoven, 2013) in R version 4.0.3, which uses the Random Forest nonparametric machine learning method to model missingness.

The formulas for calculating dynamic indices are mathematically dependent on each other (see Jahng et al., 2008). To prevent problematic levels of multicollinearity when comparing all four indices directly in a linear model (see discussion of this issue in Koval et al., 2013), we

compared three out of four indices at a time in a series of robust linear regression models using a procedure described in two previous studies (Bos et al., 2019; Koval et al., 2013). In the first model, we compared the mean, instability, and inertia and in the second model we compared the mean, variance, and inertia. This procedure was repeated for each outcome variable. As results for the models including variance and RMSSD were similar, we present the results from the models including RMSSD here and the results including variance in supplementary material. We used robust regression analyses to mitigate unnecessary influence from any outliers that we did not wish to remove given our small sample size, as well as undue influence from skew in predictor variables (Maronna & Yohai, 2000; Rousseeuw & Verboven, 2002). Variance inflation factors (VIF) were calculated to assess for multicollinearity. Predictors were removed and VIF was reassessed if VIF values were greater than 10. Residuals were examined to determine whether the linear models met the assumptions of homoscedasticity and normality.

All analyses were conducted in R (R Core Team, 2017). Robust regressions models were constructed using the *lmrob* and *glmrob* functions with the appropriate distribution using the *robustbase* package in R (Maechler et al., 2021) and model assumptions were checked using the *performance* package in R (Lüdtke et al., 2020).

Results

Aim 1: Examining the associations between baseline symptomatology and dynamics indices

Associations with baseline depressive symptoms. Correlational analyses revealed higher baseline BDI-II scores were moderately, but significantly associated, with lower mean levels of feeling down ($r = -.34, p = .045, 95\% \text{ CI } [-.61, -.01]$). Notably, when examining the association with raw mean scores of feeling down this association remained similar in size, but was no longer statistically significant ($r = 0.33, p = .053$) and the systematic effect of time on

feeling down was weakly, and not statistically associated with baseline BDI-II scores ($r = -0.15$, $p = .390$). Taken together, this suggests that the negative association between baseline BDI-II scores and mean levels of feeling down is non-robust and may be influenced by the effect of length of time in the study.

Additionally, higher baseline BDI-II scores were moderately, but significantly associated, with greater moment-to-moment variability in feeling down (i.e., RMSSD) during EMA. However, the overall variance and the resistance to change in feeling down over time (i.e., inertia) did not differ as a function of baseline depressive symptoms.

BDI-II score was significantly associated with higher mean levels of feeling anxious during EMA and this correlation was moderate to large in size. However, the overall variance, moment-to-moment variability (i.e., RMSSD), and the inertia in feeling anxious over time (i.e., autocorrelation) did not differ significantly as a function of baseline depressive symptoms.

Associations with baseline social anxiety symptoms. There was a moderate, negative, statistically significant association between baseline LSAS score and mean levels of feeling down during EMA ($r = -0.34$, $p = .049$, 95% CI $[-.61, -.002]$). When examining the association with raw mean scores of feeling down, this association remained negative, although reduced in size and was no longer statistically significant ($r = -0.04$, $p = .824$) and the systematic effect of time on feeling down was weakly and not statistically associated with baseline LSAS scores ($r = -.10$, $p = .555$). Again, this suggests that the negative association between baseline LSAS scores and mean levels of feeling down is non-robust.

Additionally, the overall variance, moment-to-moment variance, and inertia in feeling down over time did not differ significantly as a function of baseline social anxiety symptoms. Finally, there were no significant differences in mean levels, overall variance, moment-to-

moment variance, or inertia in feeling anxious over time as a function of baseline social anxiety symptoms.

Aim 2: Relative contribution of dynamics indices for characterizing baseline symptomatology

To determine the relative contributions of symptom dynamic indices in characterizing individuals with baseline symptomatology, we compared the dynamic indices (i.e., mean, RMSSD, inertia) for feeling down and feeling anxious in a series of robust linear regression models (see Table 1).

Relative contribution of dynamic indices for characterizing baseline depressive symptoms. When entered into the same model, all dynamic metrics of feeling down (i.e., mean, RMSSD, and inertia) were similarly poor predictors of baseline BDI-II. In contrast, higher mean levels of feeling anxious were moderately correlated higher baseline depressive symptoms; however, other dynamic metrics (i.e., RMSSD, inertia) were not significant predictors of baseline depressive symptoms.

Relative contribution of dynamic indices for characterizing baseline social anxiety symptoms. When entered into the same model, higher mean levels of feeling down predicted greater baseline social anxiety symptoms and this correlation was moderate to large in size. Additionally, when examining the dynamic metrics of feeling anxious (i.e., mean, RMSSD, and inertia), all were similarly poor predictors of baseline social anxiety symptoms.

Comparing these results to the results from Aim 1, this suggests that higher mean levels of *feeling anxious* during EMA may help to characterize those with higher levels of depressive symptoms; whereas, lower mean levels of *feeling down* during EMA may help to characterize individuals with higher levels of social anxiety symptoms. However, additional dynamic indices

such as RMSSD and inertia did not account for significant, and unique, amounts of variance in baseline symptoms.

Aim 3: Comparing the relative prospective predictive value of dynamic indices for future depressive symptoms.

Next, we compared the relative contributions of the dynamic indices for feeling down and feeling anxious predicting depressive symptoms approximately two months later in a series of robust linear regression models that included baseline depressive symptoms as an additional predictor (see Table 2).

We found that lower mean levels of feeling down, but higher moment-to-moment variation in depressive symptoms predicted higher levels of future depressive symptoms (small to medium effect size). However, no dynamic metrics (i.e., mean, RMSSD, inertia) demonstrated a significant relationship predicting future depressive symptoms when BDI-II was included in the model, suggesting that mean and RMSSD may predict future depressive symptoms, but that their value is redundant with standard self-report measures of depressive symptoms.

However, moment-to-moment variance (i.e., RMSSD) in *feeling anxious* remained a significant predictor of future depressive symptoms even when including baseline BDI-II score as an additional predictor of future depressive symptoms (small to medium effect size). This suggests that measuring moment-to-moment variance in *feeling anxious* offers additional information above and beyond a standard self-report measure of depressive symptoms.

Discussion

Depression and anxiety are commonly co-occurring disorders and symptom dynamics have been used to advance the characterization and prediction of clinical disorders, particularly depression (Houben et al., 2015). However, few studies have used symptom dynamics to

characterize comorbid symptomatology and even fewer studies have evaluated the *clinical value* of these dynamic indices for characterizing and predicting future symptomatology, particularly in comparison to standard self-report measures. We aimed to compare the relative contribution of dynamic indices in characterizing comorbid mood and anxiety symptomatology, as well as the relative contributions in predicting future depressive symptomatology, particularly in comparison to a standard self-report measures.

We first examined the associations between baseline symptoms and the mean, variance, instability, and inertia of feeling down and feeling anxious during EMA. Ultimately, our results revealed that both the severity of feeling down (i.e., mean), as well as the moment-to-moment variance in feeling down during EMA (i.e., RMSSD) captured similar variance in an individual's baseline depressive symptoms. This finding counters previous results suggesting that these metrics offer unique information regarding the dynamic changes in depressive symptomatology (e.g., Bos et al., 2019). However, those with higher levels of depression at baseline reported higher severity in feeling anxious during EMA, and those with higher levels of social anxiety at baseline reported lower mean levels of feeling down during EMA. These results are consistent with previous findings (Dejonckheere et al., 2019) and suggest that higher day-to-day levels of *feeling anxious* may serve as a marker of higher depressive symptoms for individuals with SAD-MDD comorbidity; whereas, lower day-to-day levels of *feeling down* may be characteristic of the daily experience of those with higher baseline social anxiety symptom severity specifically.

Additionally, our results suggest that moment-to-moment variance in *feeling anxious* during the EMA period significantly predicted future *depressive* symptoms above and beyond a self-report measure of depressive symptoms. Thus, moment-to-moment fluctuations in feeling anxious may serve as an early warning sign of future increases in depression for individuals with

SAD and depression comorbidity. Notably, we did not find evidence of inertia as a predictor of future depressive symptoms, which counters previous literature (van de Leemput et al., 2014; Wichers et al., 2020). However, previous research examined inertia in samples of individuals with primary MDD, rather than a primary anxiety and comorbid depressive disorder. Thus, our results presented here suggest that *instability in anxiety specifically* may be important for understanding future depression risk for women with SAD – MDD comorbidity.

There were notable limitations to our work. First, this was a small, homogeneous sample of women with primary SAD and current or past MDD, limiting the generalizability of our findings. We used robust regression analyses to mitigate potential undue influence of outliers on our results, given that we did not wish to reduce and bias our sample size further by removing outliers and would be underpowered to conduct any sensitivity analyses. Furthermore, researchers have suggested that dynamic indices could be calculated using a single multilevel model (Jahng et al., 2008; Trull et al., 2015). We used multilevel models to calculate each dynamic index and its association with symptomatology. Results were similar across analytic methods, thus, we presented the results of the correlational analyses here for ease of interpretation and the results from these alternate multilevel models in supplementary material. More research is needed to examine the utility of using symptom dynamic indices to characterize and predict comorbidity in larger, more diverse samples.

These findings provide useful implications for clinical practice, particularly related to measurement-based care initiatives that call for increased symptom monitoring to increase standards of care (e.g., within national healthcare systems; Lemke et al., 2017). However, what to do with those measurements and how to best incorporate them into clinical practice requires continued discussion. Routine symptom monitoring via EMA and similar methods has often

been proposed for treatment planning and predicting treatment outcomes (Torous et al., 2020). Our findings suggest that overall, mean levels of repeated EMA measures, which are considerably easier to calculate, may outperform other indices such as inertia in symptoms over time. Furthermore, with one exception, the BDI-II – a gold-standard retrospective self-report symptom measure – outperformed nearly all dynamic indices in predicting future depressive symptoms. However, moment-to-moment fluctuations in feeling anxious (i.e., higher RMSSD) predicted future depressive symptoms, even when accounting for baseline depressive symptoms. This suggests that there may be some utility in using repeated symptom monitoring to examine the within-day fluctuations in *feeling anxious* to predict future depressive symptoms for those with mood and anxiety comorbidity.

Conclusion

Overall, this study examined the relative predictive value of using symptom dynamic indices to characterize anxiety and depression comorbidity and predict future depressive symptoms. In particular, our results emphasize the relationship between moment-to-moment fluctuations in anxiety and future depressive symptoms. Smartphone technology has increased our ability to easily collect, calculate, and interpret results from repeated symptom monitoring. Our findings may be relevant for those working at the intersection of mental health and digital technology to create and curate tailored feedback based on output from intensive EMA.

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Table 1. Zero-order associations between baseline depression and social anxiety symptoms, dynamic indices of feeling down and anxious, and time variables

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1. Down-Day	--											
2. Anx-Day	.64**	--										
3. BDI-II	.19	.11	--									
4. LSAS	-.10	.12		--								
5. Down mean	-.15	-.18	-.34*	-.34*	--							
6. Down variance	.23	.04	.32	.03	-.51*	--						
7. Down RMSSD	.11	.01	.35*	.10	-.50*	.90**	--					
8. Down inertia	.20	.14	-.08	-.19	.09	.20	-.19	--				
9. Anx mean	.15	.15	.40*	.04	-.30	.08	.04	.07	--			
10. Anx variance	.25	.17	.25	.10	-.52*	.89**	.80**	.17	.12	--		
11. Anx RMSSD	.26	.16	.20	.05	-.56**	.85**	.84**	-.05	.08	.93**	--	
12. Anx inertia	-.20	-.42*	.01	.22	-.03	-.01	-.09	-.03	-.04	-.08	-.07	--

Note. Down-Day represents the systematic effect of time on feeling down in the study. Anx-Day represents the systematic effect of time on feeling anxious in the study. Down = EMA item of feeling down; Anx = EMA item for feeling anxious; BDI-II = Score on the Beck Depression Inventory – II; LSAS = Liebowitz Social Anxiety Scale. Mean refers to the average level of feeling down or feeling anxious during the EMA period. RMSSD = Root mean squared successive difference and refers to the moment-to-moment variance within the day. Inertia refers to the amount of which feeling down predicts itself from one time point to the next, within the day.

Table 2. Associations between baseline depression and social anxiety symptoms and dynamic indices of feeling down and feeling anxious.

BDI-II						
	Down			Anxious		
	B (SE)	<i>b</i>	<i>p</i>	B (SE)	<i>b</i>	<i>p</i>
Mean	-19.28 (12.80)	-0.22	.142	31.15 (8.32)	0.38	< .001
RMSSD	4.47 (4.26)	0.22	.302	3.36 (3.22)	0.16	.305
Inertia	-2.14 (13.43)	-0.03	.874	3.01 (11.91)	0.03	.802
Adjusted R ²	0.07			0.11		
LSAS Total						
	Down			Anxious		
	B (SE)	<i>b</i>	<i>p</i>	B (SE)	<i>b</i>	<i>p</i>
Mean	-48.91 (18.48)	-0.38	.013	4.50 (18.28)	0.04	.807
RMSSD	-3.51 (6.06)	-0.12	.566	2.25 (4.52)	0.07	.623
Inertia	-24.47 (21.18)	-0.21	.257	30.00 (18.34)	0.23	.112
Adjusted R ²	0.05			-0.04		

Note. BDI-II = Score on the Beck Depression Inventory – II; LSAS = Liebowitz Social Anxiety Scale. Mean refers to the average level of feeling down or feeling anxious during the EMA period. RMSSD = Root mean squared successive difference and refers to the moment-to-moment variance within the day. Inertia refers to the amount of which feeling down predicts itself from one time point to the next, within the day. Robust linear regression models were run separately for feeling down and feeling anxious.

Table 3. Relationship between dynamic indices of feeling down and feeling anxious and future depressive symptoms.

	Down			Anxious		
Mean	-1.29 (0.60)	-0.19	.032	0.49 (0.58)	0.08	.395
RMSSD	0.38 (0.18)	0.24	.041	0.58 (0.16)	0.35	.0004
Inertia	0.05 (0.77)	0.01	.950	1.13 (0.75)	0.16	.134
Accounting for BDI-II						
	Down			Anxious		
Mean	-0.56 (0.60)	-0.08	.352	-0.46 (0.60)	-0.07	.445
RMSSD	0.25 (0.19)	0.16	.199	0.34 (0.15)	0.21	.028
Inertia	0.21 (0.75)	0.03	.779	0.59 (0.71)	0.08	.410
BDI-II	0.03 (0.01)	0.43	< .001	0.04 (0.01)	0.49	< .001

Note. BDI-II = Score on the Beck Depression Inventory – II. Mean refers to the average level of feeling down or feeling anxious during the EMA period. RMSSD = Root mean squared successive difference and refers to the moment-to-moment variance within the day. Inertia refers to the amount of which feeling down predicts itself from one time point to the next, within the day. Robust generalized linear regression models specifying a Poisson distribution were first run separately for feeling down and feeling anxious, then evaluated accounting for BDI-II.