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Do daily dynamics in rumination and affect predict depressive symptoms and trait rumination? An experience sampling study

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Abstract

Background and objectives: Rumination has been shown to prospectively predict the onset of depression. However, it is unclear how rumination and affect in daily life influence the development of depressive symptoms. The present study examined whether the structure of dynamics in rumination and affect could prospectively predict depressive symptoms and trait rumination in an undergraduate sample (n = 63). *Methods*: The main index used was entropy, which reflects the instability of a system's structure. Momentary rumination and affect were assessed eight times per day for a period of seven days. Additionally, depressive symptoms and trait rumination were measured at the beginning of the experiment and at six weeks follow-up. *Results*: The results showed that entropy significantly predicted trait rumination at follow-up (and depressive symptoms at trend level) while taking into account baseline depressive symptoms and trait rumination. *Limitations*: The follow-up measurements conducted six weeks after the baseline were relatively short. Further research may test the predictive effect of the structure over a longer period and confirm its effect by using different indices that describe the structure. *Conclusions:* These findings indicate that examining the structure of the dynamics in momentary rumination and affect holds promise for understanding the risk for depression.

Keywords: depression; rumination; affect; dynamic system; entropy

Introduction

Decades of research have shown that rumination forms one of the most important cognitive vulnerability factors for the onset and maintenance of depressive episodes (for reviews, see Mor & Winquist, 2002; Nolen-Hoeksema, Wisco, & Lyubomirsky, 2008). According to the Response Styles Theory of depression, rumination can be conceived as a thinking style that repetitively focuses on the implications, causes and meanings of one's feeling and problems (Nolen-Hoeksema, 1991). In fact, several studies have consistently shown that rumination has a detrimental influence on affect (Watkins, 2008), in that it can prolong negative mood and may facilitate the development of depressive episodes (Ciesla & Roberts, 2007). Although these findings suggest an effect of the ongoing interaction between momentary rumination and affect on depressive symptomatology, it is still unclear how ruminative thinking and affect in daily life influence the development of depressive symptoms. Hence, a better understanding of daily dynamics in rumination and affect, and their contribution to depression is crucial.

Rumination and affect in daily life

Although mostly treated as a stable trait-like construct (Nolen-Hoeksema & Davis, 1999), ruminative thought in daily life is an ongoing dynamic process (Kasch, Klein, & Lara, 2001; Marchetti, Mor, Chiorri, & Koster, 2018) and can be measured accordingly through experience sampling methods (Kircanski, Thompson, Sorenson, Sherdell, & Gotlib, 2015; Moberly & Watkins, 2008). A large number of experience sampling studies have provided evidence that momentary rumination is often followed by exacerbation of negative affect (Hoorelbeke, Koster, Demeyer, Loeys, & Vanderhasselt, 2016; Moberly & Watkins, 2008; Takano & Tanno, 2011) and/or decreases in positive affect (Brans, Koval, Verduyn, Lim, & Kuppens, 2013; Hoorelbeke et al., 2016; Huffziger et al., 2013). It should be noted that in daily life, however, not only does rumination have an impact on affect, but affect also influences rumination. Indeed, previous research has shown that negative affect can predict subsequent rumination (Hoorelbeke et al., 2016; Moberly & Watkins, 2008).

The nature of the interplay between rumination and affect in daily life may be an important factor in predicting depressive symptoms. In a recent experience sampling study, Pasyugina, Koval, De Leersnyder, Mesquita, and Kuppens (2015) examined whether the average level of momentary rumination and its influence on momentary negative affect can separately predict future depressive symptoms. For this purpose, participants were asked to assess their momentary rumination since the last prompt, and to assess their momentary affect at the moment they received the prompt. They found that changes in depressive symptoms over a week were predicted by the average level of momentary rumination. In contrast, the influence of momentary rumination on negative affect did not predict changes in depression. These results indicate that the impact of rumination on negative affect itself cannot fully explain the predictive effect of rumination on depression. Therefore, how rumination and affect in daily life influence depressive symptoms remains unclear. These findings call for a closer examination of the interaction between affect and rumination.

Dynamic systems, state space, and entropy

The complex relationship between two variables interacting in a certain context can be investigated in many ways. A particularly interesting perspective is offered by the Dynamic System Theory (DST; Hollenstein, 2013; Lewis & Granic, 2000; Thelen & Smith, 1998), which has increasingly being adopted to investigate psychopathology (Hayes & Strauss, 1998; Hayes, Yasinski, Barnes, & Bockting, 2015). According to the DST, a dynamic system, which contains variables that covary over time (e.g., momentary rumination and affect), shows specific characteristics that are not detectable at the level of its single elements (Thelen, 1995). In other words, investigating how the whole system unfolds over time (i.e., structure of a system) may reveal features that are likely to be overlooked when only considering its constitutive elements (e.g., mean levels of momentary rumination and affect). Hence, understanding how a system turns from one state to another state could be of particular interest in deciphering the mutual influence of momentary affect and rumination on psychopathology. For instance, Nelson and colleagues (2017) emphasized that psychopathology should be investigated as a system, with the understanding of how the whole system changes across time being key to map the development of psychopathology. Similarly, Hollenstein and colleagues (2004) investigated the structure of the system consisting of affective states presented by both parents and children within two hours interaction, during which they were asked to perform some challenging emotional tasks. The results indicated that the structure of dynamic emotional states in parent-child interactions plays an important role in predicting psychopathology above and beyond individual content variables (i.e., mean duration) of these emotional interactions (for a review, see Hollenstein, Lichtwarck-Aschoff, & Potworowski, 2013).

To adequately investigate the structure of a dynamic system, it is necessary to first represent all the possible states of the system (also known as *state space*; Heath, 2000; Hollenstein, 2013; Lamey, Hollenstein, Lewis, & Granic, 2004) and then display the trajectory of states that the system takes over time (see Fig. 1). In our study, state refers to the co-occurrence of momentary rumination and affect at a certain time point. By doing so, different types of information can be attained. *Entropy* is the most frequently used structure-dependent metrics to investigate the structural instability of a system, as every change in the structure influences entropy (Cunningham, Dunfield, & Stillman, 2013; Mitchell, 2009; Shannon & Weaver, 1949; Young, 2003). According to the literature on the DST (for reviews, see Bravi, Longtin, & Seely, 2011; de la Torre-Luque, Bornas, Balle, & Fiol-Veny, 2016), it is a metric derived from the information domain, which represents the deterministic variability and depicts the dependency between multiple momentary measures at different time points. Whereas other measures, such as variance and standard deviation, are metrics from the statistical domain that do not usually provide information about co-occurrence of variables in a system. Specifically, a system that goes through many states provides more information, which would be reflected by higher levels of entropy, whereas a system that goes through few states would generate less entropy (Mainzer, 2007).

Recently, Koster and colleagues (2015) explored whether remitted depressive patients and healthy controls differed in terms of the predictive effect of their dynamics in rumination and affect on future depressive symptoms. They found that entropy predicted depressive symptoms at six months follow-up only in remitted depressed patients. Interestingly, entropy remained a significant predictor of future depressive symptoms after considering the contribution of depressive symptoms at baseline. These findings suggest that the structural dynamics of momentary rumination and affect, as operationalized by entropy, does have predictive power for depressive symptomatology.

In this context, previous studies have typically focused on patient samples with a history of depression (i.e., remitted depressed patients; Huffziger et al., 2013; Koster et al., 2015). However, it would also be important to account for future depressive symptoms in a healthy population, so that appropriate prevention strategies can be implemented before individuals get stuck in the vicious circle of rumination and negative affect. According to vulnerability-stress models of depression (Abramson et al., 2002; Hammen, 2005), it is critical to look for specific depressogenic mechanisms that can be detected in daily life in relation to stressful events. For this purpose, in the current study, entropy was derived in the context of ESM in a convenience sample and its predictive effect was compared with other risk factors (i.e., trait rumination at baseline and momentary measurements) during a stressful period.

Moreover, it has been assumed that a dynamic system develops and reinforces itself across different time scales (Hollenstein et al., 2013; Wichers, 2014). For example, specific mother-child interactions (e.g., real-time) may over time build a trait-like style of interaction (e.g., months or years), which in turn influences momentary interactions in everyday life. Consistent with this view, momentary changes of affect and rumination in response to minor daily life events, such as subtle stressors, may accumulatively form a stable way of emotion regulation, especially when encountering stressful events. To unveil the process in which small changes that happen at the shorter time scale become a stable construct, it would be worth examining the relationship between the dynamics of momentary rumination and affect in everyday life and habitual response styles to negative events, such as trait rumination. Specifically, in the current study, we investigated whether the structure of the dynamics between momentary rumination and affect can predict trait rumination during a stressful period.

The present study

In the current study, we examined the predictive value of the dynamic structure of rumination and affect in daily life for depression vulnerability. For this purpose, we set up a prospective study, testing whether information pertaining the structure of a system (i.e., entropy) could predict future levels of depressive symptoms and trait rumination. Specifically, we measured trait rumination and depressive symptoms at baseline and at six weeks follow-up upon confrontation with a potentially naturalistic stressor (i.e., preparation for the final exams). We also tracked momentary changes of ruminative thinking and affect in daily life using experience sampling methodology during one week following baseline assessment. In line with previous work (Koster et al., 2015), we investigated the structure of momentary rumination and affect by means of a state space grid (Hollenstein, 2013). Our first hypothesis, based on previous research (Koster et al., 2015; Wichers, 2014), was that entropy would prospectively predict depressive symptoms at follow-up. Second, we hypothesized that the structure of the system (i.e., entropy) of rumination and affect in daily life could predict the follow-up trait rumination measurement. Finally, we explored whether the structural aspects between affect and rumination predicted depressive symptoms and rumination, even when controlling for mean levels of momentary affect and rumination.

Method

Participants

Sixty-nine first-year undergraduate students from Ghent University enrolled at baseline. In order to avoid additional costs of participation to the experience sampling study, all participants were required to possess a smartphone with a monthly data plan. The study was approved by the local ethics committee of Ghent University. Based on the effect size reported in the previous study (Koster et al., 2015), we calculated the sample size required to exhibit an effect with a similar effect size (f^2 = 0.23) using G*Power 3.1 (Faul, Erdfelder, Buchner, & Lang, 2009). The results showed that a total sample size of 58 is needed in order to find a significant R^2 increase of entropy after considering the effect of depressive symptoms at baseline in the context of α = .05 and *power* = .95. In our study, we oversampled because we expected some drop out of participants during the intensive daily measurements and at the six-week follow-up assessment.

Measures

Symptom and trait measurements. Depressive symptoms were measured with the 21-item Beck Depression Inventory (BDI-II-NL; Beck, Steer, & Brown, 1996; Van der Does, 2002). Participants were asked to rate each item on a 4-point scale from 0 to 3 with regard to the occurrence and severity of depressive symptoms over the past two weeks (BDI-II at time 1: α = .79; at time 2: α = .84). Trait rumination was measured with the 22-item Ruminative Response Scale (RRS-NL; Nolen-Hoeksema & Morrow, 1991; Raes, Hermans, & Eelen, 2003; Treynor, Gonzalez, & Nolen-Hoeksema, 2003). Participants were asked to rate on a 4-point scale how they typically respond when they are feeling depressed (RRS at time 1: α = .90; at time 2: α = .91).

Daily assessment. Participants were asked to report their momentary affect and rumination with eight assessments per day within seven days. We used a stratified random sampling approach, where each day between 10:00 a.m. and 10:00 p.m. was divided into eight equal intervals and a signal was sent at a random time point in each interval. At every assessment point, participants received a text message via SurveySignal containing a link which directed them to LimeSurvey for the online measurements of momentary rumination and affect. For momentary rumination, an established valid measurement was adopted, where participants were asked to indicate their ruminative self-focus the moment just before receiving the signal on a scale from 0 (not at all) to 7 (very much). In line with previous studies (Moberly & Watkins, 2008, 2010; Hoorelbeke et al., 2016; Huffziger et al., 2013), we used the average score of two items to assess their momentary ruminative self-focus (i.e., “Focused on feelings” and “Focused on problems”). These two items were highly correlated (r = .85, p < .001).

Momentary affect experienced just before receiving the signal was assessed by rating two bipolar items (i.e., discontent-content, unwell-well) on a scale from 0 to 6 (Huffziger et al., 2013), which were also highly correlated with each other ($r = .92$, $p < .001$). The average score of these two items was used as the indicator of momentary affect. Here, higher scores reflect a more positive momentary affective state. The intraclass correlation (ICC) for the two items of momentary rumination was .88 ($p < .001$), and for the two affect items .96 ($p < .001$), implying high reliability within persons. The items were randomly presented between and within the momentary measurement of rumination and affect. All text messages were delivered using SurveySignal software (Hofmann & Patel, 2015) and paid by researchers using SurveySignal credits.

State space grid analysis. The dynamic structure of momentary rumination and affect was plotted in a state space grid and analyzed with GridWare 1.15a (Hollenstein, 2013; Lamey et al., 2004). In line with a previous study (Koster et al., 2015), 0.5 was used as the unit of change which resulted in 15 units for the rumination scale and 13 units for the affect scale (see Fig. 1). We added 1 unit as unknown state in each scale (i.e., state 15 in rumination scale and state 13 in affect scale) for missing data[1] (cf. Hollenstein, 2013). The momentary state of rumination is presented on the x-axis, ranging from 0 (no rumination) to 14 (very much), whereas momentary affect is presented on the y-axis, ranging from 0 (negative affect) to 12 (positive affect). Each point in the state space grid represents the current state of rumination and affect at that time point. Combining all the points in the state space grid reveals how ruminative thinking and affect changed over time.

To measure the structural instability of the transitions between different states, we used *Visit Entropy* as our main index (Hollenstein, 2013). One ‘visit’ refers to one or more consecutive points that are grouped into a single state, from the first point entering this state until the last point that leaves this state. According to Hollenstein (2013), entropy of the whole system was calculated by,

$$\text{Entropy} = \sum_{i=1}^{n} \left(\mathrm{P}_i * \ln\left(\frac{1}{\mathrm{P}_i}\right)\right) \quad (1)$$

where *n* denotes the number of possible states and *P* denotes the probability of the visit of a single state over all the states, which was calculated by

$$\mathrm{P} = \frac{Number\ of\ A\ \ visited}{Number\ of\ total\ visits} \quad (2)$$

where *A* denotes a certain joint state. Based on the equations, higher levels of entropy indicate more unstable transitions among different states of a system (see Fig.1).

Procedure

After signing the informed consent, participants completed the BDI-II and RRS as baseline measures of depressive symptomatology and trait rumination. Next, participants were registered to SurveySignal and given a step-by-step instruction, which included what kind of items they would see in the following experience sampling portion and the meanings of the items. The daily measurement started one day after the registration and contained eight assessments a day over a period of seven days. Signals were sent between 10 a.m. and 10 p.m., during which participants had to rate their momentary affect and rumination. At six weeks follow-up, depressive symptoms and trait rumination were reassessed using the BDI-II and RRS, after which participants received a debriefing and were reimbursed for their participation.

Results

Group characteristics

Sixty-nine participants completed the baseline assessment of depressive symptomatology and trait rumination. Two participants did not attend the follow-up assessment. Three participants were excluded from the final analysis due to poor compliance with the ESM protocol. That is, these participants showed low response rates (< 60%; range: 52-55%) and/or lack of variability or reliability of the responses (e.g., always rated the same number throughout the whole measurement period). One participant was excluded from the final analysis due to the presence of severe depressive symptoms at the follow-up assessment (BDI-II score of 33; > 3SD in BDI-II at time 2; Beck et al., 1996). None of the study variables correlated with the number of ESM prompts that were made by excluded participants. The remaining 63 participants (age: *M* = 18.48, *SD* = 1.27; 51 females) were highly compliant with the daily measurement procedure (response rate: *M* = 91.16%; *SD* = 7.54%; *range* = 68%-100%). Descriptive information concerning age, gender and measurements of depressive symptomatology and trait rumination can be found in Table 1. Our sample showed sufficient variation in trait rumination and depressive symptoms. Moreover, the final sample included 42 participants with minimal (range of BDI-II scores: 0-13), 19 participants with mild (range of BDI-II scores: 14-19) and 2 participants with moderate depressive symptoms (range of BDI-II scores: 20-28).

Zero-order correlations

First, as expected, there was a positive correlation between BDI-II and RRS at baseline, $r = .45$, $p < .001$. Then, for the mean levels of momentary measurement, it showed that the mean level of momentary affect ($M = 4.11$; $SD = 0.54$; *range* = 2.94-5.77) was negatively correlated with momentary rumination ($M = 1.90$; $SD = 1.04$; *range* = 0.22-4.81), $r = -.31$, $p = .015$, indicating that in the ESM data, less positive affect was associated with more rumination. For the structure, entropy ($M = 3.02$; $SD = 0.41$; *range* = 1.70-3.65) was significantly correlated with momentary rumination, $r = .68$, $p < .001$, and momentary affect, $r = -.28$, $p < .05$.

Predicting depressive symptoms and trait rumination at six weeks follow-up

We used Hierarchical Regression Analysis (HRA) to examine whether the structure of the dynamics in rumination and affect in daily life (i.e., entropy) can predict depressive symptoms and trait rumination separately, after controlling for the contribution of trait rumination and depressive symptoms at baseline. Due to the violation of the homoscedasticity assumption, we adopted heteroscedasticity-consistent inference (HC-inference; Hayes & Cai, 2007). In addition, given that BDI-II and RRS at time 1 as predictors in HRA are correlated with each other, collinearity issues may arise. Hence, we used relative importance analysis (Johnson, 2000; Johnson & LeBreton, 2004; Tonidandel & LeBreton, 2015) to provide additional variance partitioning information, which has been proposed to be more accurate when predictor variables correlate with one another. Therefore, the contribution of each predictor in accounting for the variance of the outcome variable was considered as follows: (1) Unstandardized regression coefficients and incremental R^2, representing the unique contribution of each predictor above and beyond other predictors; (2) relative importance analysis, representing the contribution of each predictor including its direct effect and its effect in combination with other predictors (Johnson, 2000).

In the HRA predicting depressive symptoms at time 2, we entered BDI-II and RRS at time 1 as predictors in the first step and entropy as predictor in the second step. The results are shown in Table 2 (upper part). The analysis revealed that baseline depressive symptomatology formed a significant predictor for depressive symptoms at time 2 ($p < .001$), accounting for 22% of the variance. However, trait rumination at time 1 did not significantly predict depressive symptoms at time 2 ($p = .83$). After controlling for both depressive symptomatology and trait rumination at time 1, the predictive effect of entropy was approaching significance ($\Delta R^2 = .03$, $p = .07$, $f^2 = .04$). The results showed that entropy explained 3% of depressive symptoms at time 2 above and beyond baseline depressive symptoms and trait rumination. The relative importance of entropy confirmed that it can explain 3% of the variance of depressive symptoms at time 2 ($\varepsilon = .03$).

Likewise, for trait rumination at six weeks follow-up, we entered baseline trait rumination and depressive symptomatology as predictors in the first step, and entropy as predictor in the second step. The result (see Table 3, upper part) showed that trait rumination at time 1 significantly predicted trait rumination at time 2 ($p < .001$) and accounted for 28% of the variance of trait rumination at time 2. There was a tendency for baseline depressive symptomatology to predict trait rumination at time 2 (p = .06). Importantly, entropy explained an additional 4.1% of variance in trait rumination scores at six weeks follow-up (p < .05, f^2 = .09) after controlling for baseline depressive symptomatology and trait rumination. The results of relative importance analysis indicated that the direct and combined effects of entropy in total accounted for 8% of trait rumination at time 2.

To explore the third hypothesis, the influence of mean levels of momentary rumination or affect was also taken into account in a regression model to predict depressive symptomatology at time 2 (for details, see Table 2, lower part). The results showed that the trend for entropy was not significant anymore (p = .30, f^2= .02). However, when a similar analysis was conducted to predict trait rumination at time 2 (for details, see Table 3, lower part) entropy accounted for 8% of the variance. Importantly, the predictive effect of entropy for trait rumination at time 2 remained significant after controlling for all trait and momentary variables (p < .05, f^2 = .10).

Discussion

The present study examined the predictive contribution of the dynamic structure (i.e., entropy) of rumination and affect in daily life to depressive symptoms and trait rumination during a potentially stressful period in an undergraduate sample. The results showed that, after controlling for the effect of baseline depressive symptoms and trait rumination, there was a trend for entropy to predict depressive symptoms at follow-up and there also was a significantly predictive effect of entropy on trait rumination at follow-up. Moreover, after taking into account the mean levels of momentary rumination and affect, the effect of entropy remained stable only in predicting trait rumination at follow-up but not in predicting depressive symptoms.

First, in line with the previous study (Koster et al., 2015), we found a tendency of this effect of entropy (p = .07) in predicting depressive symptoms after controlling for the effect of BDI-II and RRS at baseline during a potentially stressful period in an undergraduate sample, which indicates that more unstable patterns of thought and affect may reflect a heightened risk for depression. However, since this predictive effect of entropy was not significant anymore after adding momentary measurements as predictors (p = .30), here we can only cautiously suggest that more studies should be conducted before making a strong conclusion about this predictive effect of entropy on depressive symptoms. Similarly, our findings also showed that entropy significantly predicted trait rumination at six weeks follow-up. This is, again, consistent with the previous study (Koster et al., 2015) showing a tendency that entropy can predict depressive rumination in both remitted depressed and healthy controls over a period of six months. Although entropy showed to have a predictive effect on trait rumination in general, no significant results were found for brooding and reflection subscales specifically[2]. This might be due to the fact that momentary rumination was measured by two items concerning brooding and reflection separately, which allows for greater variability in measuring momentary rumination. Therefore, it maps more closely onto trait rumination than its subscales.

According to our findings, entropy can be considered as an informative predictor for depressive vulnerability. Using entropy, we rely on an interesting theoretical basis (i.e., Information Theory; Shannon & Weaver, 1949) to examine the system as a whole instead of its constitutive elements (i.e., momentary rumination and affect). Interestingly, although entropy was derived from momentary measurements, these latter variables did not predict future depressive symptoms. In a recent study, Connolly and Alloy (2017) found that momentary rumination self-focus itself did not predict depressive symptoms unless its interaction with stress was taken into account. Our study suggests that relative to momentary rumination in isolation, the dynamic relation between affect and rumination has a closer relation to future depressive symptoms. This latter finding is in line with theory and data that have argued for the importance of investigating momentary mental dynamics in relation to psychological well-being (Houben, Van Den Noortgate, & Kuppens, 2015; Servaas et al., 2017; Thompson, Boden, & Gotlib, 2015).

The current study extends research on dynamics in rumination and affect, showing that the predictive effect of entropy on depressive vulnerability can be found not only in individuals at risk for depression, such as a remitted depressed sample (Koster et al., 2015), but also in healthy individuals. This helps expand the potential usage of entropy from depression prediction into prevention. Further, our findings, revealing the association between entropy obtained from ESM and risk factors during a stressful period, indicate that the consistent usage of rumination in negative situation may emerge and could be predicted from the dynamics between rumination and affect in daily life. Recently, there has been growing interest in examining the specific way and timing through which healthy individuals develop depression (van de Leemput et al., 2014). Increased instability has been regarded as an early warning signal of system transition (Hayes et al., 2015). For example, it has been shown that too much instability (operationalized as higher levels of self-complexity) has a moderate depressogenic effect (Houben et al., 2015; Rafaeli-Mor & Steinberg, 2002). Similarly, our findings suggest that increased entropy of dynamics of rumination and affect in healthy individuals may connect with maladaptive coping strategies during a stressful period.

Concerning the relation between instability and mental health, a non-linear relationship has been proposed (Guastello, 2015). This suggests that adaptive systems display instability in mid-range values. In contrast, too low levels of instability would represent a rigid system, whereas too high levels of instability may represent a disordered system, both of which are assumed to be maladaptive (in terms of flexible adaptation to daily life stressors). As such, the observations in our study that higher levels of entropy were associated with higher levels of trait rumination at follow-up may indicate that individuals with more unstable systems are likely to reach the threshold where they shift to maladaptive systems. Therefore, our research raises the possibility that entropy may form an early marker of depressive vulnerability in a stressful period. Here we note that we did not directly assess stress levels in response to the exam stress where for most people this will have been a rather mild stressor. Future studies should seek more personally relevant stressors and could take into account the magnitude of stress.

Although our findings are based on a convenience sample, it suggests that entropy forms an interesting parameter of the structure of a system which could be considered in future studies in relation to clinical depression. Depressive patients have been characterized as getting stuck in rumination and negative affect (Raes, Hermans, Williams, Bijttebier, & Eelen, 2008) and such a stable system has been demonstrated to be resistant to change (Hayes & Strauss, 1998). Thus, it is important to know whether treatments affect the structure of a system and not just its momentary state. Recording daily emotion and emotion regulation, and then examining mean levels as well as dynamic patterns between variables holds the potential to help depressive patients and clinicians monitor the progress of treatment and evaluate the effects of an intervention (Hayes & Strauss, 1998; Wichers et al., 2011).

There are some limitations to our study. First, further studies should use similar methodology in investigating clinically depressed samples, which would increase our understanding of the dynamic patterns of individuals at different stages of depression. Second, the follow-up measurements were conducted after six weeks which is still relatively short for monitoring change in depressive symptomatology, especially if one wants to explore the predictive value of entropy for occurrence of depressive symptoms (e.g., entropy as an affective risk marker). This may have contributed to the limited effect of entropy on depressive symptomatology in the current study. Assessing depressive symptoms over a longer period may provide additional information about the prospective influence of the dynamic interplay. Third, there are a wealth of constructs that assess different aspects of the pattern between rumination and affect.

Though, previous research suggests that entropy forms the most representative index when compared to similar measures for system instability (Sravish, Tronick, Hollenstein, & Beeghly, 2013), future studies should still consider other dynamic attributes as well in order to gain a more comprehensive view of the dynamic pattern between rumination and affect and its predictive effect on depressive symptoms. Finally, there has been disagreement in the literature about whether to measure affect separately or on one bipolar scale and each of them has its own frameworks, hypotheses, and supportive evidence (Mattek, Wolford, & Whalen, 2017). In line with previous work (Koster et al., 2015), bipolar items were used in the current study. The items have been proved to be suitable for ESM study and, have good reliability and sensitivity for momentary change (Huffziger et al., 2013; Wilhelm & Schoebi, 2007). Nonetheless, it would be important for future studies to investigate the predictive effect of entropy when positive and negative affect are measured separately. It could be particularly interesting to investigate the interplay between entropy and mean levels and variability (i.e., standard deviation) across negative and positive affect.

Conclusion

Our experience sampling study showed that entropy is a significant predictor for trait rumination at six weeks follow-up, with a similar trend emerging for depressive symptoms. This predictive effect of entropy on trait rumination held even when controlling for mean levels of momentary rumination and affect. Overall, our findings suggest that studying the structure of the dynamics in momentary rumination and affect could contribute to understand elevated risk for depression.

Footnote

[1] We also calculated entropy when all the missing data were marked as "missing" and no additional state was visited on these occasions. We found that these two entropy indexes were identical ($r = .99$, $p < .001$). Given that we aimed to maximally retain the original information of the whole time series, we prefer using an additional state to index missing values.

[2] Here, we only provided the results for total trait rumination scores without taking into account the scores in the brooding and reflection subscales. In contrast, in the previous study no total rumination scores were available given that only the brooding and reflection subscales were assessed (Koster et al., 2015). However, it is important to note that in our current study, when we included brooding or reflection as DVs in the HRA analysis, no significant results were obtained.

Compliance with Ethical Standards

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Table 1. *Demographic characteristics and correlations (N = 63)*

	Mean	*SD*	*Range*	*BDI_II T1*	*RRS T1*	*BDI-II T2*
Age	18.48	1.27	17-22			
Gender (female : male)	51:12					
BDI-II T1	10.29	5.78	0-27			
RRS T1	41.11	10.90	23-68	.45***		
BDI-II T2	9.49	5.90	1-28	.51***	.29*	
RRS T2	38.17	10.55	23-68	.50***	.64***	.50***

Note: $^{\dagger}p < .1$; $*p < .05$; $**p < .01$; $***p < .001$. BDI-II, Beck Depression Inventory-II; RRS, Ruminative Response Scale; T1, baseline measurement; T2, six weeks follow-up.

Table 2. *Hierarchical regression analysis predicting BDI-II after six weeks*

Steps	*Predictors*	*ΔR2*	*B*	*95%CI*	*ε*
Structure only					
Step 1		.26***			
	BDI-II T1		.48***	[0.23,0.74]	.22 [.071; .431]
	RRS T1		.04	[-0.10,0.18]	.04 [.007; .175]
Step 2		.03†			
	BDI-II T1		.49***	[0.23,0.74]	.22 [.069; .422]
	RRS T1		.02	[-0.12,0.16]	.04 [.008; .156]
	Entropy		2.37†	[-0.88,5.61]	.03 [.002; .119]
Mean levels & Structure					
Step 1		.28***			
	BDI-II T1		.49***	[0.23,0.74]	.22 [.070; .419]
	RRS T1		.04	[-0.10,0.18]	.04 [.006; .160]
	Momentary Rumination		.77	[-0.56,2.10]	.02 [.001; .122]
	Momentary Affect		.62	[-2.09,3.33]	.004 [.001; .053]
Step 2		.01			
	BDI-II T1		.49***	[0.23,0.75]	.21 [.068; .414]
	RRS T1		.03	[-0.12,0.17]	.04 [.007; .150]
	Momentary Rumination		.20	[-1.58,1.97]	.01 [.002; .095]
	Momentary Affect		.66	[-2.06,3.37]	.004 [.001; .050]
	Entropy		2.20	[-2.31,6.72]	.03 [.003; .096]

Note: $^{\dagger}p< .1$; $^{*}p< .05$; $^{**}p< .01$; $^{***}p< .001$. RRS, Ruminative Response Scale; BDI-II, Beck Depression Inventory-II; T1, baseline measurement; CI, confidence interval; ε, relative importance weight.

Table 3. *Hierarchical regression analysis predicting RRS after six weeks*

Steps	*Predictors*	*ΔR2*	*B*	*95%CI*	*ε*
Structure only					
Step 1		.46***			
	RRS T1		.50***	[0.29,0.71]	.31 [.140; .506]
	BDI-II T1		.48†	[0.09,0.87]	.15 [.037; .327]
Step 2		.04*			
	RRS T1		.45**	[0.24,0.65]	.28 [.119; .471]
	BDI-II T1		.48†	[0.11,0.86]	.14 [.036; .308]
	Entropy		5.37*	[0.51,10.23]	.08 [.019; .175]
Mean levels & Structure					
Step 1		.48***			
	RRS T1		.53***	[0.31,0.74]	.31 [.136; .502]
	BDI-II T1		.49†	[0.10,0.88]	.15 [.036; .304]
	Momentary Rumination		1.09	[-0.93,3.11]	.01 [.001; .091]
	Momentary Affect		2.42	[-1.71,6.54]	.01 [.005; .060]
Step 2		.05*			
	RRS T1		.47**	[0.26,0.68]	.28 [.118; .467]
	BDI-II T1		.51†	[0.13,0.88]	.14 [.036; .297]
	Momentary Rumination		-.92	[-3.53,1.69]	.01 [.006; .066]
	Momentary Affect		2.53	[-1.45,6.51]	.01 [.005; .056]
	Entropy		7.71*	[1.08,14.34]	.08 [.025; .181]

Note: $^{\dagger}p< .1$; $*p< .05$; $**p< .01$; $***p< .001$. RRS, Ruminative Response Scale; BDI-II, Beck Depression Inventory-II; T1, baseline measurement; CI, confidence interval; ε, relative importance weight.

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*Figure 1***.** State space of momentary rumination and affect illustrating two participants in the current study. Panel A (participant No.29) displayed lower visit entropy (*entropy* = 1.699) than Panel B (participant No.56, *entropy* = 3.454), indicating a more stable pattern of the system. Missing data was depicted as scores of 15 on momentary rumination and of 13 on momentary affect.