The effects of mindfulness and positive fantasizing on rumination and depression: A network perspective

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In the past decade, network analysis has gained traction in the field of psychopathology. Major Depressive Disorder (MDD) has been one of its main research targets. In this study, we aimed to extend existing research in several ways. First, unlike most current research, which primarily focuses on contemporaneous associations between symptoms, this study utilizes momentary assessment data to investigate causal connections between symptoms. Second, this study focuses on the role of rumination – a critical feature of MDD that has been largely overlooked in network studies. And third, this study investigates the effects of common interventions from a network perspective. We start by comparing the networks of participants in remission from MDD with those of a healthy control group. Next, we show the respective effects of a mindfulness and a positive fantasizing intervention on a combined network. The results suggest that rumination plays a more critical role in the network of remitted MDD participants than healthy controls. Furthermore, the mindfulness intervention was more effective in weakening rumination's influence on the network, while positive fantasizing more strongly increased positive affect. However, our permutation testing-based network comparison test revealed only a few statistically significant differences.

Keywords: Major Depressive Disorder, rumination, network analysis, experience sampling, mindfulness

Introduction

About one in ten people currently suffer from Major Depressive Disorder (MDD; Kessler & Bromet, 2013; Tolentino & Schmidt, 2018), and more than one in five will be affected by this debilitating mood disorder at some stage in their lives (Hasin et al., 2018). Furthermore, MDD is a recurrent disorder, meaning that individuals that have endured one episode commonly experience further ones in the future. In fact, the likelihood of recurrence is greater than 80% after 15 years (Hardeveld et al., 2010; Mueller et al., 1999).

According to the *Diagnostic and Statistical Manual of Mental Disorders* (5th ed.; DSM-5; American Psychiatric Association, 2013), depression encompasses behavioral, emotional and cognitive symptoms (see Table 1). Cognitive symptoms routinely observed in depressed patients, such as poor executive control, attentional biases toward negative information, and impaired working memory, are sometimes viewed as mere epiphenomena of the emotional symptoms. However, a meta-analysis by Rock et al. (2014) shows that cognitive impairments remain detectable even in-between low-mood episodes. Accordingly, cognitive theories highlight the importance of cognitive factors in the onset and maintenance of depression (Kircanski et al., 2012).

Rumination

A commonly leading concept in cognitive theories of depression is *rumination*. Rumination is a form of repetitive negative thinking, and as such, is characterized by a repetitive, uncontrolled stream of negatively-valenced thoughts and memories that follow a common theme (Lyubomirsky et al., 2015). In particular, rumination is focused on the past or the present, revolves around themes of loss, meaning, and lack of self-worth, and involves viewing events as inevitable and uncontrollable (Nolen-Hoeksema et al., 2008).

Watkins and Roberts (2020) proposed the H-EX-A-GO-N model to explain the onset and perpetuation of rumination as a consequence of the interplay of some or all of five fundamental mechanisms. According to this model, rumination is an initially functional response to perceived goal discrepancies (GO), but over time can become a mental habit (H) triggered by low mood. As a result, rumination becomes dysfunctional, interfering with rather than stimulating efforts to reduce perceived goal discrepancies. Acquiring mental habits by repeated occasions of rehearsal and conditioning is a central route for developing pathological rumination (Watkins & Nolen-Hoeksema, 2014). Crucially, the model hypothesizes that this route from occasional, healthy rumination (or state rumination) to excessive, pathological rumination (or trait rumination) is facilitated and made more (or less) likely through the effects of the other mechanisms.

Table 1

Criteria for an MDD diagnosis. In addition to the ***required criteria****, at least five of the* ***depressive symptoms*** *must be present for at least two weeks. Furthermore, at least one of the symptoms marked with * has to be observed.*

Depressive symptoms	**Explanation**
Depressive mood*	Most of the day; near-daily
Loss of interest / pleasure*	Most of the day; near-daily
Weight loss or gain	Change of >5% body weight in a month
Insomnia or hypersomnia	near-daily
Psychomotor agitation or retardation	near-daily; observable by others
Fatigue	near daily
Feelings of worthlessness/guilt	near-daily; guilt may be delusional
Lack of concentration	near daily; observable by others or merely subjective
Thoughts of death or suicide	not just fear of dying; suicidal ideation without a specific plan
Required criteria	
Symptoms cause significant distress or impairment in social, occupational, or other important areas of functioning.	
Episode not attributable to physiological effects of a substance or another medical condition.	
Episode not better explained by, for example, schizophrenia, delusional disorder, or other psychotic disorders.	
No history of manicx or hypomanic episode.	

A lack of executive control (EX) facilitates the development of pathological rumination. Individuals with poor executive control may struggle to disengage from repetitive thinking about negative life events and personal concerns. This mechanism is supported by substantial neurobiological evidence. MDD is associated with a weak prefrontal cortex (PFC), so-called "hypofrontality." The PFC's inadequate control results in a hyperactive amygdala (for example, Johnstone et al., 2007; Siegle et al., 2007). Consequently, people suffering from MDD recover more slowly from psychological stress than non-depressed individuals. Neurobiologically, this manifests as more enduring elevated post-stress cortisol levels, which over time can damage the hippocampus (Steffens et al., 2011). This neurobiological chain reaction results in episodic negative mood changes and several cognitive deficits, among them poor executive control (Rock et al., 2014). Executive control consists of three main components: shifting, updating, and monitoring representations in working memory and inhibition of irrelevant information (Miyake et al., 2000). As Koster et al. (2011) indicate, impairment of such executive functions may contribute to rumination in at least two ways. First, problems with monitoring and manipulating information in working memory might result in the proliferation of irrelevant, negatively-valenced information in working memory, making it evermore salient and harder to disengage from. Such poor cognitive control manifests as mental "stickiness" – uncontrolled and perseverative cognition (Joormann et al., 2011). Second, as executive control is needed to instigate and maintain goal-directed behavior, its deterioration may result in difficulties in overriding ruminative habits (H) that have formed.

In addition to the effects of poor executive functions, pathological rumination is accompanied by a preferential bias for processing negatively-valenced information (Gotlib & Joormann, 2010) as well as an engagement bias that orients attention towards negatively-valenced information and a disengagement bias that hampers the ability to shift attention away from it (Beckwé & Deroost, 2016; Donaldson et al., 2007; Whitmer & Gotlib, 2013). Such biases, in turn, increase the frequency and accessibility of negative thinking, and therefore, prolong rumination (Watkins & Roberts, 2020). Stated more generally, rumination and depression appear to be linked to a universal bias for negatively-valenced information (N; Dalgleish & Watts, 1990).

The final mechanism is fundamental to understanding why rumination becomes maladaptive. Pathological rumination is characterized by an abstract processing style (A). That is, a processing style focused on generalized and decontextualized mental representations that convey the causes, consequences, and meaning of a goal or an event (the "why" aspects). Unlike the more adaptive and concrete processing style of functional rumination, however, it neglects the feasibility, mechanics, and means of goals and events (the "how" aspects; Watkins, 2008). Consequently, pathological rumination fails to alleviate goal discrepancies (GO), leading to more extended and more frequent periods of rumination, further promoting ruminative habit formation (H).

As rumination becomes increasingly maladaptive, it leads to several negative consequences. Rumination has been shown to exacerbate and prolong negative affective states such as sadness, anger, anxiety, and depressed mood (Kirkegaard Thomsen, 2006; Lavender & Watkins, 2004; Lyubomirsky et al., 1998; Lyubomirsky & Nolen-Hoeksema, 1995; Lyubomirsky et al., 1999; Nolen-Hoeksema &

Watkins, 2011; Rimes & Watkins, 2005). Similarly, it has been demonstrated that increased negative affect and decreased positive affect predict subsequent rumination (Hjartarson et al., 2021; Moberly & Watkins, 2008). These bidirectional effects lead to a vicious cycle between affective and cognitive symptoms, with each amplifying the other (Ciesla & Roberts, 2007). In individuals prone to depression, the mutual intensification between negative thinking (including rumination) and negative mood produces a forceful downward spiral, eliciting severe levels of negative affect. However, because rumination is such a complex construct, tying together affective and cognitive factors, a holistic understanding of rumination requires researchers to adopt a wider lens, investigating not the relationships it forms with individual symptoms but its role in a complex network of interdependent variables. A more comprehensive and integrated understanding of rumination may have significant clinical implications, increasing our ability to predict outcomes such as the course of illness, probability of relapse, and treatment response.

Network Analysis

Network analysis is an analytical framework that provides the tools necessary to explore the complex, interdependent interactions of multiple symptoms as one integrated system. It has entered the field of psychopathology as a result of the perceived shortcomings of the current diagnostic tools such as the DSM-5 (for a discussion, see Borsboom & Cramer, 2013). Instead of viewing mental disorders as the result of an underlying root cause (analogous to Western medicine), it conceives of them as a network of interacting elements that do not need to share a root cause. Since many mental disorders share symptoms, the established boundaries between them might need to be redrawn. Network analysis might lead to greater precision in delineating mental disorders and a more realistic understanding of comorbidities in terms of bi-directional symptom-to-symptom connections (Cramer et al., 2010). Rumination may feature prominently not just in a network of depression but in a grander network structure explaining several mental disorders conventionally regarded as (entirely) separate entities.

Network analysis is generally concerned with the measurement, description, and visualization of relational structures (Furht, 2010). The end product of such an analysis is typically a graph consisting of nodes and edges that join them. While each node represents some entity moving within the network, each edge represents a direct connection between two entities. Some connections are likely more substantial than others. The strength of a connection is referred to as the edge weight. In the visualization, this is commonly accounted for by varying the thickness of edges. Additionally, edges can be distinguished by whether they are directed or undirected, i. e., whether a connection between two nodes always runs from entity A to entity B or can go both ways. In an organization, a directed edge could indicate a well-defined chain of command. In contrast, in a network of symptoms, it would indicate a causal effect from symptom A to symptom B. These connections, then, must be explained by some underlying biological or psychological process. For example, a relationship between insomnia and fatigue can reasonably be explained by some underlying biological process. By comparison, a connection between depressed mood and feelings of worthlessness is likely psychological.

Previous Research

The network perspective on psychopathology resonates with many researchers. As a result, several studies have already used network analysis to study depression. Recently, Malgaroli et al. (2021) have systematically reviewed such studies. They attempted to combine the networks created by the 23 reviewed studies into one, specifying the most recurrent centrality and edge weight indices.

Depressed mood and fatigue were the symptoms with the most robust connections across all reviewed studies. Consequently, both of these symptoms appear to be central to MDD. Neither of these findings should be surprising, given that depressed mood is the hallmark symptom of MDD and fatigue has previously been shown to be one of the main protagonists in MDD (Cramer et al., 2010) and may even be an early sign of its onset (Contreras et al., 2019). Interestingly, at least one of the two symptoms is necessary to diagnose a depressive episode with ICD-10's MDD diagnostic algorithm (World Health Organization, 1993), underscoring their pivotal roles in the disorder.

The strongest association between variables was found for depressed mood and anhedonia. This result aligns neatly with the scientific literature, suggesting this link to be a consequence of the dopaminergic pathway and its role in initiating MDD (Stein, 2008). Feelings of worthlessness exhibit robust connections with other affective symptoms too. Malgaroli et al. (2021) consider this to be consistent with MDD's high comorbidity rates with conditions involving such experiences as guilt, particularly post-traumatic (Lee et al., 2001), obsessive-compulsive (Shafran et al., 1996), and alcohol/substance use disorders (Treeby & Bruno, 2012). Their review, however, was limited in that it only included cross-sectional studies. Their network reveals nothing about the causal directions between two symptoms, limiting the ability to make inferences on the dynamics of MDD. It is also noteworthy that the studies reviewed by Malgaroli et al. (2021) – even the ones they excluded from their review – rely on self-reported measures. Of course, many symptoms are not readily measured by objective means. However, cognitive symptoms like lack of concentration permit objective measurement, potentially increasing a network's accuracy.

Other studies used longitudinal data with large intervals between repeated measurements (for example, two years; Savelieva et al., 2021). Important information about the short-term dynamics is necessarily lost at this time scale. Even (near-)daily measurements (for example, Groen et al., 2019; Lydon-Staley et al., 2019) may fail to detect some information of clinical relevance. MDD network studies that collected measurements multiple times per day using the Experience Sampling Method (ESM) are rare. An exception is a study by Hoorelbeke et al. (2019) who collected self-reports six times a day for one week from 85 remitted depressed patients. They looked at key vulnerability and protective factors in a network of symptoms focused on indicators of emotional (dys-)regulation (mainly rumination and positive appraisal), cognitive functioning, and resilience. One of their main findings was that resilience is important in obtaining stable remission from depression, predicting weaker depressive symptomatology and lower levels of rumination. Like most current network studies, the study by Hoorelbeke et al. (2019) did not include a healthy control group, limiting their ability to draw conclusions based on their results.

The Present Study

The present study builds on and extends previous network analysis studies of depression. Our literature review divulged three main gaps we want to address in the current study. First, relatively little network research has taken temporal relationships into account. Second, rumination has not been studied in detail from a network perspective. Even though Hoorelbeke et al. (2019) included rumination as a node in their network analysis, they assessed it using two possibly too unspecific items ("focused on feelings”, and "focused on problems"). In our opinion, these two items may not be representative of rumination as they do not clearly distinguish it from other forms of repetitive negative thinking, such as worry. Even in-between depressive episodes, remitted patients report higher levels of repetitive negative thinking such as rumination than healthy individuals (for example, McMurrich & Johnson, 2008), and typically experience residual depressive symptoms (for example, Nierenberg et al., 2010). Our first research question, therefore, aims at investigating these findings from a network perspective:

Q1: What is the role of rumination in a complex network of symptoms of MDD, and how does it differ between remitted MDD patients and healthy controls?

In an initial step, thus, we create a temporal network of depressive symptoms for remitted MDD patients with a focus on rumination using the experience sampling method (ESM; Kahneman et al., 2004). Our study includes a control group of healthy individuals to improve upon a standard limitation of current network studies. The third gap we identified concerns the effects of common interventions on rumination and depression from a network perspective. Network studies investigating common interventions’ effects with ESM data are rare. And so far, no study has investigated the impact of mindfulness and positive fantasizing from a network perspective. Both interventions have proven successful at alleviating depressive symptoms in more conventional studies. However, the combination of ESM and network analysis provides an especially potent lens for exploring how the effects of an intervention unfold. Consequently, the second research question may be stated as follows:

Q2: What are the effects of mindfulness and positive fantasizing on the network of symptoms of MDD in general and rumination in particular?

While mindfulness focuses on accepting and letting go of negative thoughts, positive fantasizing focuses more on stimulating positive thoughts. Mindfulness-based therapy has received ample attention, and its efficacy in mitigating depressive symptoms has been corroborated by multiple meta-analyses (see for example, Hofmann et al., 2010). It has been suggested that mindfulness exerts its mitigating effects on depressive symptoms by reducing dysfunctional emotion regulation strategies, such as rumination (Guendelman et al., 2017). Returning to Watkins and Roberts (2020)’s HEXAGON model of rumination, we can identify a likely route this effect might take. As pointed out earlier, rumination is suggested to be a maladaptive habit (H), the formation of which is aided by poor executive control (EX). Teper et al. (2013) posit that the awareness and nonjudgmental acceptance cultivated by mindfulness training promote executive control because they heighten the meditator’s sensitivity to affective cues in their experiential field. This greater awareness of subtle changes in affective states fosters executive control because it improves the meditator’s ability to respond and intervene when such changes are detected. And indeed, a meta-review by Cásedas et al. (2020) supports moderate effects of mindfulness on executive control. This, in turn, enhances functional emotion regulation. As a result of the improved emotion regulation, the negativity bias (N) in information processing associated with rumination may decrease (see for example, Düsing et al., 2021). Given that functional emotion regulation is related to a concrete, rather than an abstract (A), processing style, this should ultimately lead to a better alleviation of goal discrepancies (GO) over time; mindfulness training can reasonably be expected to impact – directly or indirectly – all key mechanisms of rumination as postulated by the HEXAGON model.

Positive fantasizing is a primary constituent of Preventive Cognitive Therapy – a therapeutic approach that has been shown to prevent the recurrence of depressive episodes and mitigate depressive symptoms (Bockting et al., 2009). Positive fantasizing, like mindfulness, may decrease rumination (Besten et al., 2020). However, it has also been suggested

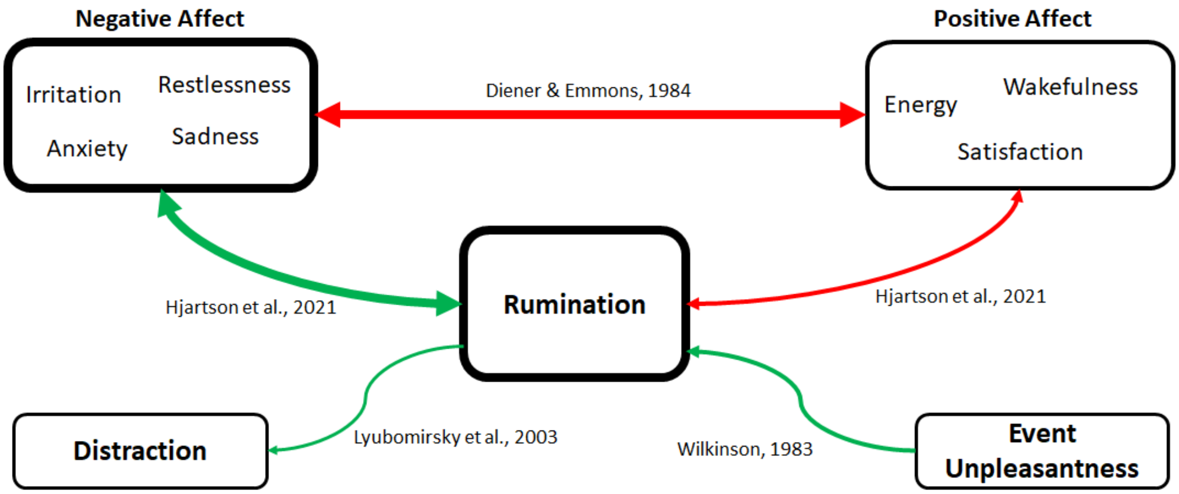

Figure 1

A simplified network of some of the main hypothesized effects. Thicker borders indicate greater centrality. Red arrows indicate a negative influence, and green arrows a positive one. The arrow's thickness indicates the hypothesized strength of an association between symptoms.

that positive fantasizing can improve the regulation of positive affect (van Tol et al., 2021). Positive affect may function as a protective factor against depression (Fredrickson & Levenson, 1998), which could explain this intervention's success in preventing relapse. The increase in positive affect might lead to a decrease in negative affect and lower mood reactivity – changes in mood following mood provocation – in general (van Rijsbergen et al., 2013). Therefore, positive fantasizing recruits a slightly different pathway than mindfulness in combating depression, potentially operating more directly on positive and negative affect. However, the positive fantasizing intervention involves identifying dysfunctional attitudes and schemata – and challenging these using positive affect and fantasy techniques – and therefore, should also impact repetitive negative thinking directly.

Network analysis, as implemented today, is mainly an exploratory tool (Borsboom et al., 2021). Strong conclusions should not be drawn based on network analysis alone but need to be supported by other statistical analyses and substantiated theoretical reasoning (Bringmann et al., 2022). For that reason, we designed a tentative "hypothesis network" for remitted MDD patients prior to having received an intervention based on the evidence reviewed in previous sections. Figure 1 shows the hypothesis network. It was reduced to some of the (likely) most central nodes. Moreover, the affect measures were combined in the hypothesis network, even though we analyzed them as separate entities.

The network indicates that rumination is expected to feature prominently in the network. Negative and, to a lesser degree, positive affect (or at least some of their constituent parts) are also hypothesized to be highly central to the network. Rumination is further expected to increase distraction and to be increased itself by the experience of an unpleasant event.

For healthy individuals, we expect negative affect and especially rumination to be less central and several associations to be significantly weaker, possibly to the extent that they do not feature in the network at all, resulting in a sparser network (reduced Global Strength). Similarly, after having gone through an intervention, the networks might shift towards those of healthy individuals. Mindfulness may impact the network by increasing executive control; consequently, its effects may start from the rumination node. By contrast, positive fantasizing might exert its influence by increasing positive affect and decreasing negative affect directly, which may subsequently lead to reduced levels of rumination.

To further assess whether mindfulness and positive fantasizing exert their effects via different routes, we utilize a sustained attention to response task (SART; Robertson et al., 1997). In research on mind-wandering, thought probes are typically included in the SART to incorporate subjective experience in the otherwise objective cognitive task. As the name suggests, the SART was devised to measure sustained attention. However, given that it requires participants to inhibit automatic responses, it has been recommended to be a better indicator of executive control than sustained attention (Head & Helton, 2014; Helton et al., 2009). Consequently, it may help us determine whether mindfulness training indeed improves executive control and whether it does so more than positive fantasizing. At the same time, including the SART allows us to investigate how this objective measure of executive control relates to momentary subjective measures of distraction and rumination, which to our knowledge has not yet been studied.

Methodology

Participants

A total of 39 individuals participated in this study. Sixteen were in remission from clinically diagnosed Major Depressive Disorder (rMDD), and 23 were never diagnosed with any mental illnesses (healthy controls; HC).

Experimental Design

The experiment was split into two blocks: each consisted of a baseline assessment phase and a peri-intervention phase lasting one week. These two blocks were separated by a washout period that lasted at least one month. On the first day of the peri-intervention phase, participants received two hours of professional training on their respective intervention. For the remainder of the period, participants were asked to perform a daily 10-minute home exercise of the same intervention. After the washout period, participants underwent another round of baseline assessment, followed by another week of intervention, receiving the intervention they had not yet gone through.

Data Collection

Throughout the experiment, cognitive and affective symptoms were assessed using experience sampling (ESM) and sustained attention to response task (SART; Robertson et al., 1997). ESM refers to the collection of self-reports regarding a participant's ongoing experience (Kahneman et al., 2004). Participants received ten daily prompts to complete a questionnaire via a smartphone app. These prompts were sent pseudo-randomly between 8 a.m. and 10 p.m. with a gap of at least 15 minutes between subsequent prompts. Appendix C lists all ESM items and describes how we chose a subset of them to use in our analyses. While ESM is used to collect self-reports, i.e., subjective measures, SART is a method for obtaining objective cognitive data. Developed by Robertson et al. (1997), SART is a go/no-go paradigm. It involves pressing a key in response to frequently presented non-targets (Go trials) and withholding the response to infrequently presented targets (No-Go trials). Because it places shallow demands on controlled processes, the SART lends itself to mind-wandering. And indeed, participants' error rates on the task are predicted by questionnaires on mind-wandering (Smallwood et al., 2006). Participants were asked to complete the SART at least twice per day.

Unless they dropped out, all subjects underwent both interventions in two blocks separated by a washout period of at least one month. Since network analysis methods, in particular, require much data, we decided to increase statistical power by treating a specific subject in block 1 as a distinct entity from that same subject in block 2. For all analyses, we excluded a subject's responses per block if they responded to less than 50% of the prompts in that block. As some subjects responded to less than 50% of the prompts in either block, they were excluded entirely. A total of 33 participants, 21 healthy controls, and 12 individuals in remission remained.

Analysis

In this study, we first wanted to investigate the network differences between individuals in remission from depression and healthy controls before any intervention. The second goal was to examine the effects of mindfulness and positive fantasizing on a combined network of symptoms (i.e., for both the rMDD and the HC group). Both goals could be broken into the same six subquestions as depicted in Table 2. To answer these subquestions, we used network analysis, following the general procedure outlined in Appendix A.

To answer the first subquestion – how symptoms are related to one another – we used multi-level vector autoregression (mlVAR; Epskamp, Waldorp, et al., 2018). These models can estimate contemporaneous and temporal networks while also considering differences between participants. The contemporaneous networks show to what extent deviations from a person's means on two variables predict one another at the same point in time . Similarly, temporal networks indicate whether a deviation from a person's mean predicts a deviation from that person's mean in another variable at the next measurement occasion.

The second subquestion concerned the influence individual nodes had on the network. This is generally referred to as a node's *centrality*. Several measurements are available for specifying centrality. In psychopathology research, typically,

Table 2
Research questions broken down into concrete questions and associated measurements.

Subquestion	Measurement
A How are nodes related to each other?	Edge weights
B What are the most influential nodes in the network?	Centrality
C What role does rumination play in the network?	Edge weights, centrality
D How densely connected is the network?	Global Strength
E How stable is the network?	Network stability test
F How do the groups differ from one another?	Network comparison test

Strength is used. A node's Strength is the sum of all absolute edge weights that are connected to it. In temporal networks, we can split Strength into *InStrength* – the sum of all absolute incoming edge weights – and *OutStrength* – the sum all absolute outgoing edge weights. InStrength characterizes how strongly a variable is influenced by other variables in the network, while OutStrength indicates how much influence the variable exerts on other variables.

A particular focus of this study was on the role of rumination in the networks of symptoms. Consequently, the third subquestion aimed at rumination and its effects on the networks. In answering this subquestion, we relied on rumination's centrality and the weights of the edges connecting it with other nodes in the network.

The next subquestion concerned the overall connectivity of a network. The more densely a network's nodes are interconnected, the more easily the network is tipped into a stable state. In a network of symptoms of depression, this translates into a greater risk of slipping into acute depression. The overall connectivity of a network can be specified by its *Global Strength*. Global Strength is the sum of all absolute edge weights in the network.

In network analysis, it is essential to determine the stability of a network. That is, whether the results are likely to be reproducible. Currently, there is no agreed-upon method of assessing the stability of temporal networks. As a consequence, in this study, we created our own network stability test based on permutation testing. This entailed shuffling the node labels per subject and fitting a new network on the permuted data set. For each network, 1,000 such permutations were performed. The centrality values, edge weights, and Global Strength for each permuted network were recorded, approximating an outcome distribution for each statistic. The statistics associated with the true network were then compared to the approximated distribution. If the true statistic was more extreme than 97.5% of the permutation outcomes (i.e., $\alpha = 2.5\%$), the statistic was deemed significant or stable.

The final subquestion aimed at comparing two networks. For the first research question, this meant comparing the baseline networks of the rMDD group with those of the HC group. In contrast, the second research question involved comparing the networks at baseline with those during the intervention phase for either intervention condition. As with stability tests, there is no state-of-the-art network comparison test for temporal networks. Therefore, we adapted our network stability test to function as a network comparison test. Instead of shuffling node labels, subjects were randomly placed either in the rMDD or the HC group. After that, new networks were estimated for either group, and the difference between the groups for the relevant statistics was recorded. The true difference score was compared to the approximated distribution to determine its significance ($\alpha = 2.5\%$).

Given the exploratory nature of network analysis, it should be combined with other methods to minimize the risk of drawing fallacious inferences. As a result, we created mixed-effects models with rumination, negative affect (mean of sadness, irritation, anxiety, and restlessness), and positive affect (mean of energy, wakefulness, and satisfaction) as the response variable, respectively. In particular, we employed Generalized Additive Mixed Models (GAMM) because they allow for nonlinearity and the inclusion of random effects.

The best-fitting models were selected in three steps: First, we checked for the best random-effects structure. We built the most complex models admissible by the study design regarding random- and fixed-effects structure. The best-fitting model structure was determined using backward selection. The models were determined using only the baseline assessment data. To determine the effects of the interventions, we applied the same models to the peri-intervention data with two changes. Instead of the raw data, we used change scores. That is, we used the deviations from the subject-level baseline assessment mean of every variable. In addition, the models were extended by the intervention predictor.

Finally, we investigated the relationship between the SART response times and mental health status, rumination, distraction, and negative and positive affect. First, we looked at the relationship between the response times per trial and the mental health group. To do so, we used only the SART data at baseline. We used backward selection to determine the best-fitting model. Subsequently, we combined the SART and ESM data to be able to incorporate the ESM variables. However, since participants were asked to complete the SART twice daily at their convenience, the sessions were not necessarily performed immediately before or after an ESM assessment. Consequently, the SART sessions had to be matched with the closest ESM assessment in time. Instead of the response times per trial, moreover, we used the mean response times per session. With the combined data, we created models to predict rumination and distraction, using the mean response times and the commission error rate (proportion of incorrectly completed no-go trials) per game as predictors. Since we had fewer SART sessions than ESM assessments, these models were based on smaller data sets. Therefore, we used Bayes factors (Dienes, 2014) to determine whether our data was sufficiently reliable to draw solid conclusions. In the same way, we also investigated the effects of mindfulness and fantasizing in the peri-intervention phase.

All analyses were conducted using R version 4.1.2 (R Core Team, 2022). Mixed-effects models were created using lme4, version 1.1.28 (Bates, 2010), mgcv, version 1.8.31 (Wood, 2011), and itsadug, version 2.4 (van Rij et al., 2022). For network analysis, we used mlVAR, version 0.5 (Epskamp, Waldorp, et al., 2018), and qgraph, version 1.9.1 (Epskamp et al., 2012).[1].

[1] All scripts can be found at https://github.com/le-clemo/EMA-mindfulness

Table 3
Response Rates by group

Group	N_{Subj}	N_{Resp}	M	SD	$Q_{0.1}$	$Q_{0.9}$
Control	23	3933	0.68	0.18	0.51	0.87
Remitted	16	2418	0.66	0.19	0.42	0.85
Total	39	6351	0.67	0.18	0.48	0.87

Results

This study aimed to determine the relationships between several affective and cognitive symptoms commonly implicated in depression and how these symptoms and their connections change after training in mindfulness and positive fantasizing, respectively. This section will first introduce the data collected via the Experience Sampling Method (ESM) and the sustained attention to response task (SART). Next, the results pertaining to our research question are laid out.

ESM Data

The data consisted of a total of 39 subjects who submitted a total of 6,351 responses via the ESM app. As shown in Table 3, the healthy control (HC) group responded at a higher rate (0.68) than the remitted MDD (rMDD) group (0.66). This difference is statistically significant, $\chi^2(1) = 5.92$, $p = .015$. In general, response rates dropped significantly from block 1 (0.72) to block 2 (0.61), $\chi^2(1) = 143.65$, $p < .001$, as well as within each block from the baseline assessment (0.71) to the peri-intervention phase (0.64), $\chi^2(1) = 53.36$, $p < .001$.

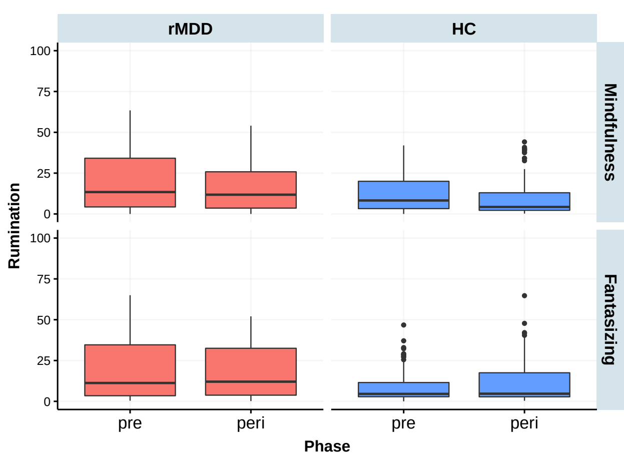

Figure 2
Daily average rumination scores per group (left column: rMDD; right column: HC), intervention (top row: Mindfulness; bottom row: Fantasizing), and phase (left: baseline; right: peri-intervention).

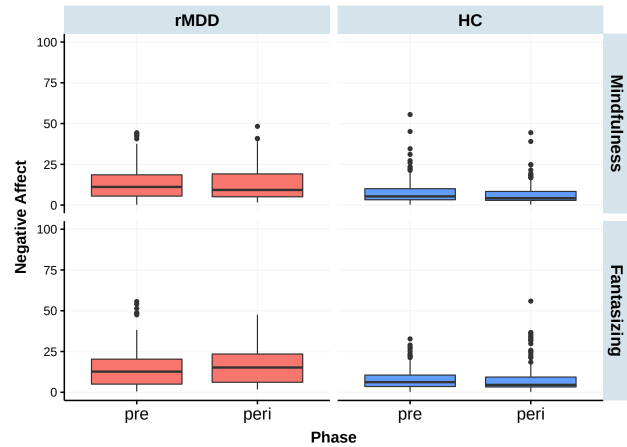

Figure 3
Daily average negative affect per group (left column: rMDD; right column: HC), intervention (top row: Mindfulness; bottom row: Fantasizing), and phase (left: baseline; right: peri-intervention).

Figure 2 shows the daily average rumination scores per group, intervention, and phase. Comparing the groups (i.e., the columns), we can see that the rMDD group, on average, shows higher levels of rumination than the HC group. Comparing the baseline (pre) with the peri-intervention phase (peri), there seems to be a lowering effect of both interventions on the average rumination level in the rMDD group. In the control group, the mindfulness intervention appears to lower rumination, whereas the positive fantasizing interven-

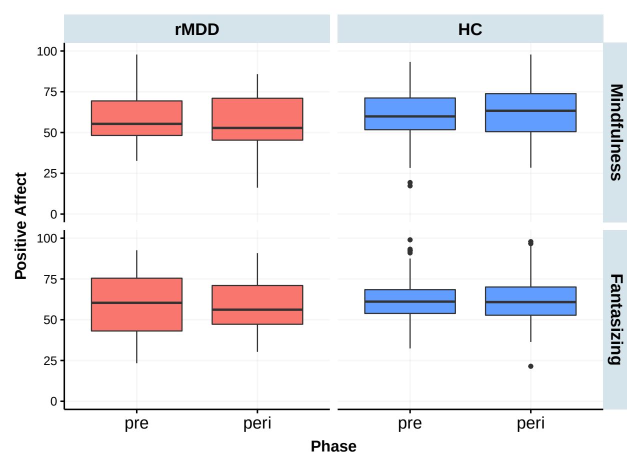

Figure 4
Daily average positive affect per group (left column: rMDD; right column: HC), intervention (top row: Mindfulness; bottom row: Fantasizing), and phase (left: baseline; right: peri-intervention).

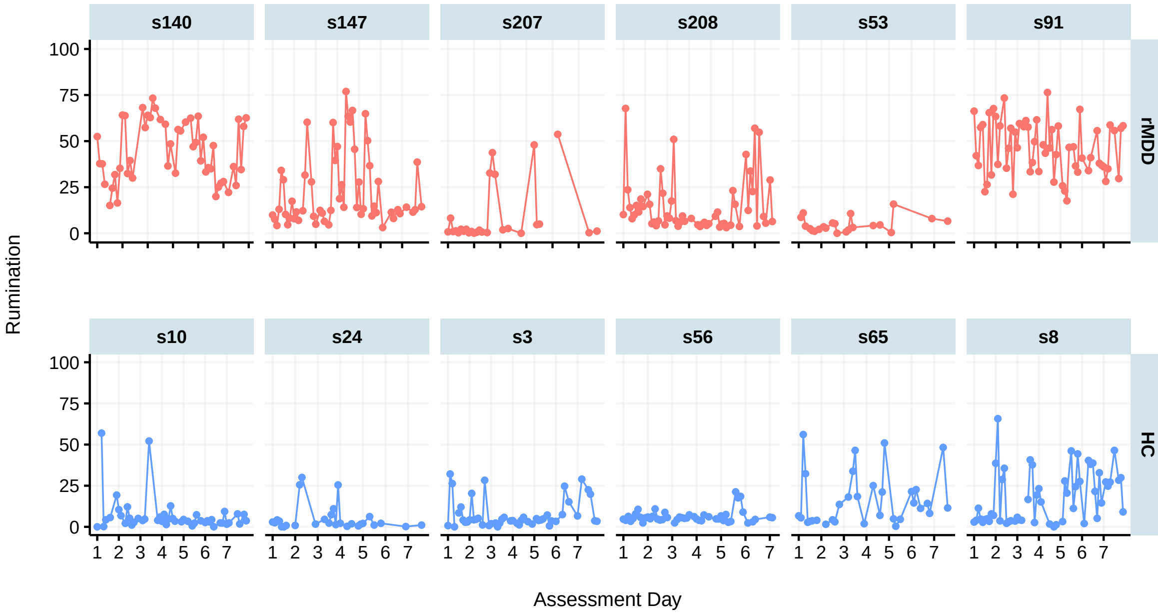

Figure 5

Rumination over the course of the baseline assessment period (block 1 only) for six randomly selected individuals for the rMDD (top) and the HC group (bottom).

tion does not.

Figure 3 depicts the negative affect scores per mental health status group, intervention, and phase. Comparing the groups, we find that negative affect is noticeably higher in the rMDD group. There is no noticeable difference between the baseline and the peri-intervention phase for either intervention condition. Figure 4 shows the same information for the positive affect scores. We neither find a striking difference between the two groups nor in the effects of the intervention conditions. Importantly, however, there are significant differences between participants, both between and within groups and within individuals over time. This is illustrated in Figure 5, which shows the rumination levels over the course of the baseline assessment period for six randomly selected individuals per group. While, on the whole, the individuals in the rMDD group indicate higher levels of rumination, s53, for example, has low levels of rumination throughout the baseline assessment period despite being in the rMDD group. Furthermore, some remitted subjects (e.g., s140 and s91) constantly display high levels of rumination, whereas others (e.g., s208) show low levels of rumination with occasional spikes. In the control group, most individuals only rarely indicated elevated levels of rumination.

A similar picture is presented in Figure 6. It depicts the negative affect levels during the baseline assessment period for the same six subjects featured in Figure 5. As with rumination, the individuals in remission from depression indicate experiencing much higher levels of negative affect than the healthy controls. Again, however, there are striking differences between individuals. s140, for example, shows very high levels of negative affect throughout the baseline assessment period, while s53 indicates hardly experiencing any negative affect. In the HC group, all subjects reported negative affect levels somewhat similar to s53. Even so, we see that some healthy subjects report more occasional spikes in negative affect than others. Overall, levels of rumination and negative affect vary vastly between individuals. In addition, for some individuals, we can visually discern phases of, for example, differing levels of rumination, even just within the seven-day assessment period.

Instead of investigating rumination and negative affect over time, we can also look at them as a function of another time-varying variable, for example, the unpleasantness of the most negative event since the last measurement. Figure 7 illustrates differences in individuals' reactions to unpleasant events regarding rumination and negative affect, respectively. In general, the rMDD group may tend to report slightly more unpleasant negative events than the control group. In all subjects but s53 (curiously enough found in the remitted MDD group), the relationship indicated by the linear regression line between rumination and the unpleasantness of a recent negative event is positive. However, there are differences in the slope of this regression line, further revealing considerable diversity across participants. Naturally, the exact nature of this relationship is unclear and may be mediated by other variables. While these inter-individual differences are no-

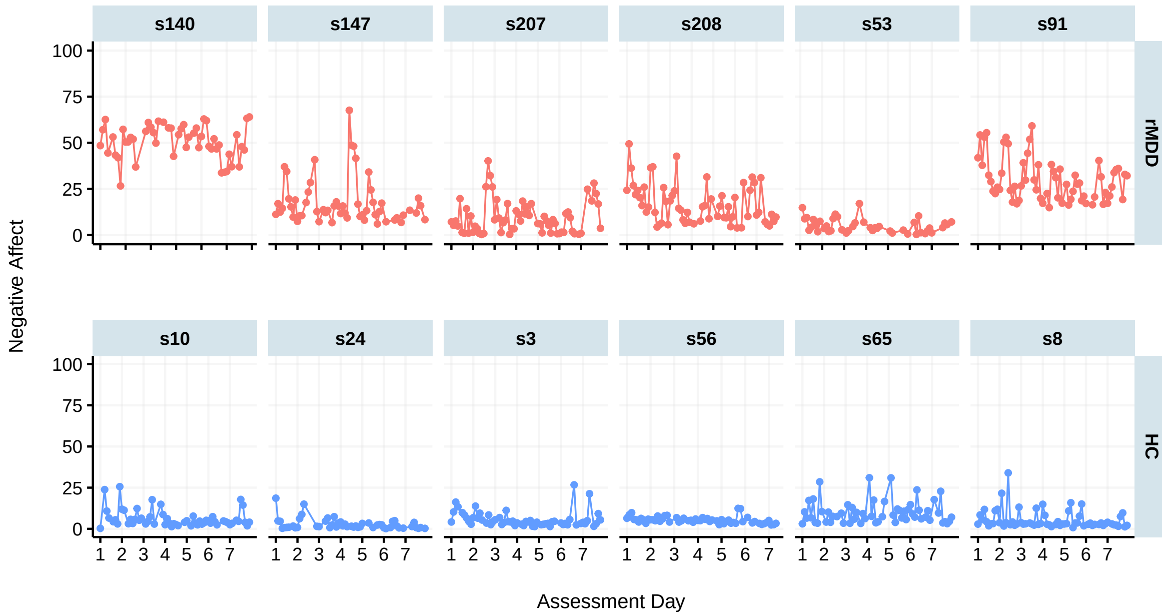

Figure 6
Negative affect over the course of the baseline assessment period (block 1 only) for six randomly selected individuals for the rMDD (top) and the HC group (bottom).

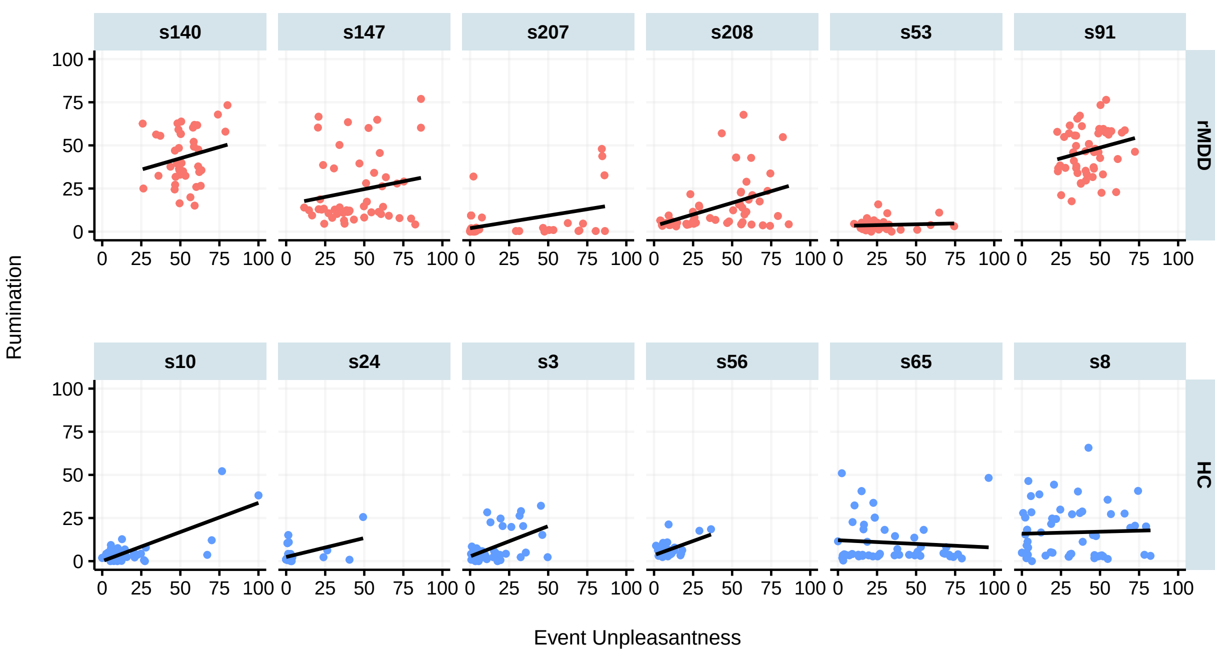

Figure 7
Rumination as a function of the unpleasantness of the most negative event since the previous measurement for six randomly selected individuals for the rMDD (top) and the HC group (bottom) in the baseline assessment phase.

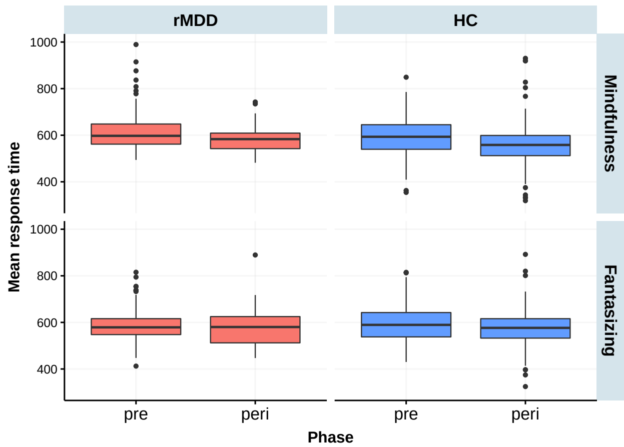

Figure 8

Average response time per SART session split by group (left column: rMDD; right column: HC), intervention (top row: Mindfulness; bottom row: Fantasizing), and phase (left: baseline; right: peri-intervention).

table in and of themselves, they are additionally crucial to consider in our further analysis since they would otherwise distort our results, and therefore, the conclusions we might draw.

SART Data

A total of 35 subjects completed at least one SART session. Fourteen were part of the rMDD group, and 21 were part of the HC group. Together, these participants submitted 589 completed sessions, corresponding to 28,221 individual trials. Figure 8 depicts the average response times per SART session split by the mental health status group, intervention condition, and phase. While there is no immediately obvious difference in mean response times between the two groups, the boxplots hint at a lowering effect of mindfulness on the mean response times of both the rMDD and the HC group. By contrast, in the fantasizing condition, the mean response times appear to be about the same at baseline and peri-intervention for either group.

Group Differences

This section presents the results pertaining to the first research question. It concerns the differences in symptom connectivity between the rMDD and the HC group. As mentioned previously, network analysis is mainly an exploratory tool. Consequently, we opted to run regression analyses before conducting network analyses to limit the probability of drawing false inferences from the networks. First, we used linear mixed-effects models to determine the extent to which the mental health status group can explain within- and between-subject variability. Next, Generalized Additive Mixed Models (GAMM) predicting rumination, negative affect, and positive affect were constructed. Finally, the actual symptom networks were created for either group and contrasted with one another.

Regression Analysis

As the first step, we examined to what extent the variability in our variables of interest is due to within- and between-person differences. Toward this goal, a simple intercept model with a random intercept was created for rumination, negative affect, and positive affect, respectively. The general structure of these models is given by

$$y_{ij} = \mu + u_i + \epsilon_{ij}, \tag{1}$$

where y_{ij} denotes the observed outcome of the *ith* subject at the *jth* assessment moment. μ is the model intercept (i.e., the average outcome), u_i is the random intercept (the average adjustment of the model intercept per participant), and ϵ_{ij} is the error term. For each of these models, only the baseline assessment phases are considered. The intraclass correlation coefficient (ICC) gives us the proportion of the variance explained by between-person effects. For the variable rumination, the ICC is 0.54, meaning that slightly more than half of the variability in the data is attributable to between-person effects. Naturally, the remaining half is explained by within-person effects. The ICCs for negative and positive affect are similar, standing at 0.59 and 0.50, respectively. This indicates that random effects need to be considered in our data analysis.

Next, we were interested in determining the extent to which the mental health status group (*group* for short) could account for between- and within-person variability. To do so, we created models that included it as a predictor. We found significant effects on rumination and negative affect but not on positive affect. On average, participants in the rMDD group reported a 10.85 points higher level of rumination than those from the HC group, $t(3073) = 2.28$, $p = 0.023$. The difference was even more pronounced for negative affect, for which rMDD subjects indicate an average of 26.49 points greater levels, $t(3073) = 2.11$, $p = 0.035$. By contrast, being part of the rMDD group led to an average reduction of positive affect by 9.84 points. However, this difference is not statistically significant, $t(3073) = -0.79$, $p = 0.426$). Comparing the between-subject variability of the intercept models with the extended models', we can determine how much of this variability is accounted for by the newly included group variable. The mental health status explains 13.11% of the between-subject variability in rumination and 9.26% in negative affect. For positive affect, the group did not explain any of the between-subject variability for this variable.

As Figure 7 demonstrates, there are differences in how individuals react to the unpleasantness of a recent event. Con-

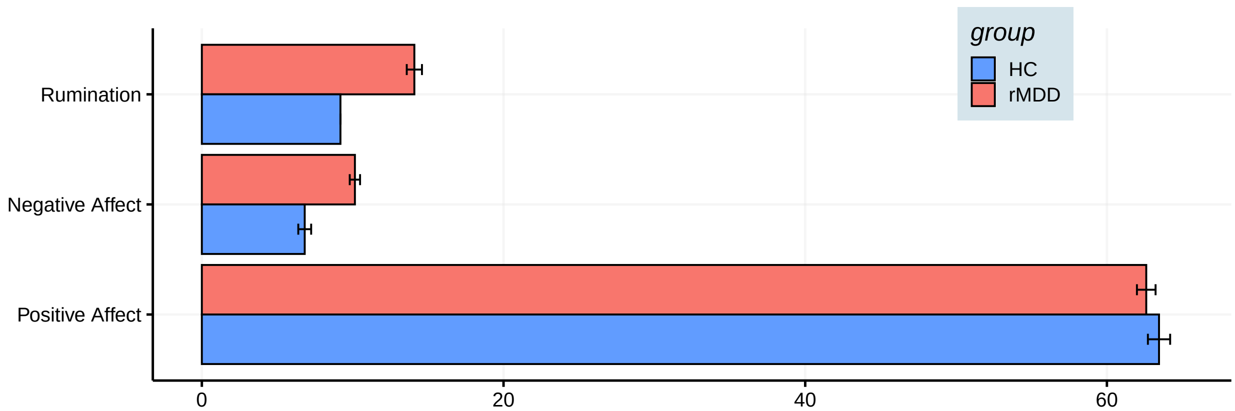

Figure 9
Estimated effects of the mental health status group on rumination (top), negative affect (middle), and positive affect (bottom) at baseline.

sequently, we wanted to investigate how much of the within-subject variability can be explained by event unpleasantness. The comparison between the models suggests that 10.06% of the within-subject variability in rumination is accounted for by the level of the unpleasantness of the most negative event since the last assessment. For negative and positive affect, the unpleasantness of such an event explains 16.60% and 9.11% of momentary fluctuations, respectively. The same analysis was conducted using the pleasantness of the most positive event since the last measurement. The results indicated that event pleasantness accounts for 7.57%, 7.22%, and 24.59% of within-subject variability in rumination, negative affect, and positive affect, respectively. Subsequently, we extended the models by the group predictor. However, this failed to explain any additional variability in the association between event unpleasantness and either outcome variable. While it did explain an additional 6.52% of the variability in event pleasantness and negative affect, it also failed to do so for either rumination or positive affect.

Next, we turn to the analysis of the associations between different symptoms and time. Toward this goal, we created three regression models, predicting our main symptoms of interest – rumination, negative affect, and positive affect – in turn. Assuming linearity may be problematic, especially when incorporating time as an additional predictor. Therefore, we used GAMM. They are a statistical method capable of separating inter- from intra-individual effects and handling nonlinearity.

The first model used rumination as its response variable. After backward selection, the model included the main effect for the group, smooths per group for assessment number, pleasantness of the current company, event pleasantness, event unpleasantness, sleep quality, and current levels of distraction, listlessness, and stickiness of thought. In addition, smooths per group were included for negative and positive affect. The random-effects structure consisted only of a random factor smooth for the assessment number per subject. No significant auto-correlation was found.

The resulting model parametric coefficient was the main effect for the mental health status group. As Figure 9 (top) depicts, the healthy controls, on average, reported 4.90 points less rumination than the remitted MDD individuals. This test result was found to be statistically significant, $t(1197.708) = -7.78$, $p < .001$. The effect size for this analysis ($d = 0.45$) was found to be small according to Cohen's (1988) convention.

The next model's response variable was negative affect. This model's fixed effects comprised the main effect for group, smooths for assessment number per group, rumination per group, and positive affect per group. Furthermore, it included smooths for the level of stickiness, distraction, listlessness, sleep quality, and company pleasantness. Again, no significant auto-correlation was found. This model suggested that the HC group reported an average of 3.33 points less negative affect than the rMDD group (see middle of Figure 9). The test result reached statistical significance, $t(1169.376) = -7.79$, $p < .001$. This effect was found to be small ($d = 0.47$).

The third model predicted positive affect (see Figure 9 bottom). It contained the main effect for the group, a smooth per group for assessment number, rumination, and event pleasantness and unpleasantness. Furthermore, it included smooths for negative affect, stickiness, distraction, listlessness, sleep quality, and company pleasantness. As with the previous models, no significant auto-correlation was detected. Unlike the other models, there was no significant effect of group on the response variable, $t(1147.329) = 1.148$,

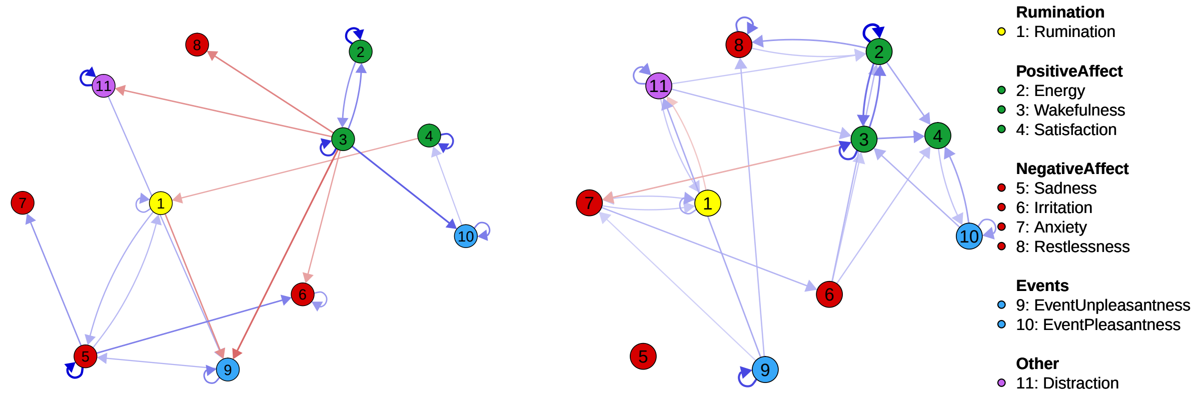

Figure 10

Temporal networks at baseline. Left: rMDD group (N = 21); right: HC group (N = 38).

$p = 0.251$.

Network Analysis

We decided to conduct network analysis to explore the relationships between the symptoms more holistically. Multilevel vector autoregressive modeling (mlVAR) was used to estimate both temporal and contemporaneous networks. We started by estimating the networks of either mental health status group during the baseline assessment period. In describing the results, we limited ourselves to mentioning only nodes and edges that reached statistical significance. The results of the stability analysis, as well as the comparison tests, can be found in Appendix B.

Figure 10 depicts the temporal networks for the rMDD group (left) and the HC group (right). In the HC network, four nodes had significant InStrength: all three positive affect measures – satisfaction (0.39), wakefulness (0.38), energy (0.36) – and the negative affect measure anxiety (0.21). Satisfaction received significant positive effects from energy, wakefulness, and event pleasantness. Wakefulness was also positively influenced by energy and event pleasantness. Energy was significantly positively influenced by itself and wakefulness. The only significant temporal effect on anxiety was the negative effect of wakefulness. Unsurprisingly, wakefulness (0.36), alongside energy (0.37), also possessed significant OutStrength – all of its significant outgoing effects were already mentioned. In addition to its effects mentioned above, energy increased reports of restlessness at the next measurement. Furthermore, irritation (0.21), event unpleasantness (0.23), and distraction (0.20) had significant OutStrength. Irritation significantly positively influenced energy, whereas event unpleasantness positively affected distraction and restlessness. Rumination's only significant effect is a negative one on distraction at the next measurement occasion. Overall, 13 of 23 edges were statistically significant. Globally, the network had a Strength of 0.87, which reached significance ($p = .011$).

In the rMDD network, event unpleasantness is the only node with statistically significant InStrength (0.42). Both rumination and wakefulness significantly negatively affected event unpleasantness at the next measurement occasion. In contrast, wakefulness (OutStrength: 0.91) and sadness (0.37) significantly influenced other nodes in the network. Wakefulness significantly increased energy and event pleasantness but lowered irritation, restlessness, distraction, and event unpleasantness. By contrast, the effects of sadness are solely positive, significantly increasing anxiety and irritation. In this network, rumination's significant effects are limited to reducing event unpleasantness and increasing sadness. Of the 16 edges present in the rMDD network, 10 reached statistical significance. The network's Global Strength was statistically significant (1.41, $p = .010$)

Comparing the networks, only a few differences reached statistical significance. The networks' Global Strengths (0.54, $p = 0.60$) were not found to be significantly different. Furthermore, there were no significant differences in centrality. Only 3 of the 46 edges significantly differed in the two networks. The positive self-loops of satisfaction and sadness were significantly more substantial in the rMDD group. However, neither of them was significant in the rMDD network itself. Conversely, the positive edge from distraction to wakefulness was significant in the HC network and was significantly different in the two networks.

Figure 11 shows the contemporaneous networks at baseline for the rMDD group (left) and the HC group (right) that are estimated from the residuals of the temporal networks. In the contemporaneous HC network, all but the nodes for anxiety and distraction reached statistically significant Strength. The three most central nodes were wakefulness (1.02), satisfaction (0.79), and restlessness (0.82). All of the associations of wakefulness were significant – its positive ones with the other positive affect measures and event pleasantness as well

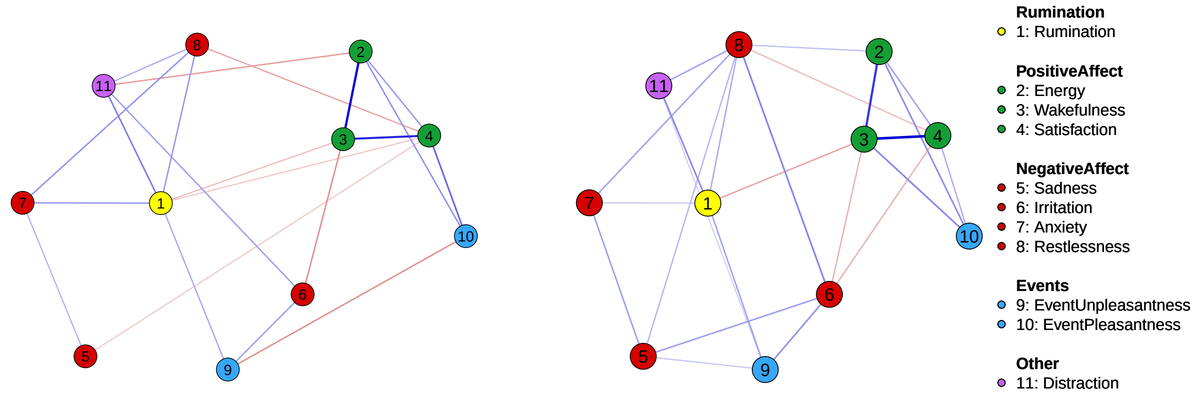

Figure 11
Contemporaneous networks at baseline. Left: rMDD group (N = 21); right: HC group (N = 38).

as its negative ones with irritation and rumination. Satisfaction, likewise, had significant positive links to the other positive affect measures and negative ones to irritation and restlessness. Restlessness had other positive associations with irritation and distraction. Rumination possessed a Strength of 0.60. It showed significant positive connections with event unpleasantness and distraction and a negative one with wakefulness. In sum, 17 of 24 edges were significant. The network's Global Strength (3.26, p = .010) reached statistical significance.

In the contemporaneous rMDD network, 9 of the 11 nodes reached statistically significant Strength. The most central nodes were the positive affect measures satisfaction (0.90), wakefulness (0.86), and energy (0.75), followed by rumination (0.74). Satisfaction showed significant negative associations with rumination and restlessness and positive ones with event pleasantness and wakefulness. Wakefulness itself had an additional positive link to energy and negative ones to rumination and irritation. Besides its positive connection to satisfaction and wakefulness, rumination's only other significant connection is a positive one with distraction, which is significantly negatively affected by energy. Of the 21 edges present in the network, 13 were statistically significant. The network's Global Strength was significant (3.08, p = .003).

Comparing the networks, we find no statistically significant differences in terms of Strength or Global Strength. The only statistically significant difference between the networks was a positive association between irritation and distraction, which was only found in the rMDD network. However, this association was not found to be significantly stable in the rMDD network itself.

SART Analysis

We were also interested in investigating the relationship of subjective measures with the possibly related objective measures obtained via the SART. The best-fitting model predicting the response times per SART trial had a random intercept per subject and a fixed-effects structure consisting of the mental health status group, whether it was a go or no-go trial (isGo), the interaction between mental health status and isGo, and the SART session number. All effects were found to be statistically significant but very small. The rMDD group, on average, took 159.43 ms longer to complete a trial, $t(15322) = 3.658$, $p < .001$; $d = 0.06$. In general, the reaction time on go trials was 56.19 ms slower than on no-go trials, $t(15322) = 2.304$, $p = 0.021$; $d = 0.04$. Of course, correctly completed no-go trials have no response time. Thus, this implies that when participants incorrectly treated a no-go trial as a go trial, they were quicker to respond than on true go trials. The interaction of the rMDD group and go trial resulted in 128.91 ms faster response times compared to the HC group and no-go trial, counteracting some of the main effects for the mental health status group and go trials, $t(15322) = -3.958$, $p < .001$; $d = 0.09$. The more trials individuals completed, the faster they got on average. Every additional trial led to an average decrease in response time by 2.60 ms, $t(15322) = -5.582$, $p < .001$; $d = 0.06$.

Next, we used the combined SART and ESM data to predict rumination and distraction. The model for rumination comprised the mental health status, the SART session number, their interaction, the levels of distraction, negative and positive affect, the mean response times, and the commission error rate (i.e., incorrectly completed no-go trials) per SART session. Moreover, a random intercept per subject was included. Only the two affect measures were estimated to have a significant effect. A one-point increase in negative affect was associated with a 0.41 points increase in rumination, $t(232) = 4.680$, $p < .001$. This was a medium-sized effect, $d = 0.62$. Conversely, the same increase in positive affect was associated with a 0.15 points decrease in rumination, $t(232) = -2.791$, $p = .006$. This effect was small, $d = 0.37$. With this analysis, we were mainly interested in

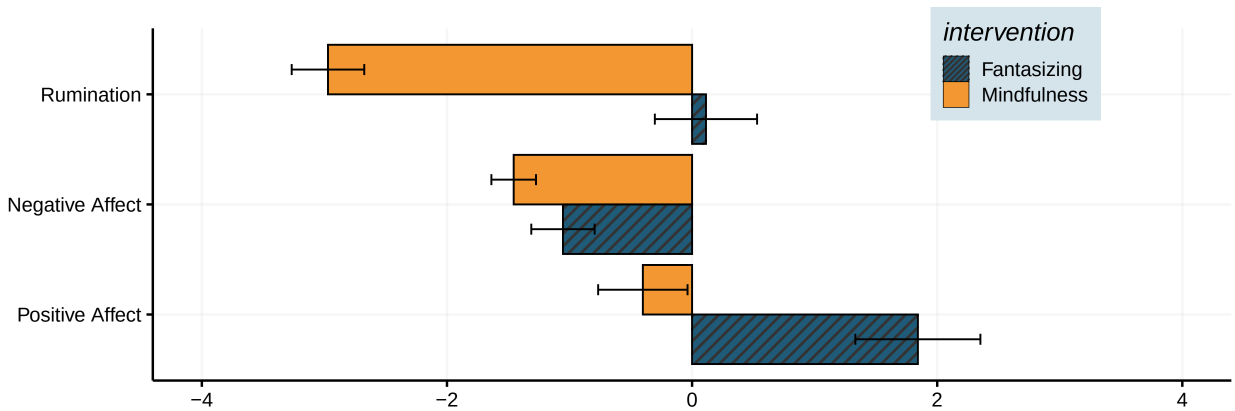

Figure 12
Estimated effects of the intervention condition on rumination (top), negative affect (middle), and positive affect (bottom) peri-intervention.

the relationship between rumination and response time and the commission error rate. Neither of the two relationships reached significance. Following the convention set by Jeffreys (1998), the Bayes factors associated with the mean response times (0.321) and the commission error rate (0.254) indicate that these results are conclusive. Our data is sufficiently reliable to conclude that neither predictor is significantly associated with rumination. Note, however, that the Bayes factor for the mean response times is quite close to the cut-off value of 1/3. The same model was used to predict distraction, replacing distraction with rumination as a predictor. The sole significant term in this model was negative affect. A one-point increase in negative affect resulted in a 0.59 points increase in distraction, $t(232) = 4.172$, $p < .001$; $d = 0.56$. The Bayes factor for the mean response time (0.377) suggests an inconclusive result, whereas the commission error rate (0.322) suggests a conclusive one if strictly sticking to the convention.

Intervention Effects

The second research question was concerned with the effects of mindfulness and positive fantasizing training on the network of symptoms of all participants combined. We first applied the baseline GAMMs to the peri-intervention phase to answer this question. After that, we created the baseline and peri-intervention networks per intervention and compared them.

Regression Analysis

We replaced the group predictor with the intervention condition to apply the baseline models to the peri-intervention phase. Moreover, instead of the normal values, we used change scores. We calculated the mean scores per subject for the baseline period and subtracted them from that subject's peri-intervention scores.

The rumination model for the peri-intervention period had one parametric coefficient – the main effect of intervention. This effect was statistically significant but small, $t(1110.87) = 7.394$, $p < .001$; $d = 0.44$). Figure 12 (top) portrays the model estimates. On average, the individuals in the fantasizing condition reported a 3.08 points smaller decrease in rumination than those in the mindfulness condition. In sum, the individuals that received mindfulness training reported a significant decrease in rumination, whereas the participants in the fantasizing condition did not report a significant change in either direction. We created another model that included the mental health status group as a predictor. The main effect for group ($t(1048.06) = -0.518$, $p = .604$) and the interaction term ($t(1048.06) = 1.556$, $p = .120$) did not reach statistical significance. By contrast, the main effect for intervention was statistically significant, albeit very small, $t(1048.06) = 3.122$, $p = 0.002$; $d = 0.19$. According to this extended model, on average, participants receiving the fantasizing intervention reported a 2.41 points smaller decrease in rumination than the ones receiving mindfulness training. The estimated effects are depicted in Figure 13 (top).

In the negative affect model that included only the intervention condition as a parametric coefficient, the effect of the intervention was estimated to be insignificant, $t(1109.677) = 1.556$, $p = .120$. As Figure 12 shows, overall, both interventions led to a decrease in negative affect compared to the baseline means. We also extended the negative affect model with the group predictor. Unlike in the extended rumination model, all three parametric coefficients reached statistical significance in this model. All three effects are small or very small according to Cohen's (1988) convention. Compared to

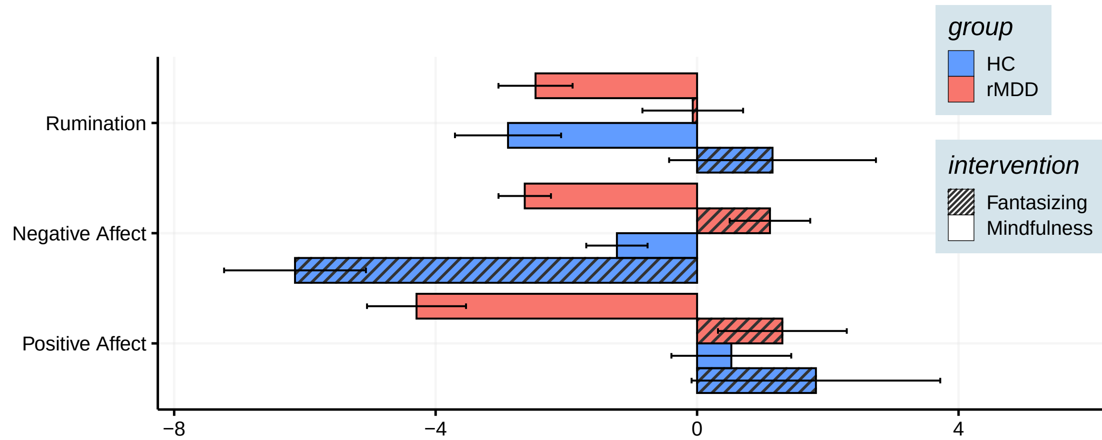

Figure 13
Estimated effects of mental health status and intervention condition on rumination (top), negative affect (middle), and positive affect (bottom) peri-intervention.

the rMDD participants, the model suggests that subjects in the control group reported a 1.41 points smaller decrease in negative affect on average, $t(1018.039) = 3.006$, $p = .003$, $d = 0.18$. Subjects in the positive fantasizing condition report 3.75 points smaller decrease in negative affect, $t(1018.039) = 6.092$, $p < .001$, $d = 0.37$. As shown in Figure 12, negative affect is significantly reduced in both conditions. Interestingly, the interaction between the HC group and positive fantasizing reverses the main effects. On average, and compared to the rMDD group receiving the mindfulness intervention, these participants reported an 8.68 points greater decrease in negative affect, $t(1018.039) = -7.422$, $p < .001$, $d = 0.45$. Consequently, while mindfulness reduced negative affect for both groups, positive fantasizing decreased negative affect in the HC group but increased it in the rMDD group.

The positive affect model estimated a very small significant effect of intervention on positive affect in both groups combined, $t(1122.055) = 4.399$, $p < .001$; $d = 0.09$. On average, the participants in the fantasizing condition reported a 2.24 points greater increase in positive affect than the participants in the mindfulness condition. This difference is depicted in Figure 12 (bottom). Extending the model with the mental health status group, the results become more interesting. The main effects of group and intervention and their interaction were significant. On average, controls reported a 4.82 points greater increase in positive affect than remitted individuals, $t(1063.529) = 5.254$, $p < .001$, $d = 0.32$. Similarly, participants in the fantasizing condition indicated a 5.60 points greater increase in positive affect levels, $t(1063.529) = 5.681$, $p < .001$, $d = 0.34$. The interaction term, again, cancels some of the main effects. The interaction between the HC group and fantasizing led to a 4.30 points greater decrease in levels of positive affect compared to remitted individuals receiving mindfulness training, $t(1063.529) = -3.531$, $p < .001$, $d = 0.21$. As depicted by Figure 13, while positive fantasizing tended to increase positive affect in either group, mindfulness lowered it in the rMDD group.

Network Analysis

Figure 14 shows the temporal networks for the mindfulness condition at baseline (left) and peri-intervention (right). In the baseline network, satisfaction is the only node with significant InStrength (0.27), and energy is the only node with significant OutStrength (0.95). Satisfaction received a significant positive influence from wakefulness and event pleasantness. Energy had a significant positive influence on wakefulness and itself. Rumination only showed one significant negative outgoing connection with distraction and one incoming one with wakefulness. In total, 12 of the 20 edges were statistically significant. The network's Global Strength reached significance (1.06, $p = .001$).

In the peri-intervention network, wakefulness (0.44), satisfaction (0.45), and event pleasantness (0.55) had significant InStrength. Wakefulness showed significant incoming connections with energy and satisfaction. Satisfaction, in turn, was significantly positively influenced by event pleasantness, which itself received significant positive influence from every positive affect measure and significant negative influence from rumination. This was rumination's only connection in the peri-intervention network. In total, 12 out of 20 edges reached significance. Furthermore, the network's Global Strength was statistically significant (0.95, $p = .001$)

The comparison test did not reveal significant differences between the baseline and the peri-intervention network.

Figure 15 depicts the contemporaneous networks for the

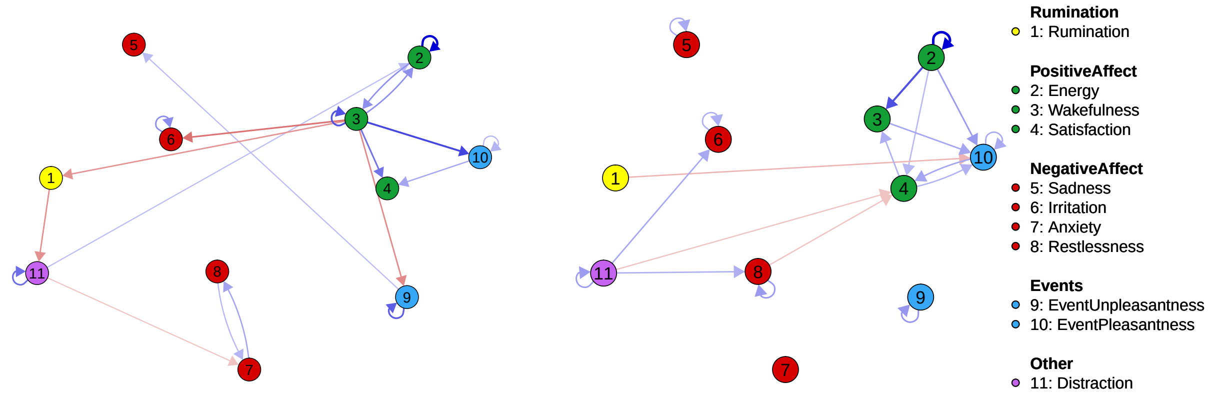

Figure 14
Temporal networks of the mindfulness condition. Left: baseline (N = 27); right: peri-intervention (N = 27).

mindfulness intervention condition at baseline (left) and during the intervention (right). In the baseline network, 6 of the 11 nodes were found to possess significant centrality, among them rumination (0.66), wakefulness (0.92), and satisfaction (0.76). Rumination's significant associations were restricted to positive ones with distraction and event unpleasantness and a negative one with wakefulness. Wakefulness, in addition, had positive connections with energy, satisfaction, and event pleasantness, as well as a negative one with irritation. Satisfaction was, additionally, positively associated with energy, event pleasantness, and restlessness. Overall, 10 out of 19 edges were found to be statistically significant. The network's Global Strength was also significant (2.97, p = .012).

In the peri-intervention network, 5 nodes showed significant Strength. Wakefulness (1.00), satisfaction (0.62), and event pleasantness (0.74) were the most influential. Wakefulness had significant positive associations with energy and satisfaction and negative ones with sadness and restlessness. Satisfaction had an additional significant negative association with restlessness and a positive association with event pleasantness. Besides its positive connection with satisfaction, event pleasantness' only other significant association was the positive one with energy. Out of the 22 edges in the network, 12 were found to be statistically significant. The network's Global Strength of 2.51 was also significant (p = .012).

The comparison test did not reveal statistically significant differences between the baseline and the peri-intervention network.

Figure 16 shows the temporal networks for the fantasizing condition at baseline (left) and peri-intervention (right). Only energy (0.28) and wakefulness (0.31) in the baseline network had significant InStrength. Energy was significantly influenced by wakefulness and itself. Wakefulness, by contrast, received significant influence from energy and event pleasantness. Only two nodes significantly influenced other nodes in the network: energy (0.36) and rumination (0.32). While energy positively influenced all positive affect measures as

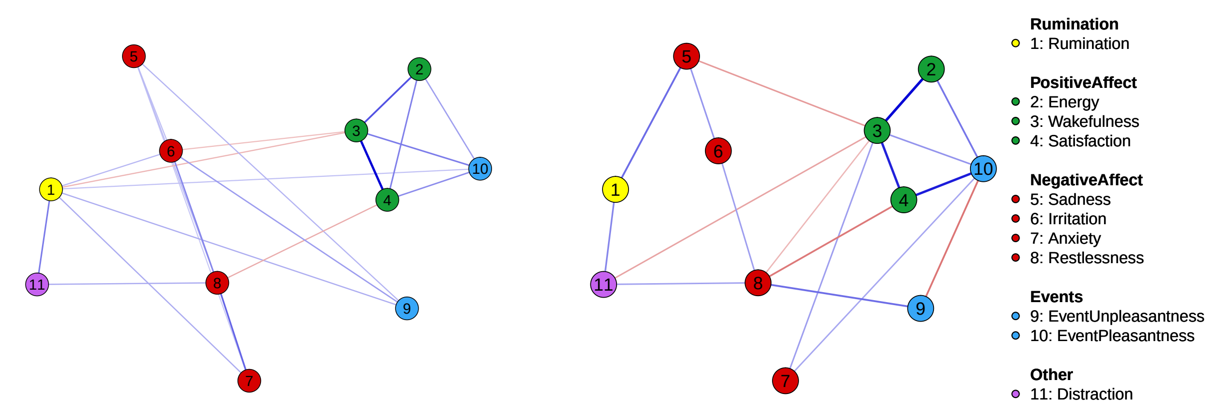

Figure 15
Contemporaneous networks of the mindfulness condition. Left: baseline (N = 27); right: peri-intervention (N = 27).

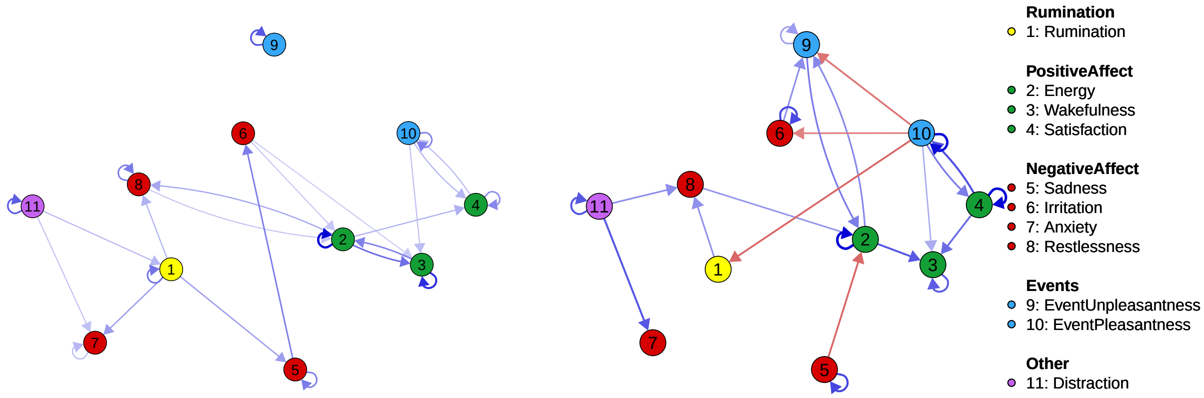

Figure 16

Temporal networks of the positive fantasizing condition. Left: baseline (N = 32); right: peri-intervention (N = 31).

well as restlessness, rumination had significant positive influence on the negative affect measures sadness, anxiety, and restlessness. In total, twelve out of 26 edges were found to be significant. The Global Strength of the network reached statistical significance (0.91, $p = .003$).

In the peri-intervention network, like the baseline network, energy (0.30) and wakefulness (0.30) had significant InStrength. However, in the peri-intervention network, only event pleasantness (0.48) showed significant OutStrength. Energy was significantly positively influenced by event unpleasantness and significantly negatively by sadness. In contrast, wakefulness only received a significant positive influence from energy and satisfaction. Event pleasantness' effects were solely negative – significantly lowering rumination, irritation, and event unpleasantness at the next measurement point. Out of 24 edges, 10 reached statistical significance. The network's Global Strength failed to reach statistical significance (0.63, $p = .113$).

Comparing the two networks, we did not find any statistically significant differences.

In Figure 17, we see the contemporaneous networks in the fantasizing condition at baseline (left) and during the intervention (right). In the baseline network, every node's centrality reached statistical significance. Wakefulness (1.15), energy (0.84), and restlessness (0.81) possessed the greatest Strength values. Wakefulness showed significant positive associations with satisfaction and energy and negative ones with sadness and irritation. Energy, by contrast, had significant positive connections with wakefulness and event pleasantness. Additionally, it showed a negative association with distraction. Rumination had a significant negative relationship with wakefulness. Moreover, it was significantly positively associated with restlessness and distraction. In sum, 17 of 27 edges were significant. The network's Global Strength was also statistically significant (3.59, $p = .003$).

In the peri-intervention network, we find significant centrality values for all nodes except for sadness and distraction. As in the baseline network, wakefulness (0.87) and

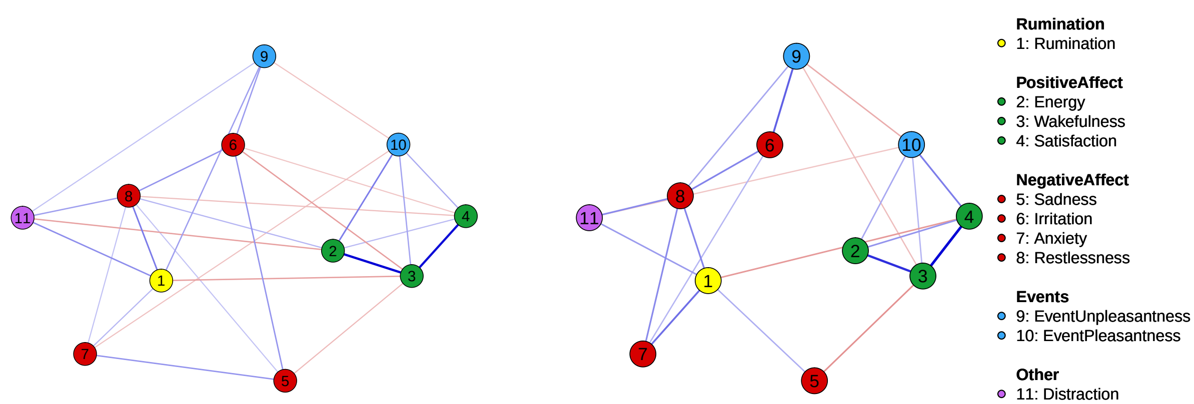

Figure 17

Contemporaneous networks of the positive fantasizing condition. Left: baseline (N = 32); right: peri-intervention (N = 31).

restlessness (0.69) are among the most central nodes. In addition, satisfaction (0.72) was highly influential in this network. Wakefulness was significantly positively associated with energy and satisfaction and negatively so with sadness and event unpleasantness. Satisfaction shared an additional significant positive edge with event pleasantness and a negative one with rumination. Thus, 14 out of 24 edges contained in this network reached significance. All edges led to a significant Global Strength of 2.93 (p = .003).

According to the permutation test results, the contemporaneous networks did not significantly differ in terms of centrality or Global Strength. The only significant difference was the positive edge between sadness and anxiety found in the baseline but not the peri-intervention network.

SART Analysis

Now we turn to the effects of the interventions on the objective measures obtained via the SART. Again, we created linear mixed-effects models. In this case, the random-effect structure again comprised a random intercept per subject. In contrast, the fixed-effects structure, determined by backward selection, included the main effect for mental health status, intervention, the SART session number, and the interaction between the intervention condition and the SART session number. All predictors but the main effect for mental health status reached statistical significance. However, all effects were very small. Participants receiving the mindfulness condition, on average, showed a 125.59 ms greater decrease in response times than participants undergoing the fantasizing condition, $t(10062) = -5.644$, $p < .001$; $d = 0.11$. This was slightly counteracted by the interaction between the mindfulness intervention and the SART session number, with every additional session leading to a 4.59 ms smaller decrease in response times compared to the fantasizing condition, $t(10062) = 4.598$, $p < .001$, $d = 0.09$. The main effect of the SART session number, however, was a decrease by 2.81 ms, $t(10062) = -4.321$, $p < .001$; $d = 0.09$.

Next, we inspected the relationship between changes compared to the baseline in the mean response times, the commission error rate, and the changes in rumination and distraction. The model for rumination included the mental health status, the intervention condition, the SART session number, the interaction between the intervention condition and the SART session number, the levels of distraction, negative and positive affect, the mean response times, and the commission error rate per SART session. Furthermore, a random intercept per subject was included. Negative affect exerted the only statistically significant effect estimated by this model. A one-point change in negative affect compared to its baseline average resulted in a 0.57 point change in rumination compared to its baseline average, $t(221) = 6.484$, $p < .001$. This effect was large, $d = 0.88$. Whereas the Bayes factor for the mean response times (0.342) indicated an inconclusive result, the Bayes factor for the commission error rate (0.254) suggested that its insignificance is conclusive. The same model was also applied to changes in distraction. In this model, only positive affect had a significant effect. A one-point increase compared to the baseline average in positive affect, decreased distraction by 0.45 points, $t(221) = -4.133$, $p < .001$. This effect was medium, $d = 0.67$. The Bayes factors for the mean response times (0.445) indicated an inconclusive result, while it suggested a conclusive one for the commission error rate (0.283).

Discussion

This thesis aimed to investigate depression from a network perspective. This section will first discuss the results of the analyses, what they imply for our research questions, and how they relate to previous research. Next, the limitations of the study are addressed. Finally, possible avenues for future research are explored.

Group Differences

The first research question concerned network differences between the rMDD and the HC group. We predicted that the rMDD group would indicate significantly higher levels of rumination and negative affect while reporting lower levels of positive affect than the HC group at baseline. The hypotheses could partially be confirmed. Being part of the rMDD group was associated with reporting more rumination and negative affect. This is in line with prior research showing that rumination is associated with symptoms of depression which tend to be higher in individuals in remission from depression (for example, Nolen-Hoeksema et al., 1993). Both effects were small. This is not surprising given that the subjects in the rMDD group are in a state of remission rather than full-blown depression. We found no effect of mental health status on positive affect. Again, this is consistent with previous research, which has demonstrated that while individuals in acute depressive states tend to dampen positive affect, no significant differences in the experience of positive affect could be found between individuals in remission from MDD and healthy controls (for example, Werner-Seidler et al., 2013).

We hypothesized that the rMDD networks would be more densely connected overall (i.e., possess lower Global Strength) than the HC networks, a consistent finding in research on networks of depressive symptoms (for example, van Rooijen et al., 2018). The results were more ambiguous. Whereas the rMDD group's temporal network was more strongly connected globally than the HC group's, the opposite was true for the contemporaneous network. This may well be an artifact of the multi-level vector autoregression model, which creates the contemporaneous networks from the residuals of the temporal networks. The existing literature is primarily concerned with contemporaneous networks, and thus, misses time-lagged relationships between symptoms. Our results might, therefore, still indicate a diminished ability to get out of a given mental frame of individuals with depressive tendencies. A second potential explanation for the mixed nature of the results is that our networks comprised not only symptoms of depression but also positive affect measures, which may have had stronger connections in the HC networks. Zooming into the positive affect measures, however, we found almost identical connection strengths in both groups' temporal networks. In contrast, the negative affect measures are much more strongly connected in the temporal rMDD network than the HC one. This supports the notion of negative affect more reliably sustaining itself from one measurement occasion to the next (on average, a span of 90 minutes) in the rMDD group.

Rumination may play a vital role in sustaining high negative affect over time. We know that rumination maintains depressive symptoms (for example, Nolen-Hoeksema et al., 2008). Our results hint at a potential pathway for this effect. Rumination both significantly influenced and was influenced significantly by sadness in the temporal rMDD but not the HC network.

We further hypothesized that rumination would be more central and more strongly connected with positive and negative affect in the rMDD networks than in the HC networks. This is confirmed by the analysis (or at least hinted at, given the lack of significance). In general, rumination has more robust absolute edge weights in the rMDD networks compared to the HC networks. It is, moreover, more strongly connected with both affect measures. This underpins rumination's stipulated important role in depression (for example, Nolen-Hoeksema & Watkins, 2011) and is one more small piece of evidence that rumination is a promising target for interventions.

Our hypothesis network also showed positive connections between rumination and distraction, as well as event unpleasantness and rumination. While rumination and distraction were positively associated in both contemporaneous networks, only the HC group's temporal network included a significant negative effect from rumination to distraction. This may be an expression of the healthy controls' use of a more adaptive form of rumination that leads to alleviating goal discrepancies, and subsequently, to less distraction and rumination. Event unpleasantness was significantly positively connected with rumination only in the HC network (though the edge weights were almost identical in both networks). Interestingly, in the temporal rMDD network, rumination lowered subsequent event unpleasantness.

A commonality of the two temporal networks was the importance of wakefulness. In both networks, wakefulness was among the most impactful nodes. Interestingly, while the node exerted its influence primarily on the other positive affect measures in the HC network, it mainly decreased negative affect measures (i.e., irritation and sadness), distraction, and event unpleasantness in the rMDD network. Alongside wakefulness, energy was also consistently a highly central node in the temporal and contemporaneous networks, significantly influencing several other nodes. Given that a lack of energy, or fatigue, is one of the criteria for the diagnosis of depression, the strong influence of both wakefulness and energy is unsurprising. High energy levels may act as a protective factor, while lower levels may be a significant risk factor for developing or slipping back into depression.

Intervention Effects

Our second research question concerned the effects of mindfulness and positive fantasizing intervention on a combined network of symptoms. We hypothesized that the mindfulness intervention would result in a greater decrease in rumination than the fantasizing condition. In contrast, the fantasizing intervention would lead to a substantially greater increase in positive affect than the mindfulness condition. Even though we also predicted that the positive fantasizing training would more directly reduce the experience of negative affect, we did not expect to find significantly lower levels of negative affect in that condition than in the mindfulness condition. This is because we believed mindfulness training would substantially reduce rumination, which was expected to have a bi-directional relationship with negative affect, ultimately leading to a comparable effect on negative affect of both interventions. All hypotheses could be confirmed.

The results suggested that the participants in the mindfulness condition reported a greater decrease in rumination than the ones in the fantasizing condition. The effect is small but independent of mental health status, pointing toward the potential of even a fairly minor mindfulness practice to help individuals, whether depressed or not, to disengage from repetitive, negative thinking. Both interventions reduced negative affect. However, no significant difference between the two conditions was found. Interestingly, while mindfulness decreased negative affect for both groups, positive fantasizing reduced negative affect in the healthy controls but increased it in the remitted ones. Regarding positive affect, fantasizing was associated with greater increases than mindfulness. Looking at the effects per intervention by group, we found that all combinations increased positive affect except for remitted individuals receiving mindfulness training. These participants reported a decrease in positive affect. Therefore, if the primary goal is to increase positive affect, positive fantasizing appears to be more promising than mindfulness.

To the best of our knowledge, the effects of mindfulness and positive fantasizing have not yet been compared in previous research. However, while the results are in line with earlier studies on mindfulness, they do not align perfectly to prior studies on positive fantasizing. Mindfulness has been suggested to mitigate depressive symptoms by reducing rumination (Guendelman et al., 2017), which is corroborated by our findings. Our results also support positive fantasizing's increasing effect on positive affect and decreasing impact on negative affect (van Tol et al., 2021). However, our results do not support its previously reported effects on rumination (Besten et al., 2020).

We expected to find the effects mentioned above in the networks too. For the mindfulness condition, we expected the rumination node's Strength and the weight of the connections between rumination and the negative affect measures to decrease, ultimately lowering negative affect's centrality. Again, the results did not reach statistical significance but generally pointed toward the expected effects. For the fantasizing condition, we expected the positive affect nodes to increase in Strength, resulting in reductions in negative affect and rumination. Our hypotheses could not be confirmed. The positive affect measures lost Strength in the peri-intervention period when viewed across both the temporal and the contemporaneous networks. Rumination and the negative affect measures increased or stayed approximately level. These results as well, however, failed to reach significance. The only significant difference was that sadness and anxiety shared a positive association in the baseline network but not in the peri-intervention network. About 85% of patients suffering from MDD, of which sadness is one of the main symptoms, also suffer from anxiety disorders, and a similar percentage of patients with an anxiety disorder have depression (Tiller, 2013). Consequently, this potential mitigating effect of positive fantasizing on the association between sadness and anxiety warrants further investigation.

We further hypothesized that both interventions would generally lead to less densely connected networks. Indeed, in both conditions, the temporal and the contemporaneous networks decreased in Global Strength from the baseline to the peri-intervention phase. However, the differences did not reach statistical significance.

SART Analysis

Following the HEXAGON model of rumination, we hypothesized that individuals in remission from depression would generally have lower levels of executive control than healthy individuals. This hypothesis is confirmed if we take the response times on the SART as a proxy for executive control. However, the effect was very small. Additionally, we were interested in the respective effects of mindfulness and fantasizing on executive control. Given that mindfulness has been shown to improve executive control (Teper et al., 2013), we hypothesized that it would more effectively increase executive control than fantasizing. This hypothesis could be confirmed. In general, individuals receiving the mindfulness intervention experienced a greater decrease in response times than individuals receiving the fantasizing condition. Even though the effect was minimal, the result gives further credence to mindfulness' stipulated impact on executive control. Not only did mindfulness improve executive control, but it also lowered rumination. Although we did not establish a causal connection between the improvements in executive control and the decreased ruminative tendencies, these findings support the HEXAGON model, which implicates executive control as a major factor in maladaptive rumination (Watkins & Roberts, 2020).

Combining the objective SART measures with the subject ESM reports, we aimed to further our understanding of the relationship between executive control and the momentary levels of rumination and distraction. We expected to find significant relationships between the SART measures and rumination and distraction. However, we could not confirm this hypothesis. No effects were found. It is important to mention that this could be the result of how we matched the SART and ESM data. We matched each SART session with the closest ESM assessment in time per subject. The ESM data are reports on the momentary levels of different symptoms. Therefore, even if the SART was performed within a few minutes of an ESM assessment, an individual's levels of symptoms may have changed by then.

Limitations

Several limitations need to be addressed. The biggest one is that the network comparison tests hardly showed any significant differences, calling into question the inferences we drew from our results, however tentatively phrased. One reason for this might have been a lack of statistical power. However, the stability analyses generally implied relatively robust results. To reach more stable networks, we combined both blocks of the experiment. Hence, subjects that had already received one intervention in the first block were regarded as independent entities when they received the other intervention in the second block. Even though there was a washout period of at least one month between the blocks, this may have resulted in the confounding of some effects. Another possible reason for the lack of significant differences was the comparison tests. There is no generally agreed on method for testing network differences for temporal networks in general and networks based on mlVAR, in particular. Consequently, for this study, we implemented our own approach based on permutation testing. The suitability of the approach was not extensively tested beforehand.

It is noteworthy that some of our regression models did not meet all model assumptions. In particular, residuals were not always normally distributed and exhibited some heteroskedasticity. Due to the floor and ceiling effect imposed by the range of the allowed scores (ranging from 0 to 100), data transformations were of little help. We tested the models on log-transformed scores, resulting in slightly better residuals without significantly changing the results. Considering the transformation's negligible impact, we opted to present the analysis involving no data transformation.

Concerning our conclusions regarding executive control, we have to note that the SART response times and commission error rates can only be viewed as rough proxies for executive control. Several factors are bound to be implicated in determining an individual's performance on the task, and thus, would have to be teased apart to draw firm conclusions.

Future Research

The study should ideally be replicated with more participants. To better understand the role of rumination in depression specifically, it may be helpful to run this study design using only symptoms of depression. This would make comparing the results with existing studies more feasible.

In working on this study, it became apparent that while network analysis provides a promising avenue to refining our understanding of psychopathology, more research, especially on temporal networks, is still necessary. Whereas there are several algorithms for contemporaneous networks, the choices for temporal networks are more limited. Moreover, while there is a best-practice approach to stability testing an individual contemporaneous network and comparing two contemporaneous networks with each other, no such best practices are available in the realm of temporal networks. This likely scares off many researchers from investigating psychopathology from this angle. A potential alternative for the permutation-based stability analysis used in this study might be a cross-validation scheme.

Conclusion

This thesis aimed to investigate two research questions. First, what is the role of rumination in a complex network of symptoms of Major Depressive Disorder (MDD), and how does it differ between remitted MDD patients (rMDD) and healthy controls (HC)? While the results did not reach statistical significance, they generally point toward a more prominent role of rumination in the rMDD network. Rumination exerted more influence in the rMDD than the HC network. In addition, we found that the rMDD group generally reported greater rumination and negative affect. The second research question was, what are the effects of mindfulness and positive fantasizing on the network of symptoms of MDD in general and rumination in particular? Network analysis did not reveal any significant effects of mindfulness on the network of symptoms. However, as rumination became less influential due to the mindfulness intervention, the results again at least hint at the expected effect. While positive fantasizing resulted in one significant difference – a positive contemporaneous association between sadness and anxiety disappeared –, the expected increase in positive affect could not be detected. Dropping the network lens, however, we found the expected effects. Mindfulness reduced rumination and negative affect significantly, whereas positive fantasizing decreased negative and increased positive affect.

In conclusion, while our network analysis did not lead to many statistically significant findings, our results support previous studies that purport heightened rumination and negative affect in depressed individuals. Similarly, our results align with research showing that mindfulness can decrease rumination and negative affect, as well as research demonstrating that positive fantasizing can increase positive and decrease negative affect.

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Appendix A
Tutorial

Following Borsboom et al. (2021), we can regard network analysis as consisting of three main phases: network structure estimation, network description, and network stability analysis (see Figure A1). The initial phase, network structure estimation, comprises two steps. First, one has to select the nodes to feature in the network. Theoretical considerations rather than methodological ones primarily drive this step. Second, using statistical tools, the conditional associations between nodes are estimated to determine the most important edges in the network. Toward this goal, several statistical methods can be employed. Model selection methods based on fit indices, such as regularized estimation procedures (Epskamp & Fried, 2018), null hypothesis testing procedures, and cross-validation approaches, are commonly used in psychological studies. These approaches typically use conditional associations to define a network structure underlying a set of variables (Robinaugh et al., 2020). Two variables are said to be conditionally associated if they are probabilistically dependent, conditional on the remaining variables in the set. The strength of this conditional association determines the edge weight between the two variables. If the association between two variables vanishes when the other variables are controlled for, the variables, i.e., their corresponding nodes will be disconnected in the visualized network structure.

The next phase, network description, involves describing the topology of the estimated network. We differentiate between global and local network topology. Globally, the essential topological feature of a network is the density of its connections. The network is said to be sparse if the number of edges relative to the number of nodes is low. Conversely, a high number of edges relative to the number of nodes indicates a dense network. This distinction is critical because some estimation procedures are more suitable for sparse networks, some for dense ones. Another way to think about a network's density is called Global Strength. In psychopathology networks, it's a measure of total symptom connectivity, or edge weights, and is hypothesized to be a central factor in an individual's vulnerability profile. Cramer et al. (2016), for example, simulated MDD networks, varying the strengths of connections between symptoms. They found that more strongly connected networks are more likely to be tipped into a state of depression than more loosely connected networks. This is in line with findings from other areas of science that show that strongly connected dynamic systems are more easily tipped from one state into another (e.g., Chen et al., 2012) and with the observation that successful therapeutic interventions are sometimes targeted at weakening symptom-to-symptom relations (such as exposure therapy).

Node centrality is the most commonly investigated local feature of a network's topology. It measures how important a node is. "Importance" within a network can be defined in different ways, and consequently, there are many measures for this property (Das et al., 2018). The most basic of these is *Degree*, which measures how many connections a node possesses. In psychological research, *Strength* – the sum of all absolute edge weights a node is directly connected to – is in high demand for specifying a node's centrality as it is generally more stable than other standard metrics (Bringmann et al., 2019). Other local features of interest include clustering nodes into subcommunities, providing insight into potentially unobserved causes and the system's dimensionality, and shortest paths between nodes, possibly yielding insights into the most predictive pathways within the network. Frequently, network analysis involves estimating multiple networks, using various statistical methods with different advantages, or comparing groups. Hence, comparing different networks is another step in the network description phase.

The purpose of the final phase, network stability analysis, is to ensure reproducibility (obtaining the same conclusions from the same data) and increasing replicability (getting the same conclusions from new data) of the estimated networks – topics that have received ample attention in the psychometric network literature recently (see for example, Bringmann et al.,

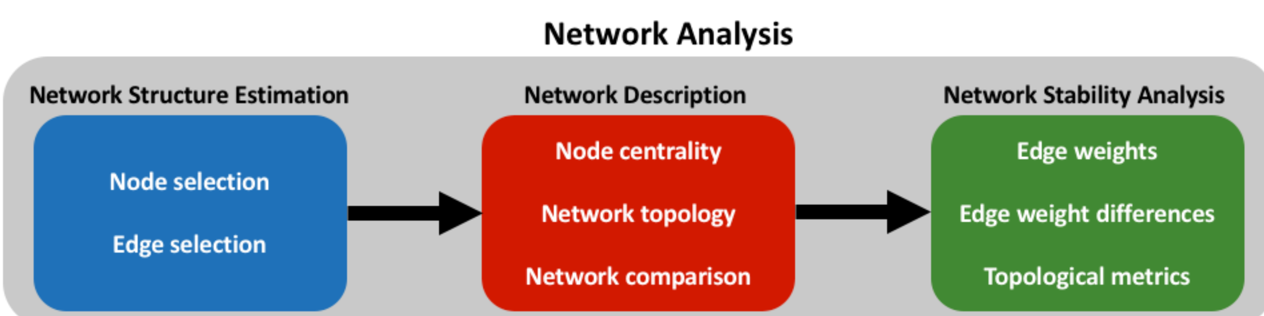

Figure A1
Schematic representation of the workflow used in network analysis. Adapted from Borsboom et al. (2021).

2022). The main targets of statistical tools for robustness analyses in networks are individual edge weight estimates, differences between edges in a network, and topological metrics, such as node centrality. In determining the robustness of edge weight estimates, measures of sensitivity to sampling errors, such as confidence intervals, credibility intervals, and bootstrapped intervals, are indicated. The degree to which such intervals overlap for the relevant coefficients gives insights into the robustness of differences between edge weights. To investigate the robustness of other network properties, such as node centrality, various approaches have been devised, including approaches based on bootstrapping (Epskamp, Borsboom, et al., 2018) and Bayesian statistics (Williams & Mulder, 2020). The final product generated with these steps is then interpreted. To make substantive inferences, however, it is necessary to combine the output with general methodological considerations and domain-specific knowledge (Borsboom et al., 2021).

Naturally, the interpretation of a network is dependent on the data used to inform its structure. Generally speaking, we can either use cross-sectional or longitudinal data. In network studies within the fields of psychology and psychopathology, cross-sectional data is most commonly used (Borsboom et al., 2021) – resulting in *contemporaneous networks*. Estimating contemporaneous networks is simpler than estimating networks from longitudinal data because, for cross-sectional data, independence of measurements can typically be assumed. Since independence is given, applying population-sample logic is warranted, lowering the requirements for an estimation model. In time-series data, two kinds of interdependence are introduced that complicate the estimation of *temporal networks*. First, data collected on two (or more) subsequent measurement points may be correlated (if somebody is happy right now, there is a high chance they are still happy in two hours). Second, responses from one person may correlate with one another more strongly in general (somebody of a happier nature will, on average, report more happiness). However, the obvious downside of contemporaneous networks is that they contain no information about the direction of effects between variables. Additionally, some researchers have voiced concerns regarding the replicability of contemporaneous networks (for example, Fried & Cramer, 2017), and have argued that they cannot necessarily be assumed to generalize to the level of the individual (for example, Bringmann & Eronen, 2018). Overall, temporal networks may be more advantageous than contemporaneous networks. Although the violation of independence assumptions places greater demands on models, the additional insights that can be extracted from it may well be worth the effort. Vector autoregressive models (see for example, Haslbeck & Waldorp, 2015) have been devised to deal with temporal data. When using such models to estimate a temporal network, one ends up with a structure of associations that remain after taking the temporal effects into account (Borsboom et al., 2021). Therefore, when using time series data, one receives (at least) two network structures, one depicting lagged associations – or temporal effects – and a kind of contemporaneous network that depicts the associations unaccounted for by the temporal effects. The temporal network, generally, can be interpreted in terms of carry-over effects at the timescale defined by the time between repeated measurements. The temporal ordering may allow for a causal interpretation. However, it is important to note that causal interpretations are not straightforward (Fried & Cramer, 2017). The contemporaneous network will capture effects at timescales different from those defined by the spacing between repeated measurements.

Appendix B
Network Stability and Comparison Results

Group Differences

Table B1

*Node stability analysis for the temporal baseline networks for the rMDD (left), the HC group (middle), and the network comparison (right). Results are based on 1000 permutations per network. Significant p-values are **bold**. InStr = InStrength; OutStr = OutStrength.*

	rMDD				HC				Difference			
Node	InStr	p	OutStr	p	InStr	p	OutStr	p	InStr	p	OutStr	p
Rumination	0.19	0.159	0.23	0.063	0.13	0.140	0.13	0.150	0.06	0.361	0.10	0.242
Energy	0.15	0.183	0.13	0.223	0.36	**0.002**	0.37	**0.002**	−0.21	0.058	−0.24	0.078
Wakefulness	0.13	0.186	0.91	**0.003**	0.38	**0.002**	0.36	**0.002**	−0.25	0.042	0.55	0.128
Satisfaction	0.07	0.532	0.10	0.359	0.39	**0.002**	0.07	0.357	−0.32	0.026	0.03	0.423
Sadness	0.19	0.110	0.37	**0.010**	0.00	1.000	0.00	1.000	0.19	0.076	0.37	0.052
Irritation	0.26	0.040	0.00	1.00	0.08	0.195	0.21	**0.025**	0.18	0.150	−0.21	0.094
Anxiety	0.13	0.229	0.00	1.00	0.21	**0.007**	0.15	0.072	−0.08	0.275	−0.15	0.082
Restlessness	0.15	0.206	0.00	1.00	0.19	0.030	0.06	0.464	−0.04	0.357	−0.06	0.279
EventUnpleasantness	0.42	**0.013**	0.09	0.442	0.00	1.000	0.23	**0.020**	0.42	0.036	−0.14	0.236
EventPleasantness	0.19	0.143	0.07	0.538	0.07	0.352	0.19	0.030	0.12	0.234	−0.12	0.263
Distraction	0.13	0.246	0.10	0.329	0.16	0.040	0.20	**0.017**	−0.03	0.435	−0.10	0.186

Table B2

Edge stability analysis for the temporal baseline networks for the rMDD (left), the HC group (middle), and the network comparison (right). Results are based on 1000 permutations per network. Only edges with a significant weight in either network or the comparison test are shown. Significant p-values are ***bold****.*

	rMDD		HC		Difference	
Edge	Weight	p-value	Weight	p-value	Weight	p-value
Rumination –>Sadness	0.10	**0.023**	0.00	1.00	0.10	0.134
Rumination –>EventUnpleasantness	−0.14	**0.010**	0.00	1.00	−0.14	0.060
Rumination –>Distraction	0.00	1.00	−0.06	**0.002**	0.06	0.096
Energy –>Energy	0.29	0.146	0.29	**0.002**	0.00	1.00
Energy –>Wakefulness	0.13	**0.007**	0.16	**0.002**	−0.03	0.363
Energy –>Satisfaction	0.00	1.00	0.10	**0.010**	−0.10	0.094
Energy –>Restlessness	0.00	1.00	0.11	**0.002**	−0.11	0.098
Wakefulness –>Energy	0.15	**0.003**	0.15	**0.002**	0.00	0.519
Wakefulness –>Satisfaction	0.00	1.00	0.12	**0.002**	−0.12	0.218
Wakefulness –>Irritation	−0.11	**0.017**	0.00	1.00	−0.11	0.188
Wakefulness –>Anxiety	0.00	1.00	−0.09	**0.005**	0.09	0.192
Wakefulness –>Restlessness	−0.15	**0.007**	0.00	1.00	−0.15	0.064
Wakefulness –>EventUnpleasantness	−0.18	**0.003**	0.00	1.00	−0.18	0.108
Wakefulness –>EventPleasantness	0.19	**0.003**	0.00	1.00	0.19	0.100
Wakefulness –>Distraction	−0.13	**0.007**	0.00	1.00	−0.13	0.068
Satisfaction –>Rumination	−0.10	**0.023**	0.00	1.00	−0.10	0.086
Satisfaction –>Satisfaction	0.21	0.478	0.00	1.00	0.21	**0.010**
Sadness –>Sadness	0.31	0.093	0.00	1.00	0.31	**0.020**
Sadness –>Irritation	0.15	**0.003**	0.00	1.00	0.15	0.110
Sadness –>Anxiety	0.13	**0.003**	0.00	1.00	0.13	0.114
Irritation –>Energy	0.00	1.00	0.08	**0.012**	−0.08	0.058
Anxiety –>Irritation	0.00	1.00	0.08	**0.015**	−0.08	0.036
EventUnpleasantness –>Restlessness	0.00	1.00	0.08	**0.020**	−0.08	0.096
EventUnpleasantness –>Distraction	0.00	1.00	0.09	**0.007**	−0.09	0.158
EventPleasantness –>Wakefulness	0.00	1.00	0.09	**0.017**	−0.09	0.140
EventPleasantness –>Satisfaction	0.07	0.056	0.11	**0.002**	−0.03	0.220
Distraction –>Wakefulness	0.00	1.00	0.08	**0.022**	−0.08	**0.022**

Table B3

*Node stability analysis for the contemporaneous networks at baseline for the rMDD group (left), the HC group (middle), and the network comparison (right). Results are based on 1000 permutations per network. Significant p-values are **bold**.*

	rMDD		**HC**		**Difference**	
Node	Strength	p	Strength	p	Strength	p
Rumination	0.74	**0.003**	0.60	**0.002**	0.14	0.242
Energy	0.75	**0.003**	0.65	**0.002**	0.10	0.293
Wakefulness	0.86	**0.003**	1.02	**0.002**	−0.16	0.240
Satisfaction	0.90	**0.003**	0.79	**0.002**	0.11	0.301
Sadness	0.18	0.289	0.45	**0.012**	−0.27	0.066
Irritation	0.41	**0.020**	0.67	**0.002**	−0.26	0.076
Anxiety	0.38	0.047	0.34	0.042	0.04	0.377
Restlessness	0.52	**0.003**	0.82	**0.002**	−0.30	0.108
EventUnpleasantness	0.40	**0.023**	0.42	**0.010**	−0.02	0.461
EventPleasantness	0.49	**0.020**	0.43	**0.012**	0.06	0.375
Distraction	0.54	**0.007**	0.35	0.037	0.19	0.136

Table B4

*Edge stability analysis for the contemporaneous baseline networks for the rMDD (left), the HC group (middle), and the network comparison (right). Results are based on 1000 permutations per network. Only edges with a significant weight in either network or the comparison test are shown. Significant p-values are **bold**.*

	rMDD		**HC**		**Difference**	
Edge	Weight	p-value	Weight	p-value	Weight	p-value
Rumination – Wakefulness	−0.09	**0.013**	−0.12	**0.002**	0.03	0.281
Rumination – Satisfaction	−0.08	**0.010**	0.00	1.00	−0.08	0.138
Rumination – EventUnpleasantness	0.12	0.053	0.13	**0.015**	−0.01	0.409
Rumination – Distraction	0.17	**0.013**	0.16	**0.005**	0.01	0.391
Energy – Wakefulness	0.33	**0.003**	0.28	**0.002**	0.06	0.202
Energy – Satisfaction	0.14	0.050	0.13	**0.015**	0.01	0.437
Energy – EventPleasantness	0.15	**0.020**	0.15	**0.002**	−0.01	0.423
Energy – Distraction	−0.13	**0.003**	0.00	1.00	−0.13	0.054
Wakefulness – Satisfaction	0.29	**0.003**	0.35	**0.002**	−0.06	0.184
Wakefulness – Irritation	−0.15	**0.003**	−0.11	**0.002**	−0.04	0.220
Wakefulness – EventPleasantness	0.00	1.00	0.16	**0.002**	−0.16	0.042
Satisfaction – Sadness	−0.08	**0.017**	0.00	1.00	−0.08	0.114
Satisfaction – Irritation	0.00	1.00	−0.11	**0.002**	0.11	0.132
Satisfaction – Restlessness	−0.12	**0.003**	−0.09	**0.002**	−0.0300	0.269
Satisfaction – EventPleasantness	0.20	**0.007**	0.11	0.037	0.09	0.116
Sadness – Irritation	0.00	1.00	0.13	**0.012**	−0.13	0.086
Sadness – Anxiety	0.10	0.096	0.13	**0.020**	−0.0300	0.325
Irritation – Restlessness	0.00	1.00	0.17	**0.002**	−0.17	0.042
Irritation – EventUnpleasantness	0.13	0.056	0.15	**0.005**	−0.02	0.385
Irritation – Distraction	0.13	0.053	0.00	1.00	0.13	**0.024**
Anxiety – Restlessness	0.14	**0.023**	0.13	**0.012**	0.02	0.417
Restlessness – Distraction	0.11	0.056	0.13	**0.012**	−0.02	0.369
EventUnpleasantness – EventPleasantness	−0.15	**0.003**	0.00	1.00	−0.15	0.094

Intervention Effects

Mindfulness

Table B5

*Node stability analysis for the temporal networks in the mindfulness condition at baseline (left), peri-intervention (middle), and the network comparison (right). Results are based on 1000 permutations per network. Significant p-values are **bold**. InStr = InStrength; OutStr = OutStrength.*

	Baseline				**Peri**				**Difference**			
Node	InStr	p	OutStr	p	InStr	p	OutStr	p	InStr	p	OutStr	p
Rumination	0.13	0.198	0.13	0.099	0.00	1.000	0.12	0.188	0.13	0.147	0.01	0.489
Energy	0.21	0.030	0.13	0.158	0.00	1.000	0.56	**0.010**	0.21	0.045	−0.43	0.147
Wakefulness	0.13	0.158	0.95	**0.010**	0.41	**0.010**	0.14	0.178	−0.28	0.105	0.81	0.047
Satisfaction	0.27	**0.010**	0.00	1.00	0.450	**0.010**	0.25	0.030	−0.18	0.187	−0.25	0.185
Sadness	0.08	0.257	0.00	1.00	0.00	1.000	0.00	1.000	0.08	0.267	0.00	1.000
Irritation	0.17	0.129	0.00	1.00	0.140	0.218	0.00	1.000	0.03	0.446	0.00	1.000
Anxiety	0.16	0.119	0.11	0.139	0.00	1.000	0.00	1.000	0.16	0.222	0.11	0.172
Restlessness	0.11	0.228	0.09	0.238	0.13	0.238	0.10	0.386	−0.02	0.464	−0.01	0.429
EventUnpleasantness	0.14	0.129	0.08	0.366	0.00	1.000	0.00	1.000	0.14	0.112	0.08	0.287
EventPleasantness	0.22	0.030	0.11	0.198	0.55	**0.010**	0.14	0.228	−0.33	0.062	−0.03	0.466
Distraction	0.13	0.099	0.15	0.139	0.00	1.000	0.36	**0.010**	0.13	0.177	−0.21	0.122

Table B6

*Edge stability analysis for the temporal networks in the mindfulness condition at baseline (left), peri-intervention (middle), and the network comparison (right). Results are based on 1000 permutations per network. Only edges with a significant weight in either network or the comparison test are shown. Significant p-values are **bold**.*

	Baseline		**Peri**		**Difference**	
Edge	Weight	p-value	Weight	p-value	Weight	p-value
Rumination –>EventPleasantness	0.00	1.00	−0.12	**0.020**	−0.12	0.085
Rumination –>Distraction	−0.13	**0.020**	0.00	1.00	0.13	0.112
Energy –>Energy	0.30	**0.010**	0.41	**0.010**	0.11	0.212
Energy –>Wakefulness	0.13	**0.010**	0.28	**0.010**	0.15	0.150
Energy –>Satisfaction	0.00	1.00	0.11	**0.030**	0.11	0.217
Energy –>EventPleasantness	0.00	1.00	0.16	**0.010**	0.16	0.145
Wakefulness –>Rumination	−0.13	**0.010**	0.00	1.00	0.13	0.040
Wakefulness –>Energy	0.13	**0.010**	0.00	1.00	−0.13	0.115
Wakefulness –>Satisfaction	0.16	**0.010**	0.00	1.00	−0.16	0.145
Wakefulness –>Irritation	−0.17	**0.012**	0.00	1.00	0.17	0.100
Wakefulness –>EventPleasantness	0.22	**0.010**	0.14	**0.010**	−0.07	0.312
Wakefulness –>EventUnpleasantness	−0.14	**0.011**	0.00	1.00	0.14	0.095
Satisfaction –>Wakefulness	0.00	1.00	0.13	**0.011**	0.13	0.217
Satisfaction –>EventPleasantness	0.00	1.00	0.12	**0.010**	0.12	0.264
Anxiety –>Restlessness	0.11	**0.010**	0.00	1.00	−0.11	0.080
EventPleasantness –>Satisfaction	0.11	**0.020**	0.14	**0.010**	0.03	0.374
EventUnpleasantness –>Sadness	0.08	**0.010**	0.00	1.00	−0.08	0.252
Distraction –>Irritation	0.00	1.00	0.14	**0.010**	0.14	0.117
Distraction –>Restlessness	0.00	1.00	0.13	**0.012**	0.13	0.145

Table B7

*Node stability analysis for the contemporaneous networks in the mindfulness condition at baseline (left), peri-intervention (middle), and the network comparison (right). Results are based on 1000 permutations per network. Significant p-values are **bold**.*

	Baseline		**Peri**		**Difference**	
Node	Strength	p	Strength	p	Strength	p
Rumination	0.66	**0.010**	0.28	0.059	0.38	0.055
Energy	0.52	**0.010**	0.41	**0.020**	0.11	0.304
Wakefulness	0.91	**0.010**	1.00	**0.010**	−0.09	0.334
Satisfaction	0.76	**0.010**	0.62	**0.012**	0.14	0.247
Sadness	0.34	0.050	0.37	0.030	−0.03	0.451
Irritation	0.55	**0.010**	0.21	0.168	0.34	0.072
Anxiety	0.38	0.040	0.19	0.129	0.19	0.167
Restlessness	0.67	**0.011**	0.57	**0.010**	0.10	0.357
EventUnpleasantness	0.34	0.030	0.30	0.050	0.04	0.434
EventPleasantness	0.53	0.030	0.73	**0.010**	−0.20	0.092
Distraction	0.28	0.099	0.32	0.050	−0.04	0.449

Table B8

*Edge stability analysis for the contemporaneous networks in the mindfulness condition at baseline (left), peri-intervention (middle), and the network comparison (right). Results are based on 1000 permutations per network. Only edges with a significant weight in either network or the comparison test are shown. Significant p-values are **bold**.*

	Baseline		**Peri**		**Difference**	
Edge	Weight	p-value	Weight	p-value	Weight	p-value
Rumination – Wakefulness	−0.10	**0.010**	0.00	1.00	0.10	0.045
Rumination – Sadness	0.00	1.00	0.16	**0.020**	0.16	0.187
Rumination – EventUnpleasantness	0.11	**0.020**	0.00	1.00	−0.11	0.125
Rumination – Distraction	0.17	**0.018**	0.13	0.040	−0.05	0.327
Energy – Wakefulness	0.23	**0.010**	0.27	**0.010**	0.04	0.307
Energy – Satisfaction	0.17	**0.010**	0.00	1.00	−0.17	0.087
Energy – EventPleasantness	0.13	0.089	0.14	**0.011**	0.02	0.424
Wakefulness – Satisfaction	0.33	**0.013**	0.23	**0.010**	−0.10	0.085
Wakefulness – Sadness	0.00	1.00	−0.11	**0.010**	−0.11	0.190
Wakefulness – Irritation	−0.09	**0.010**	0.00	1.00	0.09	0.237
Wakefulness – Restlessness	0.00	1.00	−0.08	**0.013**	−0.08	0.052
Wakefulness – EventPleasantness	0.17	**0.011**	0.11	0.030	−0.06	0.302
Satisfaction – Restlessness	−0.11	**0.010**	−0.14	**0.001**	−0.03	0.307
Satisfaction – EventPleasantness	0.15	**0.020**	0.24	**0.009**	0.09	0.162
Irritation – Restlessness	0.16	**0.020**	0.10	0.089	−0.06	0.267
Anxiety – Restlessness	0.20	**0.012**	0.00	1.00	−0.20	0.030
Restlessness – EventUnpleasantness	0.00	1.00	0.15	0.020	0.15	0.127
EventPleasantness – EventUnpleasantness	0.00	1.00	−0.15	0.010	−0.15	0.102

Fantasizing

Table B9

*Node stability analysis for the temporal networks in the fantasizing condition at baseline (left), peri-intervention (middle), and the network comparison (right). Results are based on 1000 permutations per network. Significant p-values are **bold**. InStr = InStrength; OutStr = OutStrength.*

	Baseline				**Peri**				**Difference**			
Node	InStr	p	OutStr	p	InStr	p	OutStr	p	InStr	p	OutStr	p
Rumination	0.08	0.269	0.32	**0.007**	0.12	0.193	0.09	0.425	−0.04	0.419	0.23	0.227
Energy	0.28	**0.013**	0.36	**0.003**	0.30	**0.020**	0.22	0.047	−0.02	0.496	0.14	0.279
Wakefulness	0.31	**0.010**	0.15	0.179	0.30	**0.010**	0.00	1.000	0.01	0.504	0.15	0.227
Satisfaction	0.18	0.063	0.08	0.302	0.10	0.276	0.25	0.047	0.08	0.387	−0.17	0.332
Sadness	0.11	0.133	0.15	0.113	0.00	1.000	0.12	0.233	0.11	0.204	0.03	0.466
Irritation	0.15	0.146	0.13	0.189	0.10	0.332	0.09	0.375	0.05	0.401	0.04	0.392
Anxiety	0.19	0.043	0.00	1.00	0.13	0.189	0.00	1.000	0.06	0.379	0.00	1.000
Restlessness	0.19	0.053	0.07	0.472	0.17	0.146	0.08	0.439	0.02	0.471	−0.01	0.429
EventUnpleasantness	0.00	1.00	0.00	1.00	0.29	0.030	0.10	0.266	−0.29	0.105	−0.10	0.229
EventPleasantness	0.08	0.346	0.16	0.090	0.13	0.163	0.48	**0.003**	−0.05	0.359	−0.32	0.090
Distraction	0.00	1.00	0.16	0.103	0.00	1.000	0.22	0.060	0.00	1.000	−0.06	0.459

Table B10

*Edge stability analysis for the temporal networks in the fantasizing condition at baseline (left), peri-intervention (middle), and the network comparison (right). Results are based on 1000 permutations per network. Only edges with a significant weight in either network or the comparison test are shown. Significant p-values are **bold**.*

	Baseline		**Peri**		**Difference**	
Edge	Weight	p-value	Weight	p-value	Weight	p-value
Rumination –>Sadness	0.11	**0.003**	0.00	1.00	−0.11	0.239
Rumination –>Anxiety	0.12	**0.010**	0.00	1.00	−0.12	0.080
Rumination –>Restlessness	0.09	**0.021**	0.09	0.043	0.00	0.431
Energy –>Energy	0.30	**0.020**	0.20	0.286	−0.10	0.090
Energy –>Wakefulness	0.17	**0.003**	0.13	**0.007**	−0.04	0.347
Energy –>Satisfaction	0.09	**0.020**	0.00	1.00	−0.09	0.212
Energy –>Restlessness	0.10	**0.007**	0.00	1.00	−0.10	0.112
Wakefulness –>Energy	0.15	**0.003**	0.00	1.00	−0.15	0.137
Satisfaction –>Wakefulness	0.00	1.00	0.11	**0.013**	0.11	0.122
Satisfaction –>EventPleasantness	0.08	0.037	0.13	**0.010**	0.05	0.399
Sadness –>Energy	0.00	1.00	−0.12	**0.003**	−0.12	0.107
Sadness –>Irritation	0.15	**0.003**	0.00	1.00	−0.15	0.042
Irritation –>EventUnpleasantness	0.00	1.00	0.09	**0.020**	0.09	0.212
EventPleasantness –>Rumination	0.00	1.00	−0.12	**0.003**	−0.12	0.082
EventPleasantness –>Wakefulness	0.08	**0.020**	0.06	0.056	−0.02	0.352
EventPleasantness –>Satisfaction	0.09	**0.017**	0.10	0.027	0.01	0.414
EventPleasantness –>Irritation	0.00	1.00	−0.10	**0.020**	−0.10	0.110
EventPleasantness –>EventUnpleasantness	0.00	1.00	−0.11	**0.007**	−0.11	0.127
EventUnpleasantness –>Energy	0.00	1.00	0.10	**0.017**	0.10	0.085
Distraction –>Rumination	0.08	**0.017**	0.00	1.00	−0.08	0.274
Distraction –>Anxiety	0.07	0.037	0.13	**0.013**	0.06	0.329

Table B11

*Node stability analysis for the contemporaneous networks in the fantasizing condition at baseline (left), peri-intervention (middle), and the network comparison (right). Results are based on 1000 permutations per network. Significant p-values are **bold**.*

	Baseline		**Peri**		**Difference**	
Node	Strength	p	Strength	p	Strength	p
Rumination	0.69	**0.003**	0.67	**0.003**	0.02	0.461
Energy	0.84	**0.002**	0.49	**0.003**	0.35	0.032
Wakefulness	1.15	**0.002**	0.87	**0.003**	0.28	0.105
Satisfaction	0.70	**0.003**	0.72	**0.003**	−0.02	0.449
Sadness	0.46	**0.010**	0.23	0.123	0.23	0.147
Irritation	0.63	**0.003**	0.43	**0.007**	0.20	0.222
Anxiety	0.41	**0.010**	0.41	**0.017**	0.00	0.524
Restlessness	0.81	**0.003**	0.69	**0.003**	0.12	0.344
EventUnpleasantness	0.43	**0.013**	0.48	**0.003**	−0.05	0.411
EventPleasantness	0.58	**0.003**	0.53	**0.003**	0.05	0.389
Distraction	0.49	**0.003**	0.34	0.050	0.15	0.162

Table B12

*Edge stability analysis for the contemporaneous networks in the fantasizing condition at baseline (left), peri-intervention (middle), and the network comparison (right). Results are based on 1000 permutations per network. Only edges with a significant weight in either network or the comparison test are shown. Significant p-values are **bold**.*

	Baseline		Peri		Difference	
Edge	Weight	p-value	Weight	p-value	Weight	p-value
Rumination – Wakefulness	–0.13	**0.003**	0.00	1.00	0.13	0.035
Rumination – Satisfaction	0.00	1.00	–0.12	**0.003**	–0.12	0.102
Rumination – Anxiety	0.10	0.060	0.18	**0.003**	0.08	0.229
Rumination – Restlessness	0.18	**0.007**	0.15	**0.013**	–0.03	0.362
Rumination – Distraction	0.15	**0.010**	0.12	0.027	–0.03	0.319
Energy – Wakefulness	0.34	**0.010**	0.25	**0.003**	–0.09	0.110
Energy – EventPleasantness	0.18	**0.003**	0.11	0.037	–0.07	0.145
Energy – Distraction	–0.13	**0.003**	0.00	1.00	0.13	0.045
Wakefulness – Satisfaction	0.33	**0.003**	0.31	**0.003**	–0.02	0.451
Wakefulness – Sadness	–0.09	**0.003**	–0.13	**0.003**	–0.04	0.377
Wakefulness – Irritation	–0.13	**0.002**	0.00	1.00	0.13	0.027
Wakefulness – EventUnpleasantness	0.00	1.00	–0.08	**0.010**	–0.08	0.222
Satisfaction – Irritation	–0.08	**0.013**	0.00	1.00	0.08	0.239
Satisfaction – Restlessness	–0.09	0.007	0.00	1.00	0.09	0.282
Satisfaction – EventPleasantness	0.11	0.047	0.16	**0.007**	0.05	0.264
Sadness – Irritation	0.14	**0.007**	0.00	1.00	–0.14	0.052
Sadness – Anxiety	0.14	**0.003**	0.00	1.00	–0.14	**0.010**
Irritation – Restlessness	0.14	**0.010**	0.15	**0.003**	0.01	0.431
Irritation – EventUnpleasantness	0.13	**0.007**	0.19	**0.003**	0.06	0.182
Anxiety – Restlessness	0.08	0.116	0.14	**0.007**	0.06	0.307
Anxiety – EventPleasantness	–0.08	**0.003**	0.00	1.00	0.08	0.130
Restlessness – Distraction	0.13	0.030	0.14	**0.017**	0.01	0.466
EventPleasantness – EventUnpleasantness	–0.08	**0.003**	–0.10	**0.003**	–0.02	0.421
EventPleasantness – Distraction	0.00	1.00	–0.07	**0.010**	–0.07	0.075

Appendix C
ESM Questionnaire

Positive affect measures are marked with "PA", and negative affect measures with "NA". Note: the questionnaire was presented in Dutch.

1. Is this the first time today that you have completed this questionnaire?

   Yes -> if yes: continue

   No -> if no: go to question 8

2. What was the quality of my sleep like?

   Scale 1 -100

3. What time did I go to bed?

   Format hh:mm

4. What time did I try to fall asleep?

   Format hh:mm

5. How long did it take me to fall asleep?

   In minutes

6. What time did I finally wake up?

   Format hh:mm

7. I felt rested when I woke up

   Scale 1 -100

8. At the moment, I feel wakeful (PA)

   Scale 1 -100

9. Right now, I'm feeling sad (NA)

   Scale 1 -100

10. At the moment, I feel satisfied (PA)

    Scale 1 -100

11. Right now, I feel irritated (NA)

    Scale 1 -100

12. Right now, I feel energized (PA)

    Scale 1 -100

13. At the moment, I feel restless (NA)

    Scale 1 -100

14. Right now, I feel stressed

    Scale 1 -100

15. At the moment, I feel anxious (NA)

    Scale 1 -100

16. At the moment, I feel lethargic/listless

    Scale 1 -100

17. At the moment, I am thinking of

    - The activity I'm doing (1)

    - Stimuli from the environment (2)

    - How I feel right now (3)

    - My concerns (4)

    - I'm daydreaming (5)

    - Other (6)

18. At the moment, I am ruminating

    Scale 1 -100

19. At this moment, my thoughts do not let go of me

    Scale 1 -100

20. At this moment, I feel comfortable with the thoughts I experience

    Scale 1 -100

21. At the moment, my thoughts are about - The past (1)

    - The present (2)

    - The future (3)

22. At the moment, my thoughts are

    - Negative (1)

    - Neutral (2)

    - Positive (3)

23. At the moment, my thoughts are about

    - Myself (1)

    - Someone else (2)

    - Neither (3)

24. At the moment, I am easily distracted

    Scale 1 -100

25. I am looking forward to the rest of the day

    Scale 1 -100

26. At the moment, I am

    - alone (1) -> go to question 28

    - In company (2) -> go to question 27

27. I like the company

    Scale 1 -100

28. I enjoy being alone right now

    Scale 1 -100

29. Think of the most enjoyable event or activity since the last measurement moment. How pleasant was this?

    Scale 1 -100

30. How intense was this event?

    Scale 1 -100

31. Think of the most unpleasant event or activity since the last measurement moment. How unpleasant was this?

    Scale 1 -100

32. How intense was this event?

    Scale 1 -100

33. Note down any other comments here

    Open field

Since including all items was neither feasible due to insufficient statistical power nor necessarily desirable because it would have made interpreting the results of the network analysis and the GAMM difficult, we only used a selection of the items presented above. We chose items based on the results of hierarchical clustering analysis (performed with the R-package languageR, version 1.5.0; Baayen & Baayen, 2019) and theoretical reasoning. FigureC1 shows the results of the hierarchical clustering. The condition number for this set of items was 29.06, pointing towards potentially troublesome multicollinearity. We dropped all measures related to sleep but Sleep Quality because of their high correlation (e.g., Spearman ρ^2 of 0.62 between sleep quality and Restedness upon waking up). The pleasantness of the most pleasant event since the last measurement occasion (EventPleasantness) and the intensity of this negative event (NegativeEventPleasantness) shared a correlation of 0.45. Therefore, we dropped the intensity of the event. The pleasantness of the current thoughts (ThoughtPleasantness) and the positivity of the outlook for the rest of the day (OutlookPositivity) were removed because they were highly correlated with the positive affect measures (satisfaction, wakefulness, and energy; all correlations >= 0.40). Stress was dropped because of its high correlation with restlessness (0.51). Consequently, the items used for the GAMM comprised the positive affect measures (satisfaction, wakefulness, energy), the negative affect measures (sadness, irritation, anxiety, restlessness), sleep quality, event pleasantness, event unpleasantness, listlessness, distraction, rumination, and stickiness. However, the positive and negative affect measures were grouped, leaving us with a total of nine variables and a condition number of 16.63.

In the network analysis, we decided to split the affect measures. In turn, we dropped sleep quality, listlessness, and stickiness. As a result, eleven variables (rumination, energy, wakefulness, satisfaction, sadness, irritation, anxiety, restlessness, event unpleasantness, event pleasantness, and distraction) were used in the network analysis. The condition number for this set of items was 21.60.

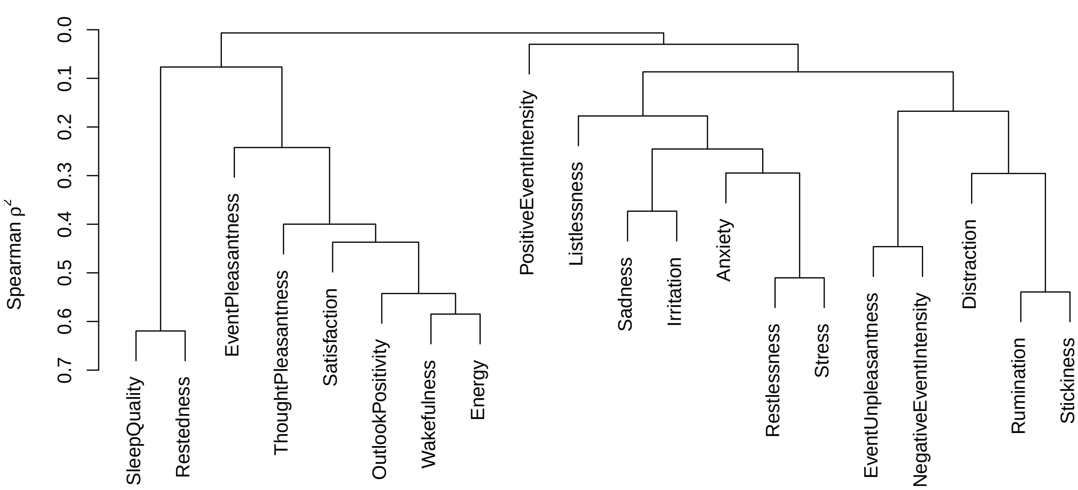

Figure C1
Hierarchical clusters of ESM items.

Appendix D
Further ESM Data Exploration

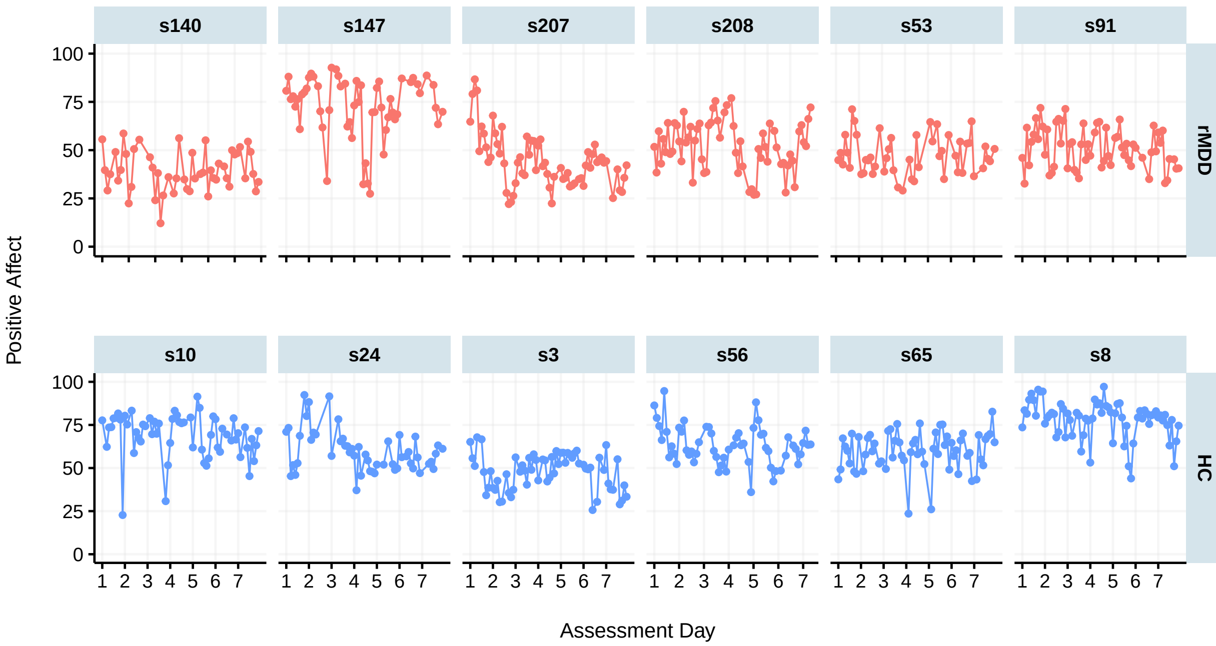

Figure D1

Positive Affect over the course of the baseline assessment period (block 1 only) for six randomly selected individuals for the rMDD (top) and the HC (bottom).

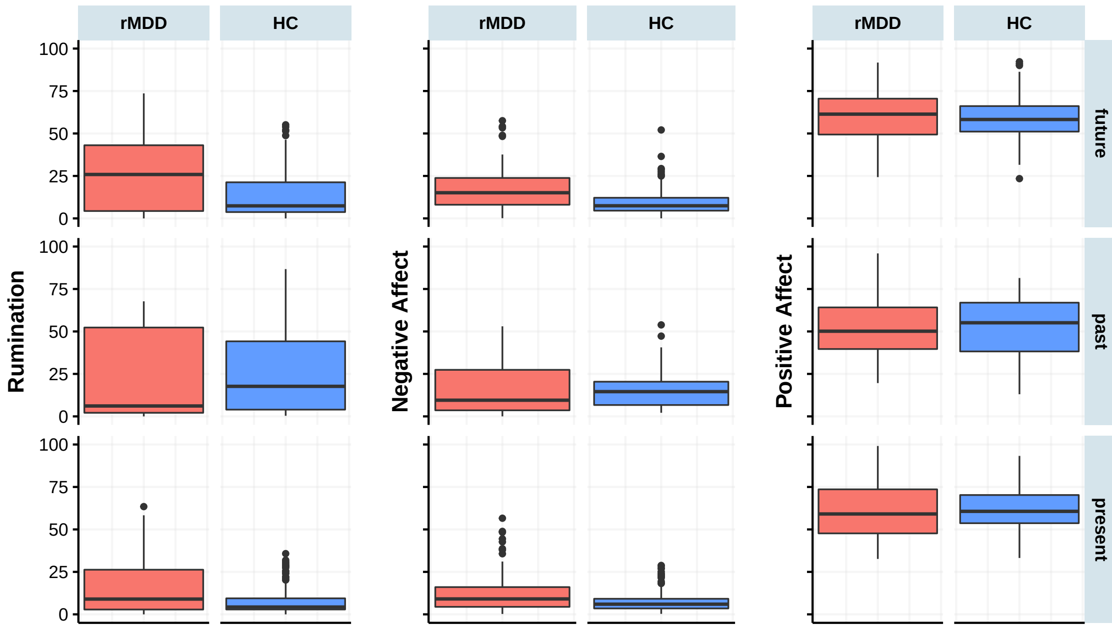

Figure D2

Daily average rumination (left), negative affect (middle), and positive affect (right) by time orientation of current thoughts per group at baseline.

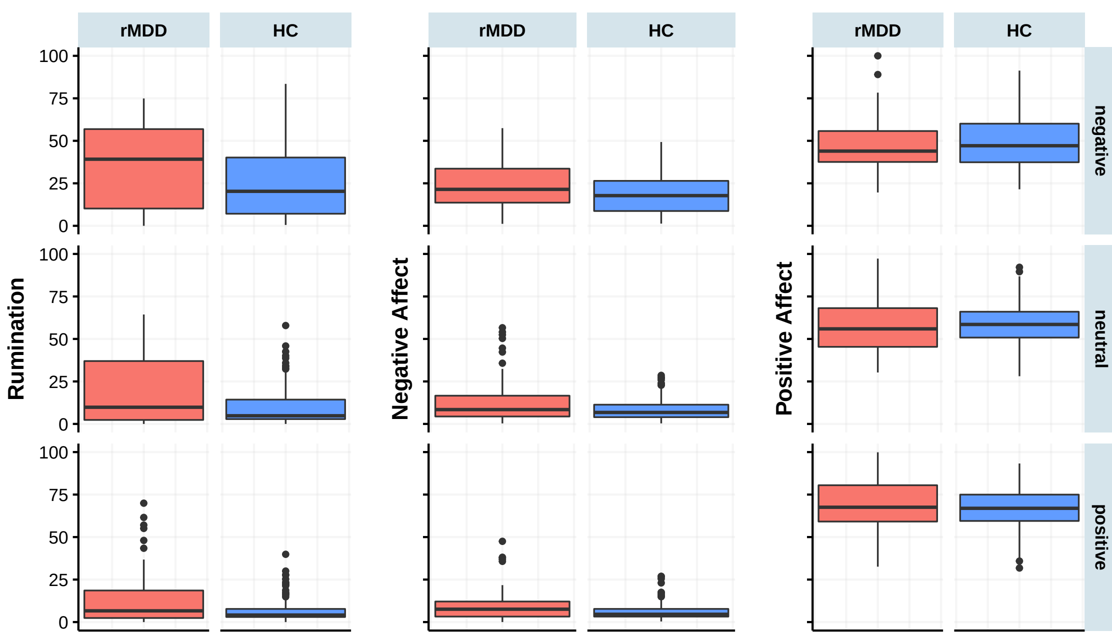

Figure D3

Daily average rumination (left), negative affect (middle), and positive affect (right) by the valence of current thoughts per group at baseline.

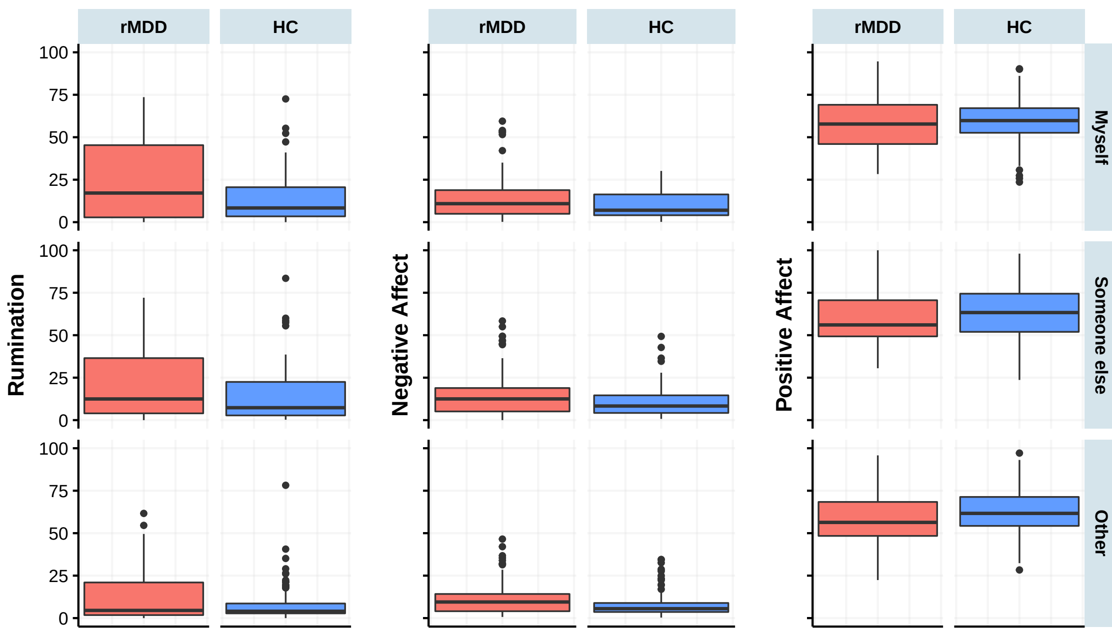

Figure D4

Daily average rumination (left), negative affect (middle), and positive affect (right) by the object of current thoughts per group at baseline.

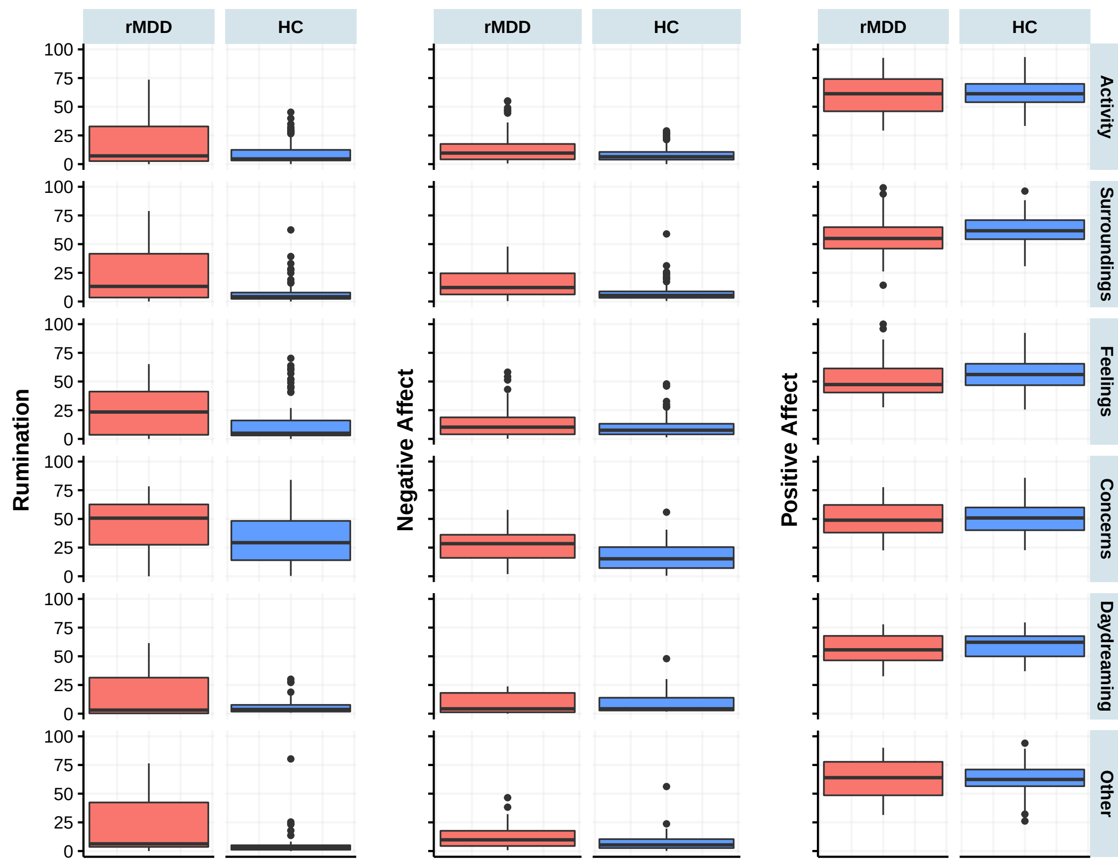

Figure D5

Daily average rumination (left), negative affect (middle), and positive affect (right) by the object of current thoughts per group at baseline.