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How Does Rumination Impact Cognition? A First Mechanistic Model

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Abstract

Rumination is a process of uncontrolled, narrowly focused negative thinking that is often self-referential, and that is a hallmark of depression. Despite its importance, little is known about its cognitive mechanisms. Rumination can be thought of as a specific, constrained form of mind-wandering. Here, we introduce a cognitive model of rumination that we developed on the basis of our existing model of mind-wandering. The rumination model implements the hypothesis that rumination is caused by maladaptive habits of thought. These habits of thought are modeled by adjusting the number of memory chunks and their associative structure, which changes the sequence of memories that are retrieved during mind-wandering, such that during rumination the same set of negative memories is retrieved repeatedly. The implementation of habits of thought was guided by empirical data from an experience sampling study in healthy and depressed participants. On the basis of this empirically derived memory structure, our model naturally predicts the declines in cognitive task performance that are typically observed in depressed

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patients. This study demonstrates how we can use cognitive models to better understand the cognitive mechanisms underlying rumination and depression.

Keywords: Mind-wandering; Rumination; Associative memory; Depression; Sustained attention

1. Introduction

Rumination is the process of narrowly focused uncontrolled repetitive negative thinking—mostly self-referential—that lies at the core of depression (Marchetti, Koster, Klinger, & Alloy, 2016; Nolen-Hoeksema & Morrow, 1991; Treynor, Gonzalez, & Nolen-Hoeksema, 2003). Despite the serious clinical consequences of this process, there is to date no coherent computational cognitive theory that describes it. While there are several verbal theories (Marchetti et al., 2016), those can only explain their own limited set of experiments and cannot make quantitative predictions.

To develop a theory of rumination, we built on recent research and modeling of mind-wandering, because rumination can be thought of as a highly constrained form of mind-wandering (Christoff, Irving, Fox, Spreng, & Andrews-Hanna, 2016). Mind-wandering is a process of task-unrelated thinking that takes up approximately 50% of our waking time (Killingsworth & Gilbert, 2010; Smallwood & Schooler, 2015), and it can sometimes help and sometimes hinder performance. For example, in undemanding contexts, mind-wandering can serve useful functions for creativity (Baird et al., 2012) and planning (Baird, Smallwood, & Schooler, 2011). On the other hand, it disrupts performance when it takes away cognitive resources that are needed to perform the task, and this occurs in particular when mind-wandering is unintentional and uncontrolled (Ottaviani, Medea, Lonigro, Tarvainen, & Couyoumdjian, 2015; Seli, Risko, Smilek, & Schacter, 2016), as is the case with rumination. This could explain why people that suffer from rumination typically also report having difficulties concentrating (Lyubomirsky, Kasri, & Zehm, 2003). In addition, this could explain why depressed people reported higher levels of off-task thinking and especially higher levels of negative-valence thought in a simple choice response time task (Hoffmann, Banzhaf, Kanske, Bermpohl, & Singer, 2016).

So far, the theories of rumination can be broadly divided into three classes (that are not mutually exclusive). One class of theories suggests that rumination arises from an increased bias toward negatively valenced information (Dalgleish & Watts, 1990). When attention is focused more on negative information, this reduces people's ability to focus on other things (Whitmer & Gotlib, 2013). Another class of theories instead focuses on inhibition and suggests that the primary deficit underlying rumination is an inability to disengage from information, in particular when this information is negative and self-focused (Whitmer & Banich, 2007, 2010). The third theory of rumination—which we refer to as "habits of thought"—focuses not on control processes such as attention and inhibition, but rather on the content of thoughts during mind-wandering. Patterns of memory associations that are frequently rehearsed can become something like an attractor (Cramer et al., 2016), and therefore will be replayed any moment there is time for mind-wandering.

To start to distinguish between these different theories of rumination, it is helpful to specify them in more detail by implementing them as a computational model in a cognitive architecture, and to simulate their predictions for performance on a simple sustained attention task. A well-suited cognitive architecture for implementing such theories is Adaptive Control of Thought - Rational (ACT-R; Anderson, 2007; Anderson, Fincham, Qin, & Stocco, 2008). The advantage of ACT-R is that it is capable of simulating complete tasks from stimulus to response.

To implement our theory of rumination, we will make use of our recent computational model of mind-wandering (Taatgen, van Vugt, Daamen, Katidioti, & Borst, submitted; van Vugt, Taatgen, Bastian, & Sackur, 2015). This model frames mind-wandering in terms of resource competition, in which task goals compete with mind-wandering goals, and mind-wandering occurs when that goal wins the competition. The mind-wandering process itself is modeled as a process of memory retrieval. While memory retrieval is not the only cognitive process that takes place during mind-wandering (mind-wandering could, for example, also involve the replaying of visual stimuli), still mind-wandering most often involves the replay and preplay of episodic memories (Christoff, Gordon, & Smith, 2011). In addition, mind-wandering involves activation of the medial temporal lobe sub-system of the default mode network, a brain network that has been associated with memory retrieval (Christoff et al., 2016; Fox, Spreng, Ellamil, Andrews-Hanna, & Christoff, 2015).

Given the important role of memory retrieval in our mind-wandering model, it is uniquely suited for implementing the third theory of rumination, which says that rumination is driven by the existence of thought habits that are maladaptive. We hypothesize that these thought patterns are what cause people to get caught in a funnel of repetitive negative thinking and disconnect from the current task, which leads to the perceived problems in concentration. Based on this, we predict that a model of rumination with exactly the same production rules but a different memory chunk structure should perform worse on a sustained attention task than a "healthy model." Future work should implement the other two theories of rumination and examine how their predictions may differ.

2. Methods

2.1. Mind-wandering model

We implemented our mind-wandering model (which forms the basis for the rumination model) in the ACT-R architecture (Anderson, 2007; Anderson et al., 2008). ACT-R is a cognitive architecture that has been used to predict task performance in a range of paradigms such as free recall (Anderson, Bothell, Lebiere, & Matessa, 1998)), multitasking (Salvucci & Taatgen, 2008), and driving a car (Salvucci & Macuga, 2002). Models in this cognitive architecture consist of production rules: if-then statements that describe under what conditions, what information is transferred between the different cognitive resources (vision, motor, working memory, etc.) of the model. For example, a production may say the equivalent of "when a visual stimulus appears, send a signal to the memory module to find out its identity." The execution of each of these productions takes a certain amount of time, and the sum of these times is the response time produced by the participant. The model is then given the same task as the human participant, and its produced responses and response times are compared to those produced by the human participant. The set of production rules used for a particular model is first determined by a detailed analysis of the task at hand, and second by seeing what rules can together predict behavior satisfactorily. In addition to these production rules, ACT-R has a number of subsymbolic parameters that govern things such as noise in various processes and the speed of memory decay. These parameters are left as much as possible at their default values (model parameters that we did not leave at their defaults are mentioned in the Appendix).

The most important module of ACT-R for the purposes of our model is the memory module (named the "declarative module"). This module describes how memories are stored and retrieved. Each memory "chunk" has an activation that determines how likely it is to be retrieved, and how long that takes (the more active a memory, the faster it can be retrieved). The activation of each memory depends on two components: how often and how recently a memory has been retrieved, as well as activation that spreads from other, related memories (Anderson, 1983; Salvucci & Macuga, 2002). This spreading activation is mediated through the attributes of chunks. More concretely, in the context of our model, such attributes are the mood associated with each memory (to facilitate comparison with behavioral data [see below], those moods are cheerful, content, down, suspicious, and insecure [Wigman et al., 2015]). The specific moods in that study were chosen because they maximally differentiated between control, depressed, and psychotic patients. We decided to keep these moods merely as symbolic attributes instead of modeling them physiologically (Dancy, 2013; Dancy, Ritter, Berry, & Klein, 2015) to keep the model as simple as possible.

Our mind-wandering model rests on two basic assumptions: first, that there is a continuous competition between a mind-wandering and a task process, and consequently, mind-wandering is likely to kick in when there is a spare moment in the task; and second, that mind-wandering is primarily a process of memory retrieval (van Vugt et al., 2015; Taatgen et al., submitted) implemented as retrieving chunks from declarative memory. As is usual in ACT-R's memory retrieval, the most active chunk is the one that will be retrieved by the declarative module. Each chunk's activation is determined by three factors: the amount of recent use (more recent and more frequent use imply a larger chunk activation), the spreading activation from other chunks, and random activation noise. More specifically, the activation A_i of memory chunk i is determined by the following equation:

$$A_i = \ln\left(\sum_{j=1}^{n} t_j^{-d}\right) + \beta_i + \sum_k \sum_j W_{kj} S_{ji} + \epsilon_i \tag{1}$$

This equation sums over all the previous times t the memory chunk has been retrieved, discounted by the decay parameter d. Each chunk also has a fixed-level activation β, independent of how often it has been retrieved. To this is added the activation spreading through other chunks in buffers weighted by weights W_k from each buffer k, which is multiplied by the strength of association S_{ji}. Only memory chunks whose activation exceeds the retrieval threshold can be retrieved from declarative memory.

Since each chunk has a slot containing its emotional valence, the spreading activation from the imaginal buffer (in which an item is placed after retrieval) ensures that chunks with the same emotional valence are more likely to follow each other than chunks with different emotional valence, in line with previous empirical data (van Vugt, Shahar, & Britton, 2012). This spreading activation could therefore be a good tool for creating the funneling effect of negative self-referential thinking that is so characteristic of rumination (Harel, Tennyson, Fava, & Bar, 2016).

The mind-wandering memory retrieval process continues until a specific memory chunk that is retrieved reminds the model of its main task. Once the reminder of the main task has been retrieved, the main goal switches from mind-wandering to being on-task. During the period of mind-wandering, the declarative module is busy retrieving memories, which means that responses to incoming stimuli will be done in automatic mode by giving the default response and will not involve memory retrievals. In addition, since ongoing memory retrievals first have to be finished before a response is made, the mind-wandering process may lead to an increase in the variability of response times during mind-wandering, in line with behavioral findings (Bastian & Sackur, 2013; van Vugt & Broers, 2016).

The mind-wandering model was given a sustained attention to response task—SART (Cheyne, Carriere, & Smilek, 2009; Smallwood et al., 2004) to produce testable predictions for behavior. In this task, participants see a stream of digits, presented at a pace of one per three seconds, and they press a button whenever a digit is presented, except when it is the number three. The number three, the nogo stimulus, is presented on roughly 10% of the trials. This means that when participants do not pay attention, they will revert to an automatic mode of responding and fail to inhibit responses to the rare nogo stimuli.

2.2. *Adaptations for modeling rumination*

Our rumination model implemented the "habits of thought" theory of rumination. The main idea underlying this theory is that rumination consists of a set of well-rehearsed thought patterns made up of memory retrievals that are predominantly negative and self-referential. We tried out different methods for generating strong loops of self-referential negative thinking (funneling) by generating a population of models that varied either in the number of chunks with different moods or in the strength of the connection between these chunks and the memory chunk that reminds the participant of the main task. For the number of chunks, we created models that had 1, 5, or 10 of each of the five moods (cheerful, content, down, suspicious, and insecure), resulting in $3^5 = 243$ different models. Similarly, for the connection strengths (S_{ji}) we tried values of 0.1, 0.5, and 1.0 for the connection between each of the five moods and the return-to-task chunk (resulting in another 243 different models). We found that the most effective way was to increase the number of chunks with negative valence, such that these negative-valence chunks are more likely to be retrieved. In addition, our simulations demonstrated that the total number of chunks had a large influence on the model's behavior, which meant it was crucial that the rumination model and the control model had the same number of chunks.

On the basis of the simulations of this family of models, we decided on a final non-depressed model has 55 chunks in total, 11 per mood (cheerful, content, down, insecure, suspicious—these moods were derived from the empirical data described below). The final depressed model also has 55 chunks, but those consist of 5 chunks of each of the positive moods (cheerful and content) and 15 chunks of each of the negative moods (down, insecure, and suspicious). For both models, the association strengths (S_{ji}'s) were 0.1 between moods of the same valence, and 0.01 between moods of different valence. These association strengths were chosen such that the spreading activations were roughly balanced with the base level activations and slightly adjusted to better fit the empirical data. Our rumination model differs from our previous mind-wandering model in that there are two chunks that remind the user of the main task—one with positive and one with negative valence—instead of just one with a positive valence as was the case in the previous model. This allowed for the emergence of a symmetric positive and a negative-valence mind-wandering network instead of biasing the model toward a positive mind-wandering network.

To assess model performance, we simulated data for 100 participants suffering from rumination and 100 participants with the usual model structure (i.e., without rumination). We chose 100 participants because this is in the same ballpark as the empirical data. We then measured how many chunks of each mood the model recalled during mind-wandering episodes, together with their transition probabilities. These measures were compared to the experience sampling data described below to adjust the model. Once the models' memory structures were adjusted to exhibit thought contents similar to what was observed in the experience sampling data, we made predictions for how rumination would impact performance on a sustained attention task. The final model code and model outputs for 10 sample participants can be downloaded from http://www.ai.rug.nl/~mkvanvugt/depression_model_Maarten.zip.

2.3. Experience sampling data on depression

We configured the set of memory chunks and their associative structure on the basis of an experience sampling study (Wigman et al., 2015). In experience sampling participants are prompted several times a day to respond to a brief questionnaire about their thoughts and experience. This particular study found that depressed patients had an increase in the number of negative-valence thoughts, more difficulty concentrating, and most important, a network of negative thoughts (specifically, suspicious, down, and insecure) that was much more separate from the network of positive thoughts (content and cheerful) than in the control subjects. The experience sampling data we used in this study were collapsed across all participants in the depression and control groups. It contained data from 129 depressed patients and 212 non-depressed controls, who were sampled 10 times per day for a period of 5–6 days.

3. Results

3.1. Average thought frequencies

Rumination is associated with increased negative memories and an increased prevalence of negatively valenced thoughts. To examine whether our model could reproduce those findings, we first compared the activation of positive-valence and negative-valence chunks, as well as the frequency of retrieval of the different subcategories. A challenge in this comparison is that the empirical data consist of the average rating of positive and

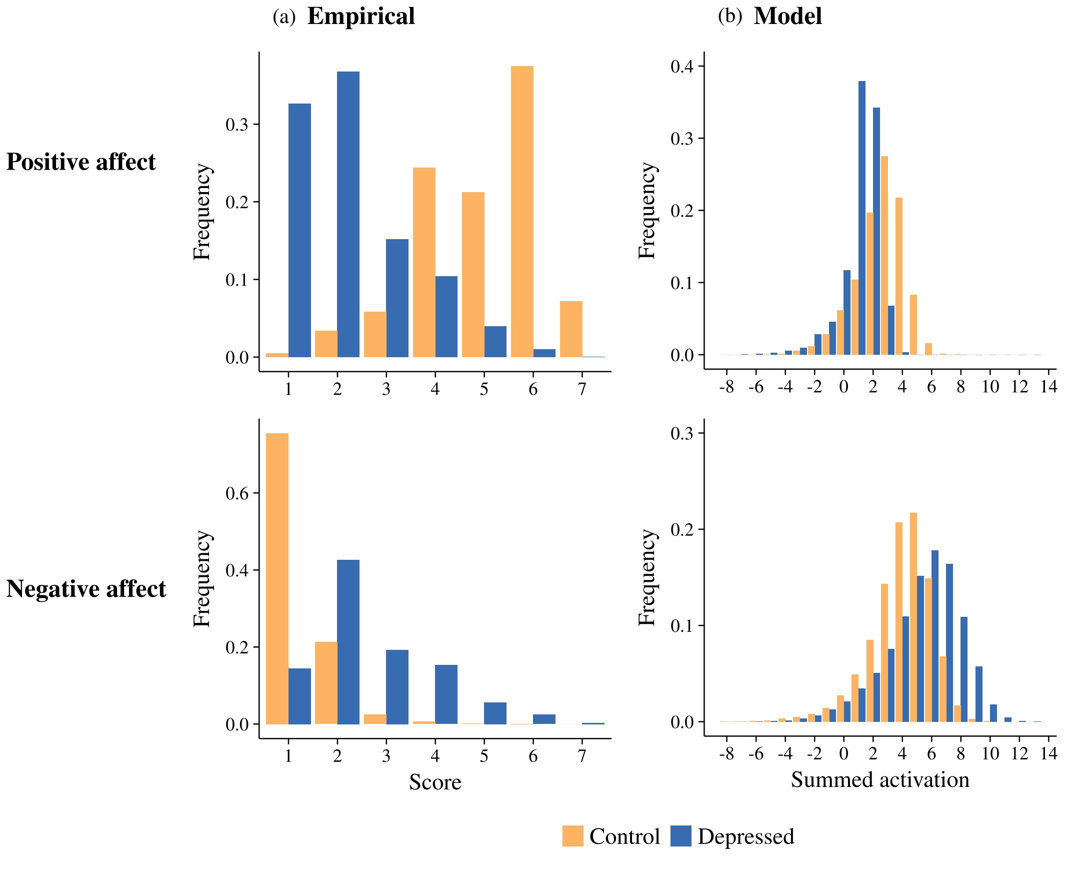

Fig. 1. Reported positive and negative effect. (a) This shows the frequency with which participants reported experiencing particular degrees of positive and negative effect in the experience sampling data, while (b) shows the summed activation of positive and negative chunks produced by the model (our closest proxy for the continuous affect ratings in the empirical data).

negative emotions on a 7-point Likert scale (the rating frequencies in the complete sample are shown in Fig. 1a). This rating has no direct correlate in the model. Since the judgment is supposed to reflect a participant's general mood, we used the summed activation of all positive/negative chunks as a proxy for positive and negative effect, respectively.

We were able to reproduce an increase in the summed memory activation of negative chunks and a decrease in the summed memory activation of positive chunks (Fig. 1b). We then examined how frequently positive and negative memory chunks were retrieved by healthy and depressed models. Fig. 2a shows that while the healthy model retrieves

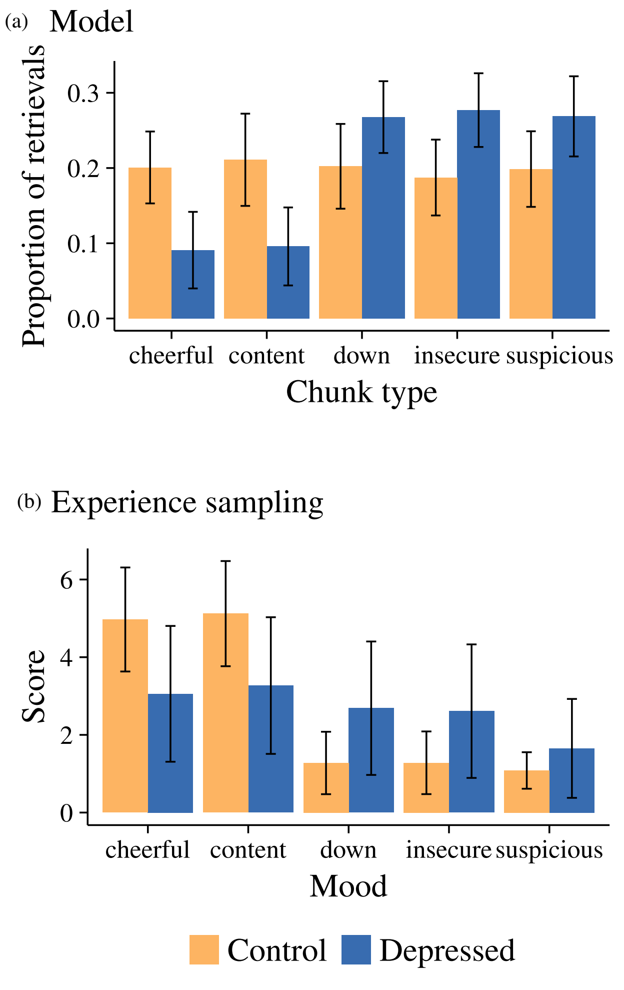

Fig. 2. The probability of memories being retrieved depends on their emotional valence. (a) The control model retrieves every mood more or less equally often, while the depressed model preferentially retrieves negatively-valenced items. (b) Empirical data show that depressed participants experienced each mood with comparable intensity, while non-depressed controls displayed a bias toward positive moods. Error bars reflect standard error of the mean.

positive and negative valence equally frequently, the depressed model tends to retrieve negative chunks more frequently (which then leads to a feedback loop, because these negative chunks then become more active, which makes it likely that they will be retrieved even more often). The empirical data (Fig. 2b) are somewhat similar, although here it appears as if healthy participants relatively suppress negative memory chunks. Note that this is at odds with a substantial body of literature that reports a negativity bias for depressed patients (Whitmer & Gotlib, 2013) instead of a positive facilitation in healthy controls (but see Levens and Gotlib, 2010).

3.2. Transitions between moods

A unique feature of the data presented in Wigman et al. (2015) was that not just frequencies of different types of thought were presented but also the network of the transitions between different moods. In the empirical work by Wigman et al., these transitions were measured by fitting a multilevel linear mixed effect model to the data. Each score at time $t-1$ was used to predict the score at time point t, and this resulted in a fixed-effect coefficient for each connection between moods. The differences in magnitude of these coefficients between depressed and control participants are compared in Fig. 3a. The largest difference between healthy and depressed participants that our model needs to capture is a higher number of transitions between negative-valence chunks for the depressed patients compared to controls, together with a lower number of transitions between positive and negative valence chunks for depressed patients. As before, we cannot produce exactly the same measure in our model, which retrieves one memory chunk at a time. The closest approximation to the regression coefficients in the empirical data is transition probabilities between retrieved memory chunks with different moods. Fig. 3b shows that when we measure the transitions for the depressed and control networks, we reproduce the somewhat stronger between-negative connectivity and the somewhat weaker positive-to-negative connectivity for the depressed model. With the exception of the cheerful category, the within-mood transitions are very close to the empirical data. In short, the modeled network resembles the empirical network.

3.3. Novel predictions: Task performance

After having developed a rumination model by adapting the memory structure (i.e., thought patterns) on which it operates, we can examine how it performs on a cognitive task. In the data reported by Wigman et al. (2015), depressed participants reported having significantly more difficulty in concentrating than healthy controls ($t(4098.8) = -44.1$, $p < 2.2 \times 10^{-16}$).[1] Consequently, we predicted that the rumination model would exhibit an impairment in performance on a sustained attention task that is typically used to measure mind-wandering, and that it would be distracted more frequently. Fig. 4a shows that performance on a sustained attention to response task was worse for the depressed relative to the control model ($t(196.5) = 2.2$, $p = 0.03$). A potential reason for this decline in

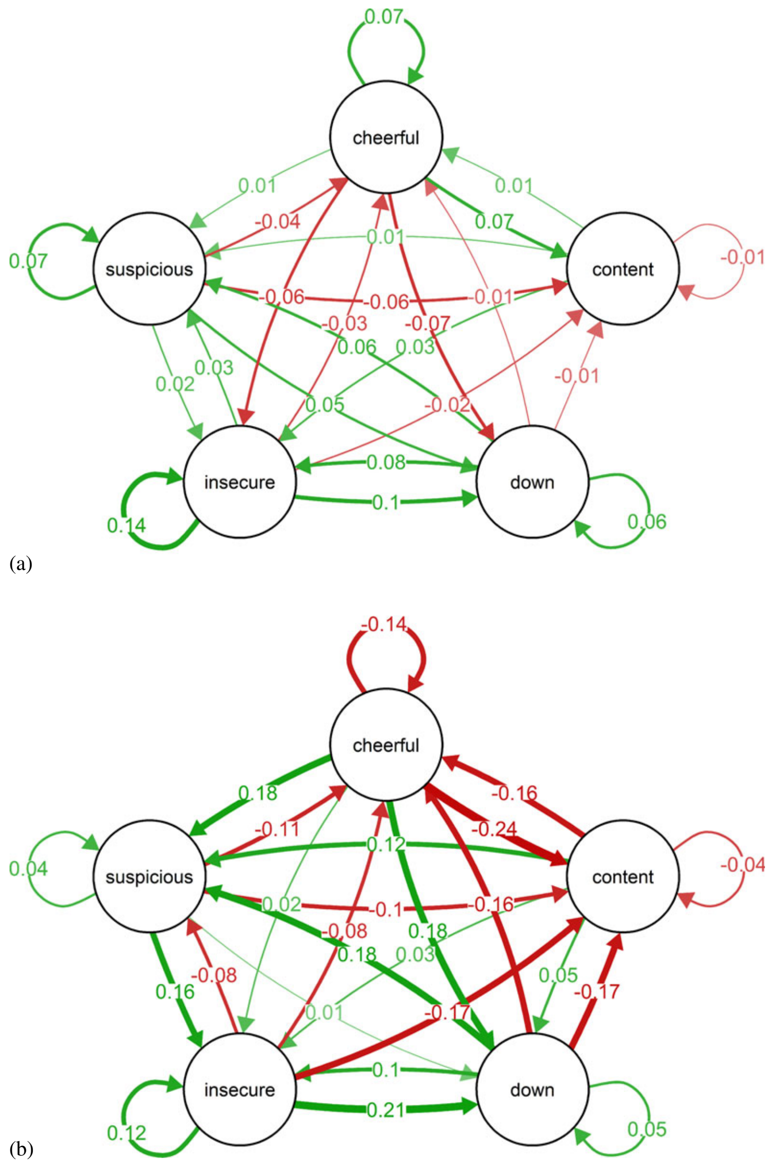

Fig. 3. Transitions between different moods. (a) Difference between control and depressed networks in empirical data from Wigman et al. (2015) on the basis of regression coefficients. (b) Modeled network difference between depressed and control participants on the basis of transition probabilities. Green: control > depressed. Red: depressed > control.

performance is an increase in the amount of off-task thinking (Fig. 4b, although this change in off-task thinking was not statistically significant, $t(197.8) = 0.53$, $p = .60$). There is also no significant difference in the coefficient of variation of response time

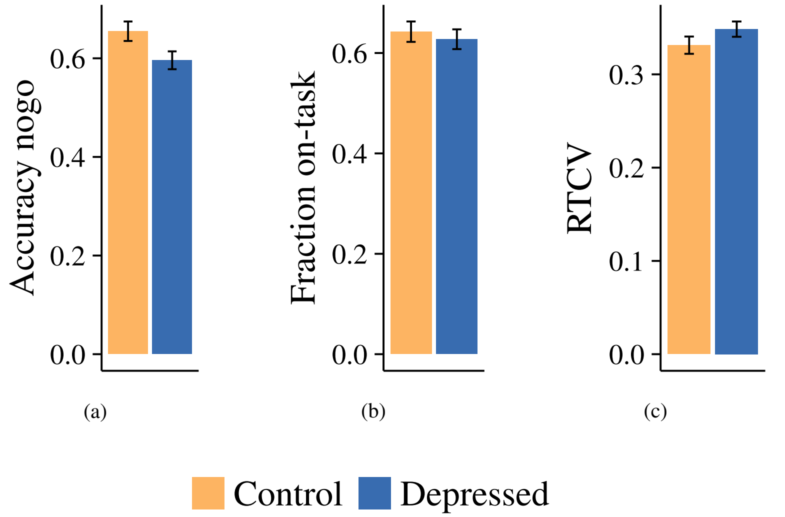

Fig. 4. Comparison of performance of the control (orange) and rumination (blue) model on a sustained attention to response (go/nogo) task. The depressed model shows lower accuracy (a) but no difference in the fraction of mind-wandering (b), or coefficient of variation of response time to correct responses. (c) Error bars reflect standard error of the mean.

(Fig. 4c; $t(195.1) = 1.39$, $p = .17$), which is considered to be a sensitive index of off-task thinking.

4. Discussion

In summary, we have developed a novel approach to modeling psychopathology by means of cognitive architectures. We structured the model's memory on the basis of experience sampling data. We then used our existing mind-wandering model to make predictions for how performance on a sustained attention task would be impacted by rumination. We found that merely by modifying the structure and contents of the model's memory, we were able to produce retrieval frequencies and sequences similar to what was observed in the experience sampling study. In addition, our model predicted impairments on a sustained attention task, in line with subjective reports of depressed patients of difficulty with concentration (Lyubomirsky et al., 2003).

While the model's performance was qualitatively in line with the observations from (Lyubomirsky et al., 2003), we were not able to fit the exact patterns. This failure to fit could either point at a structural limitation of our individual model, of the general ACT-R cognitive architecture, or at inaccuracies in the data. It turned out to be very difficult to "create" cycles of rumination because ACT-R only adapts chunk activation, and not the associations between chunks, which may be the true habits of thought.

Another potential reason for this failure is our highly simplified representation of moods. Previous studies have represented mood in terms of physiology (Dancy, 2013) or in terms of expectations and desirability of the state of the world (Marsella & Gratch, 2009). Theories focused on physiology will be most suitable for making predictions for how emotions affect physiological parameters such as cortisol. Theories focusing on expectations instead could help to explain how a person manages larger-scale goals such as which one of many actions to perform, but not so much performance on a circumscribed cognitive task. In addition to the simplifcation of moods, we also highly simplified self-report and assumed that the model's mood was simply the summed activation of its chunks, without implementing a theory of self-report. Future iterations of our model could use existing work by, for example, Petrov and Anderson (2005) on extracting self-report scores from continuous data (in our study the continuous data would be the summed activations of chunks). This would ensure that the data on self-report is more comparable to the model results.

Finally, the data used to inform our model could be unrepresentative of the real world. What argues for this is that the experience sampling data show a positivity facilitation for healthy controls, instead of a negativity facilitation for depressed patients, which has been reported more frequently in the literature (Whitmer & Gotlib, 2013). Nevertheless, the sample size is quite large (almost 200 per group), which makes it unlikely that these are merely chance fluctuations. A possible reason for these discrepancies is that previous assertions about facilitation by affective valence are based on laboratory experiments, whereas experience sampling data are from daily life. This is consistent with previous work that only shows a small correlation between a tendency to mind-wander in experience sampling and in the laboratory (Kane et al., 2017; McVay, Kane, & Kwapil, 2009).

This study contributes to the nascent field of computational psychiatry (Adams, Huys, & Roiser, 2016). So far, computational psychiatry involved mostly simple reinforcement learning models of psychiatric problems (but see Kottlors, Brand, & Ragni, 2012). These models explain, for example, why patients who suffer from rumination have a decreased sensitivity to punishment (Whitmer, Frank, & Gotlib, 2012).

The advantage of using cognitive architectures compared to simpler reinforcement learning theories is that they make it possible to simulate performance on many different tasks. Moreover, it becomes possible to examine changes in cognitive strategies (the "software of cognition") in the same context as changes in mental habits (the "hardware of cognition," encoded in synaptic connections in the brain), as we have demonstrated in this paper. Finally, cognitive architectures can implement verbal theories of rumination directly and assess their consequences for cognitive processing. While we have only simulated a single theory of rumination, future work should implement the negative attentional bias and inihibition-deficit hypotheses of rumination as well. Each of these theories may have slightly different effects on the phenomenology and dynamics of mind-wandering and cognitive task performance. In addition to that, our modeling has focused on an attention task. Nevertheless, another core problem of depressed patients is a significant reduction in working memory capacity (Onraedt & Koster, 2014). Future work should examine how rumination may cause this reduction in working memory capacity (Sari, Koster, & Derakshan, 2017). One potential mechanism may be that rumination prevents rehearsals of stimulus materials in spare moments during the task, a mechanism we have demonstrated to occur when we induced self-referential processing in healthy participants (Daamen, van Vugt, & Taatgen, 2016; Taatgen et al., submitted).

Another computational approach that is gaining popularity in the field of depression research is the modeling of network dynamics (Bernstein, Heeren, & McNally, 2017; Fried et al., 2016; van Borkulo et al., 2015) of depression symptoms. Similar to our approach, this approach focuses on the dynamics of depression and rumination. For example, Cramer et al. (2016) demonstrated that depressed patients had a tendency to quickly move to a depressed state when only lightly disturbed, whereas control participants had a more resilient dynamic. In addition, Koster et al. (2015) showed that increased entropy in rumination/mood scores was predictive of future depressive relapse. Bernstein et al. (2017) showed that self-reported self-criticism is a crucial component in generating rumination. However, in contrast to our approach, these studies focus on the responses to questionnaires, not so much the cognitive mechanisms that generate those. Consequently, unlike our modeling, these approaches cannot make predictions for impairments on specific cognitive tasks.

A final modeling approach that has been used to understand rumination and depression is more neuro-biologically oriented. For example, Ramirez-Mahaluf, Roxin, Mayberg, and Compte (2015) used a spiking neuron network of the anterior cingulate cortex and dorsolateral prefrontal cortex to demonstrate how the balance between cognitive and emotional processing may be shifted in people suffering from depression. While their model validated predictions for patterns of neural activity observed in healthy and depressed patients, it did not make detailed behavioral predictions.

In summary, we have demonstrated how cognitive architectures can be beneficial in computational psychiatry. Cognitive architectures allow us to implement a cognitive theory of rumination and make testable predictions about performance on a sustained attention task. This leads to new avenues for better understanding what the exact mechanisms are that underlie rumination and depression in general. For example, in line with the idea that habits of thought are crucial for rumination, recent work (Benoit, Davies, & Anderson, 2016) has shown that changing thought patterns can reduce future fear-related rumination.

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Note

1. *T*-tests used Welch's correction for degrees of freedom.

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Appendix

Overview of model parameters that were not at their default

Name	Abbreviation	Value	Default
Retrieval threshold	:rt	3.0	0.0
Spread activation from the imaginal buffer	:imaginal-action-activation	1.0	0.0
How long the indication that something visual changed remains active	:visual-onset-span	0.7	0.5
Enable randomness in modules	:er	t	nil
The amount of spreading activation	:mas	2	nil
Multiplier to generate retrieval times from activations	:rt	0.85	1.0

(continued)

Table. (continued)

Name	Abbreviation	Value	Default
Noise in activation values	:ans	0.13	nil
How long does an attentional shift take?	:visual-attention-latency	0	0.085
Utility learning	:ul	t	nil
Noise in utilities	:egs	0.1	0
How much retrievals change the activation of memory chunks	:bll	0.5	nil
Optimized learning (when set to true, it does not compute activation for individual memory chunks)	:ol	nil	t