**Oversampled and undersolved: Depressive rumination from an active inference
perspective**

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Abstract

Rumination is a widely recognized cognitive deviation in depression. However, researchers have struggled to explain why patients cannot disengage from excessive rumination, although it clearly depresses their mood and fails to lead to effective problem-solving. In this integrative review, we connect insights from cognitive science, neuroscience and computational psychiatry to rethink rumination as repetitive but unsuccessful mental problem-solving attempts. In particular, appealing to an active inference account, we first suggest that adaptive problem-solving is based on the generation, evaluation, and performance of possible behaviors (candidate policies) that increase epistemic value and minimize prediction errors. Next, we discuss how this problem-solving algorithm is distorted in depression. Specifically, we propose that depressive rumination can be understood as engaging in excessive yet unsuccessful Bayesian sampling of candidate behaviors that do not resolve uncertainty. Further, as policy candidates are sampled from policies that were selected in emotional states resembling the current one, similar candidates are re-sampled repetitively, resulting in a time-consuming feedback-loop, a ruminative „halting problem“. This leads to high opportunity costs, because potentially better policy candidates are not selected, as well as to learned helplessness as problem-solving attempts remain unsuccessful. Besides reviewing the evidence for the conceptual paths of this model of depressive rumination, we discuss the evidence for its neurophysiological correlates, particularly with respect to distorted connectivity patterns of different brain networks, such as an overactive default mode network. We conclude by suggesting future research directions into behavioral and biological features of our model and highlight clinical implications.

Keywords: rumination, depression, active inference, Bayesian sampling, mental simulation, problem-solving

Introduction

Rumination is a fascinating aspect of the human mind. It makes people think repetitively about their current mood, their problems, and how they got there - without finding helpful answers to their questions. Intriguingly, people often find themselves unable to disengage from rumination, although it clearly depresses their mood and prevents active problem-solving (Nolen-Hoeksema et al., 2008; Thomsen, 2006). So, the question is, why can't people stop doing something that makes them feel worse and even paves the way to mental disorders such as major depression (MDD)? How do people transgress the line between adaptive problem-solving and self-perpetuating maladaptive ruminating? Although rumination has been the subject of extensive scrutiny over past decades, including the proposition of many elaborated models (Conway et al., 2000; Nolen-Hoeksema, 1991; Wells and Matthews, 1996), rumination's function is still largely unclear, as an in-depth review concluded (Smith and Alloy, 2009). The present article seeks to rethink these questions and offers a new framework - originally developed in theoretical neuroscience - to approach them. We recast rumination (as opposed to adaptive problem-solving) through the lens of an active inference framework, and review evidence on how it can result in pathologies linked to depression. In doing so, our aim is to apply current accounts based on active inference to provide a new conceptual model of depressive rumination.

The active inference framework is closely related to the Bayesian brain hypothesis, which views the brain as a probabilistic, hypothesis-testing organ (Friston et al., 2014). Active inference assumes that a central function of perception and action is to reduce uncertainty by minimizing prediction errors (PEs). More specifically, it rests on the idea that the brain applies principles of Bayesian statistics by combining a prior prediction (referred to as "prior") with new information (referred to as "likelihood") to compute an updated prediction, referred to as "posterior" (Clark, 2013; Friston, 2009, 2005).

Neurobiologically, prior predictions may reflect descending signals originating from higher levels of the cortical hierarchy, which are then compared with sensory input at lower

cortical levels to generate a PE (Bastos et al., 2012; Friston, 2008; Kanai et al., 2015). The ensuing mismatch signal is sent back up the hierarchy to update the prediction, corresponding to the activity of deep pyramidal cells (Barrett and Simmons, 2015). When updating, the reliability (or predictability) of both the prior and data is considered, referred to as precision weighting.

In addition to the idea that the brain employs predictions to infer its sensations, active inference postulates that living organisms change their environment in a way that makes their priors become reality. Metaphorically speaking, nervous systems reduce prediction errors by actively generating self-fulfilling prophecies (through their actions in the world) (Da Costa et al., 2020; Friston et al., 2016).

Different theories adjacent to the Bayesian brain hypothesis - and especially active inference accounts - have provided new perspectives on psychiatric conditions such as psychosis (Corlett et al., 2019; Powers et al., 2017; Sterzer et al., 2018), autism (Lawson et al., 2014; Rozenkrantz et al., 2021), post-traumatic stress disorder (Kube et al., 2020a; Linson et al., 2020; Wilkinson et al., 2017), persistent somatic symptoms (Henningesen et al., 2018; Kube et al., 2020b; Van den Bergh et al., 2017) and depression (Barrett et al., 2016; Eldar et al., 2016; Kube et al., 2020c). Here, we propose an active inference account of rumination, which is a key facet of MDD (and to a lesser extent of other psychiatric conditions) (Joormann et al., 2011; LeMoult and Gotlib, 2019; Newby and Moulds, 2012).

An Active Inference Perspective on Rumination

Generative Models

Before we can lay out the central tenets of our account of rumination, we must first consider how the brain construes its internal model of the world in active inference. In essence, active inference assumes that neural activity can be approximated by a *generative model* as *hierarchically* structured states that are connected by *transitions* and form a *mental map* of the world (Friston et al., 2017). The term *generative model* refers to models that describe how sensory data is generated by events (from so-called hidden variables) in the

outside world that cannot be known directly but have to be inferred by the brain in a way that resembles probabilistic reasoning, referred to as Bayesian inference. The models are called *hierarchical* because it is postulated that the computations of “lower” layers serve as PEs for “higher layers” while these “higher layers” convey their updated predictions back to the “lower” layers. Layers closer to sensory input or closer to motor output are called “lower” in this sense, whereas layers receiving their neural input from those lower layers are called “higher” layers. The term *transition* means that generative model encodes prior beliefs about how a given state evolves into another state depending on the policy that the agent chooses to pursue.

The term *mental map* describes the idea that organisms possess a model of their environment and possible interactions with this environment to enable effective action. This action is necessary to make predictions about vital parameters (essential for survival) become reality (e.g., body temperature, saturation, sleep). In short, agents act in a way that fulfills their own predictions about parameters that are pivotal to their own existence and thereby create “self-fulfilling prophecies” (hence the term *active inference*). For example, an agent might predict its own body temperature to remain within a narrow range around 37 degrees Celsius. Regulative processes would in turn ensure that this temperature is maintained by the organism and hence that the prediction concerning body temperature becomes reality. For a comprehensive explanation of generative models within the active inference framework, see Smith et al. (2022).

Mental Simulation for Model Optimization

New transitions between states are learned through experience, resulting from the interplay of prediction, perception, and overt action, but also through mental simulation (Gupta et al., 2010; Hunt et al., 2021). Mental simulation is conceptualized as “running imaginary actions” that produce “fictive actions and predictions [which] can be optimized [...] without overt action” (Pezzulo, 2012). Mental simulation is important for our rumination model as it plays a foundational role in sentient behavior at two levels. First, deciding what to do next entails active planning as inference (Attias, 2003; Botvinick and Toussaint, 2012; Hesp

et al., 2020; Millidge, 2020); namely, rehearsing plausible plans or “policies” (sequences of actions) to evaluate them in terms of their epistemic (exploration) and pragmatic value (exploitation) (Friston et al., 2015). Epistemic value describes a policy’s expected ability to improve an organism’s knowledge of the world, while pragmatic value describes a policy’s expected ability to make prior beliefs come true to ensure survival. Formally, these evaluations entail the PE, i.e., the surprise or free energy expected under a particular policy (Schwartenbeck et al., 2015, 2013). Because expected surprise is uncertainty, one can construe policy evaluation in terms of how much uncertainty it will resolve. In that case, a given policy is chosen over another policy if the expected surprise of pursuing it is larger than when perusing an alternative policy.

The second way in which mental simulation is implemented in active inference is through a process known as structure learning or Bayesian model selection (Gershman, 2017; Smith et al., 2020; Tervo et al., 2016). Here, offline simulation is used not to evaluate competing policies, but to evaluate the underlying generative model per se. In brief, in the absence of new sensory evidence, the minimization of PE — or maximization of model evidence — rests upon reducing model complexity and thereby increasing epistemic value: put simply, finding a more parsimonious account of past experience that involves joining the dots and eliminating redundant associations (Friston et al., 2017; Hinton et al., 1995). In the brain, this process may be evinced at multiple timescales; for example, the regression of frontal radiations during neurodevelopment (Chini and Hanganu-Opatz, 2021; Mills et al., 2016), synaptic regression during sleep (Tononi and Cirelli, 2006), and through planning in wakeful resting (Mattar and Daw, 2018; Momennejad et al., 2018). Mental simulation plays a crucial role in both evaluating courses of action and optimizing generative models of the world. As such, any distortions in the ability to generate, simulate, or evaluate plans and narratives can have profound implications for how we behave and think, such as excessive rumination.

For our account of rumination, the process of mental simulation is of particular importance. We propose a simplified subdivision into three steps: First, from all the possible

experiences across one's lifespan, how do we find promising candidates for simulation (candidate generation)? Second, how do we choose a candidate to focus on (policy evaluation)? Third, how do we utilize the focused candidate to reduce PEs (mental problem-solving)? In the next section, we spell out what these steps involve before explaining how distortions therein can result in depressive rumination.

Candidate Generation

In the context of mental simulation, candidate generation is regarded as identifying policies about policies (Sandved-Smith et al., 2021). This means that for each policy, there is a meta-policy that represents a prediction (with a corresponding precision) about the policy's effect on minimizing PEs. When looking for a lost key for example, the behavioral policy "check the usual places" may be associated with a predicted PE minimization of large magnitude at first. After failed attempts however, the mental policy "mentally trace the last place I had the key" may be associated with a better predicted PE minimization because subsequent search attempts may be more successful. After losing a key several times, even the mental policy "analyzing why I keep losing that key" may promise a promising path to PE minimization: An answer to this problem and a solution – e.g., a bell on the keyring – may effectively reduce long-term PEs. Due to the incalculably large number of possible candidates to do or to "think about", we propose that Bayesian sampling may be a biologically plausible approximation strategy to describe how candidates are chosen for subsequent analysis¹. In Bayesian sampling, the brain is not trying to simulate an (intractable) probability distribution, but instead samples a subset of "fitting" candidates. Fitting means that candidate samples are chosen based on past behavior in similar contexts ("What did I do last time when I was sad?"), as well as current mood states and circumstances. Hence, the chosen samples are by no means un-biased. They are not independent from each other but rather constitute "a stream of samples, each of which is a

¹ Of note, we appeal to Bayesian sampling – instead of other frameworks for approximating Bayesian inference – because it succeeded in approximating data from direct recordings in animals (Madl et al., 2014). Bayesian sampling procedures can also account for numerous cognitive biases in humans (Sanborn and Chater, 2016) and were successfully used to enhance robot planning (Lai et al., 2020).

variant on the last” (Chater et al., 2020). The “right” starting point therefore quickly leads to candidates that can be evaluated in subsequent steps. “Bad” starting points, on the other hand, can lead to a sampling process that finds no candidates that promise sufficient PE reduction, resulting in a continued search. An important assumption of Bayesian sampling in the brain is that drawing additional samples takes time. In sequential sampling models of decision making for example, the less clear a decision is, the more samples seem to be drawn to reduce uncertainty if the decision is important enough (Shadlen and Shohamy, 2016). In the case of the lost key, an individual may spend time just sampling possible plans or policies without deeply engaging in any one of them yet.

Policy Evaluation

In its attempts to minimize PEs by maximizing epistemic and pragmatic value in an optimal trade-off (Friston et al., 2017), the brain seeks to choose the policy expected to reduce future PEs the most. In doing so, the brain faces the problem that, due to its limited computational resources, there are always opportunity costs when one specific policy – instead of another – is chosen (Lieder and Griffiths, 2019). Thus, it is an important trade-off whether a specific mental problem-solving policy offers enough epistemic value to outweigh the opportunity costs of “missing” generating other – potentially better – candidates.

Mental Problem-solving

Whenever the policy evaluation step identifies a promising candidate, the candidate for action is engaged during the problem-solving step. While the policy evaluation step specifies *which tasks* will be more deeply thought through, the mental problem-solving step specifies *how to profit* from pursuing the selected task.

Since a perfect solution is not computable for most tasks, approximations have to be computed. While the specific algorithms at work are debatable, finding paths from a given state to a target state on the mental map is plausible for planning tasks (Hunt et al., 2021). Allowing the starting state to lie in the past or future offers a generalization of this model to structure learning. When progress is made approximating a sufficiently good path, the PEs along the path are reduced and future engagement with that task’s details becomes less

probable (Kolling et al., 2018). Further, an individual may learn about a given task's complexity which can inform future evaluations regarding the expected epistemic value gained from performing it.

Because the tree of possible paths grows exponentially with its path-length, computational costs are necessarily limited, and not all potential paths can be simulated. There is evidence that humans may use pruning, probably implemented by its Bayesian counterpart, Occam's window (Madigan and Raftery, 1994), as one strategy. That means that simulation is stopped at branches based on expected reward or – with reference to active inference frameworks - based on the expected PE minimization (Friston et al., 2021; Huys et al., 2012). To conclude: many problems do not offer a solution that can be computed in acceptable time; however, there are usually solutions based on approximation strategies that lead to good results in many cases.

Successful Problem-solving

With these three steps, we can formulate mental simulation as an ongoing process of minimizing PEs, which ideally results in an optimal trade-off between sampling for promising prospective tasks (exploration) and engaging in mental problem-solving (exploitation). Human beings live in changing environments that make it necessary to continually adapt to new circumstances. This might be the case after a dramatic life event, when previously adaptive policies no longer led to the expected outcomes. The resulting overall imprecision of predictions has been connected to mood (Clark et al., 2018). Negative mood may hereby reflect the belief that current predictions about the world are too imprecise. It follows that negative mood is associated with increased mental simulation, as there is a greater demand for policies with high epistemic value. In many cases, mental simulation will indeed lead to an updated generative model (through a process of structure learning or Bayesian model reduction) (Smith et al., 2020; Tervo et al., 2016).

In this case, the overall precision of predictions rises, and the epistemic value of deeper mental simulation falls because good approximations from starting states to preferred states have been detected, and in-depth instrumental learning is no longer needed. Next, the

sampling of policies promoting overt behavior increases again. In other words, we conceptualize mental simulation as a foundational and transitory process that underwrites planning as inference and structure learning, and adapting an internal or generative model to the world; especially in a changing environment (e.g., after significant changes in circumstances).

Rumination as Continued Sampling

Next, we discuss how perturbations of this problem-solving process can lead to maladaptive depressive rumination. In brief, we consider depressive rumination as oversampling of policy candidates, which fail or are or prematurely discontinued, such that effective mental problem-solving does not occur. As a result, patients get stuck in an endless loop of sampling and discarding candidate policies that are unable to effectively reduce PEs.² Before we explain these mechanisms in-depth, figure 1 provides an overview concerning successful problem-solving, unsuccessful problem-solving and depressive rumination according to our model.

² Of note, we acknowledge that some creative mental processes may very well require many sampling steps until a promising policy candidate is found. However, the problem with rumination is that the samples drawn are unsuitable for deeper mental problem-solving for the reasons discussed next.

Figure 1
A Model of Rumination Development and Maintenance

Note. PE = prediction error. The model describes a two-step policy selection process. At first the candidate sampling step samples for broader policies (“What to think about?”) while the policy evaluation step selects candidates based on their solvability (Policies with high prediction errors and a high probability of reducing them are chosen first). After selection, the mental problem-solving step evaluates policies in more detail (“How to do it?”) In earlier stages of unsuccessful problem-solving, the large expected epistemic value of mental problem-solving candidates leads to an increase in mental problem-solving. Later during MDD development, the epistemic value of policy candidates decreases, leading to rapid candidate recycling and rejection during the policy evaluation step without engagement in deeper instrumental learning.

Imprecise Generative Models can Cause Rumination

According to the model we propose it is necessary for rumination to emerge that the generative model does not predict the current environment adequately (“suboptimal model”) (Schwartenbeck et al., 2015). This state could again be triggered after a dramatic change in circumstances. The need for mining epistemic value will (as in successful problem-solving) lead to negative mood and to increased mental problem-solving. When the attempts at problem-solving produce no policies able to lead to preferred outcomes, however, the respective PEs remain large, which is why the candidate sampling process starts anew to find promising candidates to evaluate.

There are pitfalls in this process leading to rumination - they hinder successful mental problem-solving and lead to a repetitive cycle of policy sampling and discarding. First, we describe factors that hinder successful mental problem-solving. Second, we present factors that prevent engagement in mental problem-solving altogether, especially after numerous failed attempts. Third, we present characteristics of the sampling process itself that promote repetition. Ultimately, we describe a vicious circle by discussing the negative consequences of long-term rumination.

Unsuccessful Mental Problem-solving Stabilizes Rumination

Despite trying, a depressed individual may find it impossible to generate a good approximation to a complex problem’s solution. Several factors may contribute to this:

High computational complexity: As discussed earlier, humans are restrained in evaluating complex tasks in similar fashion than computational approximation algorithms (Bossaerts and Murawski, 2017). While simple problems like 2-dimensional navigation in limited spaces have efficient solutions, interpersonal relationships and social situations may produce much more dense and complex maps with uncertainty on many levels. Thus, real world problems are likely to have the property that attempts to solve them can fail under many circumstances, even if the organism spends a lot of time approximating a solution.

Unrealistic precision demands: Due to the complex nature of typical rumination problems, a perfect solution is usually unattainable. Instead, solutions can be approximated

to a certain extent. How much time is needed to compute such an approximation strongly depends on how close to the optimal solution the approximation should be (Tarbouriech et al., 2021). The more adverse an event is, the higher the costs of allowing residual uncertainty to prevent it. This factor may play a special role in rumination and worrying after traumatic events as well as in states of sorrow or anxiety (Gagne et al., 2018).

Excessive pruning: As described above, problem-solving can be optimized via pruning implemented by Occam's Window (Friston et al., 2021; Huys et al., 2012). However, state evaluation may be influenced by the individual's current physical and emotional state (Clark et al., 2018). In depression, this could lead to overestimating losses when exploring the search tree. Accordingly, if an actually successful path starts with a minor loss and ends with large gains, depressed people may fail to pursue that path because of their initial loss. In Bayesian terms, this means that single tree branches will never be selected for deeper computation if the anticipated PE minimization at early branches is insufficient to justify deeper engagement. Pruning may be one usually successful way of saving computational resources that can hinder complex mental problem-solving in negative emotional states. Note, however, that there is a study with a small sample of MDD patients where no pruning differences (to controls) were detected (Faulkner et al., 2021).

Missing action policies: A behavioral repertoire can also be limited because certain behaviors have not occurred in that individual's experience. In this case, there may be no solutions readily available, and computational effort may be significantly increased. Interpersonal fear and especially interpersonal skill – and problem-solving deficits are known to be risk factors for depression (Klein et al., 2020; Sondermann et al., 2020) and lead to rumination partly by limiting the number of suitable solutions for simulation.

One-sided Policy Selection After Prolonged Rumination

Biases in policy evaluation may cause the resources spent on action planning, mental problem-solving, and candidate sampling to be off-balance:

Learned helplessness: After relevant experiences with a large PE, policy candidates with high epistemic value will be sampled to reduce the large PE. If attempts at problem-

solving remain unsuccessful, their epistemic value will decline. Put simply, one learns that uncertainty cannot be resolved. In other words, epistemic value disappears in the face of irreducible uncertainty (e.g., “I am confident that attempts at deeper problem-solving are fruitless”). Because of the brain’s hierarchical organization, it is likely that after many unsuccessful attempts at various tasks, the hyperprior over mental problem-solving’s epistemic value itself will shift. The system learns that engaging more deeply in problem-solving steps no longer fulfills the promise of sufficient PE reduction.

Owing to the higher rejection rate of sampled policies, less time will be spent on actual mental problem-solving, and more time on candidate sampling. Tasks that would otherwise be easily solvable become unengaged with anymore, which leads to a further reduction in the overall model fit. In other words, rumination itself may lead to “learned helplessness”, not in terms of overt behavior, but in terms of less problem-solving oriented mental exploration that has lost its epistemic value.

Lack of alternative behavioral policies: Due to the generative model’s poor model fit, behavioral exploitation policies prove to be so ineffective that their estimated pragmatic value is reduced. Especially when active behavioral states require effort (making them thus prone to pruning), it should be increasingly improbable that any undertrained behavioral policy will beat the expected PE reduction of continued sampling (and discarding) of alternative behavioral policies.

Biased and Intercorrelated Sampling During Rumination

The process of sampling policy candidates may yield a limited and biased set of policy options:

Autocorrelation of samples drawn: Due to behavioral inactivity, depressed individuals may spend a large amount of time per day in similar physical and emotional states (e.g., lying in bed, feeling sad). Because policy candidates are to be sampled from policies selected in states close to the current one, it is probable that similar candidates will be sampled again and again, creating a maladaptive feedback-loop (Smith et al., 2018).

Drawing from autocorrelated samples seems common across cognitive tasks (Sanborn and

Chater, 2016; Zhu et al., 2020) and mood-induced negative recall biases are well documented (Dalglish and Watts, 1990). In depression, however, autocorrelation further reduces the probability of sampling a policy candidate that promises significant epistemic value.

Less precision of sensory inputs: Because sensory data are less informative due to the poor model fit and inefficient action policies, the precision of sensory PEs is reduced (Barrett et al., 2016). Cognitively generated PEs are over-weighted, exacerbating rumination instead of promoting overt behavior.

Negative Long-term Consequences of Rumination

Further reduced model fit: We propose that rumination's strongest negative effects lie in the opportunity costs it brings about. Neither pragmatic nor epistemic value is mined during depressive rumination, which leads to a decline in behavioral output and general model fit. This, in time, aggravates the biases described above and constitutes a vicious circle (Smith et al., 2018).

Restructuring the generative model: Since the brain continuously optimizes its knowledge structure in hierarchical fashion (Momennejad, 2020), ruminative states, where the psyche is stuck oversampling candidates, may become learned as the default responses in many situations, thereby hindering effective problem-solving to reduce *epistemic uncertainty* (sometimes referred to as intrinsic motivation) (Barto et al., 2013; Oudeyer and Kaplan, 2009; Schmidhuber, 2010; Schwartenbeck et al., 2019).

Neurobiological Correlates

In this section, we aim to link our account of depressive rumination, particularly the abnormalities in policy evaluation and continued candidate sampling, to findings from the neuroimaging literature. We suggest that an *overactive default mode network* (DMN) drives the repetitive oversampling of policy candidates during depressive rumination. The DMN is a large-scale network primarily consisting of mediofrontal, superior temporal, temporoparietal, cingulate, and parietal brain regions (Mars et al., 2012). Traditionally, it has been considered as a neural correlate of introspection, mind wandering, self-referential thinking, and

autobiographical recall (e.g. Raichle, 2015). Recent theoretical considerations (Stawarczyk et al., 2021) and neuroimaging studies (Beatty et al., 2015; Hearne et al., 2015, 2017) expanded this viewpoint by suggesting that the DMN is also involved in mental problem-solving and creative thinking, especially when the process depends on information flow from declarative memory and not primarily on rapid multisensory updating.

In influential research, Andrews-Hanna and colleagues suggested that the DMN has two subsystems: a dorsomedial subsystem involved in meta-cognitive processes (like considering one's own current mental state), and a medial temporal lobe subsystem involved in recalling past experiences and in simulating the future (Andrews-Hanna et al., 2014, 2010). Parts of the DMN like the medial prefrontal areas (mPFC) and posterior cingulate cortices (PCC) are thought to be important for spontaneous thought (D'Argembeau, 2013; Yankouskaya et al., 2017).

To enable memory recall, a coupling of mPFC areas with PCC and parietal regions was suggested (Philippi et al., 2013; Shapira-Lichter et al., 2013). Dynamic causal modelling found the mPFC to be recall's "main driver" with positive connections to all the other structures involved (Nawa and Ando, 2020). Dynamic causal modelling also suggests that the activation of other areas (PCC, parietal areas, hippocampus) follows in lockstep with mPFC activation, emphasizing that the region provides "general schemes" (self or situation-related) about which the parietal and PCC regions provide fitting samples (e.g. Boccia et al., 2019). Magnetoencephalography has confirmed the idea that mPFC activation drives the neural activity in other regions during autobiographical recall (McCormick et al., 2020) and represents self-referential values ("What does it mean to me?") of re-called memories (Lin et al., 2016).

A meta-analysis that compared functional magnetic resonance imaging (fMRI) studies of rumination with control conditions found significant activations during rumination in mPFC and PCC regions (Zhou et al., 2020). Further, a meta-analysis of the correlation between resting-state fMRI and rumination found that MDD patients (compared to healthy controls) revealed stronger coupling between subgranular prefrontal (sgPFC) and thalamic structures

and the DMN, also demonstrating PCC hyperactivation (Hamilton et al., 2015). These authors interpreted this connection as causing the inversely focused, negatively valenced, and withdrawn ruminative process typical for MDD.

With respect to the functions described above, DMN regions (mPFC, PCC) may initiate and control candidate sampling during mental simulation and during depressive rumination. In case of a mismatch between a desired self-related prior (“I’m fine”) and sampled self-related states (“I feel horrible”), it creates a PE with respect to this prior and connects with parietal/PCC regions to seek relevant samples to employ for engaging in deeper problem-solving when the expected PE reduction is large enough. Especially when DMN regions couple with the sgPFC (like in depressive rumination) this process becomes prone to deliver affect laden, negatively valenced samples. Because Bayesian sampling is biased and heavily reliant on the starting point, “bad starting points” make the simulation process vulnerable to exhaustive but unsuccessful searches for policy candidates for reasons we discussed in the last chapter.

The overactivation of PCC regions may reflect the candidate oversampling itself. In our conceptualization, candidate behavior that is sampled during depressive rumination typically does not promise sufficient PE reduction to justify mental problem-solving, which is why a repetitive oversampling of declarative memories become the default mode of depressive cognition. Since sampling episodic memories requires PCC activation (Boccia et al., 2019) resting state fMRI meta-analyses of rumination (Hamilton et al., 2015; Zhou et al., 2020) may find the brain region overactivated and hyperconnected for exactly that reason.

Lastly, we propose that the oversampling causes a hypoactivation of the brain’s control networks (CNs). Meta-studies suggest that CNs – frontoparietal networks planning and controlling action– exhibit reduced within-network connectivity in MDD (Kaiser et al., 2015; Mulders et al., 2015). Furthermore, the between-network connectivity of CNs with the DMN was also found to be reduced in depressed patients (Mulders et al., 2015). Studies have highlighted the importance of DMN coupling with CNs for successful problem-solving (Beaty et al., 2015; Gordon et al., 2020; Vatansever et al., 2017). However, when the

samples drawn by mPFC-PCC connections do not promise sufficient PE reduction, a coupling with CNs for deeper engagement becomes unlikely, leaving the DMN trapped in unsuccessful looping over policy primitives.

When CNs are underactivated and disconnected from the DMN, sensory predictions from different modalities become less cognitively relevant. Therefore, PEs from interoception become less precise. This reduced precision (and greater precision of “internally” generated PEs) has been dubbed the “depressive locked-in state” (Barrett et al., 2016). Empirical evidence for the claim that interoceptive PEs lose precision comes from fMRI studies that found the insula’s resting state activity and its connection to frontal brain regions to be decreased in MDD (e.g. Hu et al., 2019; Javaheripour et al., 2021; Wang et al., 2018). The insula is a major interoceptive integration hub that is important for integrating external and internal multisensory information. Furthermore, recent theorizing suggests that the anterior insula may serve as a switch between DMN-driven (i.e., self-reflective, metacognitive) and CN-driven (i.e., action oriented) neural activity (Molnar-Szakacs and Uddin, 2022). When cognition is dominated by DMN activity (like during rumination), there is no need for updates of multisensory information or for switching to CN-driven cognition. This possibly explains the patterns of insula hypoactivity and hypoconnectivity found in MDD according to neuroimaging studies.

In the previous section, we aimed to re-interpret the existing imaging literature to explain depressive rumination as continued sampling primarily hosted by the brain’s decoupled DMN. As a consequence of such decoupled DMN overactivation, mental problem-solving and online integration of information from the outside loses relevance, possibly explaining why the underlying brain networks (CNs, insula) have found to be underactive and hypoconnected in imaging studies of MDD. Figure 2 visualizes alterations in brain network connectivity patterns during depressive rumination.

Figure 2
Connectivity Alterations in Brain Networks During Depressive Rumination

Notes: PE = prediction error, epist. = epistemic. Descriptions of brain regions are listed from anterior to posterior. Both subfigures show the left hemisphere. For visibility reasons, the upper subfigure depicts the hemisphere from a medial view, while the lower subfigure depicts it from a lateral view. Depressive rumination is correlated with reduced network activity/connectivity of frontoparietal control networks and interoceptive integration hubs (blue boxes) as well as with an increase in default mode network activity/connectivity (orange boxes). The posterior cingulate and parietal cortices deliver the samples from explicit memory to the frontal parts of the DMN during candidate sampling. The medial prefrontal cortex was shown to evaluate these samples based on self-referential measures ("What does it mean to me?"). Due to rapid rejection of candidates in depressive rumination, integration with other brain networks is decreased, because candidates that are evaluated in the policy evaluation step do not promise sufficient PE reduction for enabling mental problem-solving by the respective networks.

Clinical Implications

By recasting depressive rumination as the unsuccessful sampling of ineffective candidate behaviors, our account enables implications to be derived for depression therapy, with all due caution because of its tentative nature. Acknowledging the effectiveness of existing treatment approaches such as cognitive behavioral therapy (CBT) and pharmacotherapy (Cuijpers et al., 2020, 2019), we seek to improve these approaches rather than offer an entirely new treatment idea.

One idea originating from our model is to provide the candidate sampler (i.e., the patient) with better “starting points” to overcome autocorrelation problems. A way of achieving this might be to re-introduce previously lost behavioral samples via behavioral activation (Cuijpers et al., 2007). In this approach, patients are asked which activities have improved their mood in past situations and how difficult they are for the patients to do again now. As a result, an activity schedule is worked out and progress with activity engagement is checked regularly.

Another idea to avoid autocorrelated sampling is to verify the context, mood, or bodily states in which problem-solving occurs. Treatments to help change mood and bodily sensations should involve activities like endurance training, which has been shown to induce hippocampal neurogenesis and thereby reduce rumination (Déry et al., 2013; Schuch et al., 2016). Experimental treatments that increase the brain’s signal entropy (and might broaden sample variance) include pharmacological manipulation with ketamine or psilocybin (Carhart-Harris et al., 2017; Mertens et al., 2020; Vidal et al., 2020). An empirically well-supported potential experimental treatment is the addition of the emotional flanker task-training to CBT, in which patients learn to shift attention away from “bad starting points” that lead into ruminative loops (Daches et al., 2019; Sanchez-Lopez et al., 2019b, 2019a; Werner-Seidler et al., 2018).

An important step in transforming rumination into an adaptive process is to select problems offering a beneficial trade-off between resource investment and potential benefits. Metacognitive – and acceptance and commitment therapy have yielded promising results in

reducing rumination by applying techniques to guide selection processes, e.g., by practicing adaptive modes of cognition and deriving beneficial goals from values (Bai et al., 2020; Normann and Morina, 2018). However, we propose that treatments might benefit from explicitly incorporating problem complexity estimations and from listing the costs and benefits of mental engagement in a given task including expected opportunity costs. Patients should be enabled to accurately predict how long it takes to solve relevant problems by mental simulation and whether that process outweighs the benefits of overt action. As discussed, intricate interplay between DMN and CNs seems crucial for problem-solving (Cocchi et al., 2014; Hearne et al., 2015). There is research evidence that the exact proportion of network activation and coupling depends on the task difficulty. Thus, individual assessments of task difficulty whereby the DMN and CNs effectively re-couple, and adjusting cognitive training accordingly is another potentially promising idea.

When individuals have stopped engaging in mental problem-solving, it may be important to de-bias generalized negative expectations regarding the epistemic value of deep problem-solving. This may be achieved by completing (computerized) problem-solving tasks with a high success rate and positive reinforcements. In earlier stages of MDD, when mental problem-solving has started but is terminated prematurely, classical CBT tools may be helpful to structure the process and thus lessen the impact of overpruning.

Limitations and Future Directions

We aimed to explain rumination in MDD through the lens of an active inference model, thereby extending and further specifying previous computational perspectives on depression (Barrett et al., 2016; Clark et al., 2018; Kube et al., 2020c). Although we believe that this account may provide new insights into the fine structure of rumination, we also recognize that it has some limitations that demand discussion.

Foremost, our model largely considers “typical” depression where goal-directed behavior is reduced. However, there are also states of “agitated depression” where behavioral output is increased despite considerable rumination (Faedda et al., 2015).

Although research suggests these states to possibly reflect masked bipolar-like syndromes (Akiskal et al., 2005), an elaboration on these phenomena is beyond the scope of this paper.

Another limitation is that the temporal order of developing abnormalities in the resting state function of relevant neural networks is largely unknown. Which networks develop abnormal connectivity at earlier stages of the disorder and which networks become dysfunctional as a cause of these early changes? While there is evidence that all the discussed networks show abnormalities that predate MDD development, the biological basis of disorder progression remains enigmatic.

Our model is based on approaches from computational psychiatry and integrates different strands of literature; however, it is conceptual rather than a mathematical formalization and it is not based on simulations. Future work could formalize our concepts and develop a mathematical framework, e.g., by using a hierarchical partially observable Markov decision making process to enable computer simulations of rumination that can be compared to empirical data.

In addition to the ideas discussed in the previous chapter, Table 1 presents additional hypotheses derived from our model that may be tested in future research.

Table 1*Hypotheses and Ideas for Future Empirical Examinations Derived from the Model*

Hypotheses		Empirical Examination
MDD reduces the precision of predictions regarding the opportunity costs and the importance of mental simulation	Decreased accuracy in estimating time usage and overestimated utility for mental simulation (compared to overt action) predicts rumination and correlates with MDD symptoms.	In momentary experience sampling studies, MDD patients that are asked to what extent they feel the need to simulate important problems of their lives, indicate a greater urge to do so compared to healthy participants. Further, MDD patients indicate that they believe less in being able to solve their problems through overt action. Both measures correlate with trait rumination and with other depressive symptoms.
Rumination increases with problem complexity	Rumination tendency increases with problem complexity. This increase is also observable with neuroimaging e.g., by finding a higher DMN activation after thinking about complex problems.	In laboratory tasks, instructing individuals to think for an extended time about hard / unsolvable problems (compared to problems that are easily solvable) leads to higher rumination levels during a subsequent resting period. Resting state fMRI shows an increased activation of DMN structures in the resting period of the “hard problem” condition.
(Adverse) life events increase mental problem solving	Mental problem solving generally increases after important life events. Focus on unsolvable or extremely complex cognitive subtasks prolongs the problem-solving process and predict future depression.	Using momentary experience sampling studies to search for differences in time usage for mental simulation versus action-oriented behavior with respect to the temporal distance from a live changing event. When mental simulation tendency stays high for a longer time period, state rumination and the probability for developing MDD increase.
Long periods of unsuccessful problem-solving induces rumination	After extended periods of unsuccessful problem solving following important live events, rumination and MDD development probability increases.	Using cohort studies to investigate whether subjects that cannot solve problems resulting from important live events show an increased tendency for rumination as well as develop MDD with a higher probability compared to subjects that show long term adaptation.
Variation of context / internal states increases problem solving	Mental problem solving in varying contexts and internal states (e.g., changed posture and after physical activity, mood induction) leads to increased variability in topics and improve instrumental learning while decreasing rumination.	Combining paradigms that induce rumination with the induction of different mood states, with body-oriented interventions or with pharmacological manipulation influences the variance of topics that are simulated, the perception of negative emotions during the thinking process as well as the frequency with which action-oriented ideas are generated.
Rumination decreases the ability to sequence/terminate tasks	Individuals that tend to ruminate frequently show difficulties in behavioral tasks that involve choosing from a large set of possible subtasks that can be selected and switched at any time-point.	Development of laboratory / online tasks with numerous subtasks that can be chosen freely by the participant. MDD patients show worse performance with regard to task performance / success with task switching and task sequencing in comparison to healthy participants.

Notes. MDD = Major depressive disorder, fMRI = Functional magnetic resonance imaging, DMN = Default mode network.

Conclusions

This review aimed to synthesize different approaches from the neurosciences, computational psychiatry and cognitive science to create a new framework for investigating depressive rumination. In contrast to classical theories that try to cast the phenomenon in terms of exploitation (reinforcement learning), our account includes both exploitation (How to reach preferred states?) an exploration (How to learn something about the world?) within an active inference account. In essence, we propose that rumination can be regarded as an extreme case of failed mental problem-solving. We suggest that too much time is spent on candidate sampling, while the computation of solutions is aborted prematurely. Our model can explain why people with MDD cannot disengage from this dysfunctional process: The failure to find and implement adaptive behaviors for overcoming unpleasant internal states urges the individual to continue sampling from “bad starting points”, thereby creating a vicious circle. This has implications for the treatment of MDD, pointing to the potential of improving sampling and policy selection by re-activating circuits for executive control and interoceptive integration.

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Conflict of interest statement

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