Too Much Flexibility in a Dynamical Model of Repetitive Negative Thinking?

van Vugt, Marieke; Jamalabadi, Hamidreza

Published in:
Psychological Inquiry

DOI:
10.1080/1047840X.2022.2149195

Too Much Flexibility in a Dynamical Model of Repetitive Negative Thinking?

Marieke van Vugt & Hamidreza Jamalabadi

PSYCHOLOGICAL INQUIRY
2022, VOL. 33, NO. 4, 276–279
https://doi.org/10.1080/1047840X.2022.2149195

COMMENTARIES

Too Much Flexibility in a Dynamical Model of Repetitive Negative Thinking?

Marieke van Vugt[a] and Hamidreza Jamalabadi[b,c]

[a]Bernoulli Institute of Mathematics, Computer Science and Artificial Intelligence, University of Groningen, Groningen, Netherlands; [b]Department of Psychiatry and Psychotherapy, University of Marburg, Marburg, Germany; [c]National Center of Affective Disorders, Marburg, Germany

Mind-wandering is the process of task-independent thought, or stimulus-independent thought, that occurs almost half of the time. Given that mind-wandering disturbances are associated with a wide range of psychiatric disorders (Marchetti, Koster, Klinger, & Alloy, 2016), it is critical to better understand how, when, and why it occurs. A particularly important dimension of mind-wandering for determining its adaptiveness is how easy it is to disengage from it (van Vugt & Broers, 2016). Most studies thus far use behavioral experiments and neuroimaging to understand when and how mind-wandering happens. These studies have consistently observed that mind-wandering is associated with (i) decreases in task performance (Smallwood & Schooler, 2015); (ii) decoupling from the environment; and (iii) the activation of brain regions associated mostly with the default network (Poerio et al., 2017; Zhang et al., 2022) as well as hippocampus (Faber & Mills, 2018) and prefrontal cortex (Fox, Spreng, Ellamil, Andrews-Hanna, & Christoff, 2015).

There are extensive theories of the mechanisms underlying mind-wandering (for a recent review see Christoff, Irving, Fox, Spreng, & Andrews-Hanna, 2016). An issue with these theories that are described in words is that they cannot sufficiently constrain predictions (van Rooij, 2022) because they make only qualitative predictions that can be mapped onto measurements in different ways (Borsboom, van der Maas, Dalege, Kievit, & Haig, 2021; Fried, 2020). Making precise predictions requires tools, such as computational modeling. Thus far, however, there are limited attempts at building computational models of mind-wandering (Ciaramelli & Treves, 2019). An example is a model that Taatgen et al. (2021) developed in the Adaptive Control of Thought-Rational architecture (Anderson et al., 2004), which is based on the idea that mind-wandering and performing a task are in direct competition for the same cognitive resources. When mind-wandering takes over, task performance is relegated to habitual responding, which tends to lead to more errors. Response times become more variable because, at the time of stimulus appearance, the system is busy with the mind-wandering process. This model could adequately account for both the patterns in behavioral data and self-reported mind-wandering (van Vugt, Taatgen, Bastian, & Sackur, 2015).

A particularly interesting domain for studying mind-wandering is repetitive negative thinking in depression. In an early study, Watts and Sharrock (1985) showed that depressed patients had an increased number of distraction occurrences during reading. Hoffmann, Banzhaf, Kanske, Bermpohl, and Singer (2016) showed that participants with depression mind-wandered more during a sustained attention task and that their thoughts were more negative, self-focused, and related to the past. Also in everyday life, Ottaviani et al. (2014) showed more negative thinking, which was also more difficult to disengage from. Smallwood et al. (2003) showed that rumination was associated with mind-wandering that was more preoccupied with the self.

The computational model of mind-wandering by Taatgen et al. was also able to capture differences between depressed and healthy individuals by assuming the mind-wandering process had become "stickier" during repetitive negative thinking (Joormann, Levens, & Gotlib, 2011). This increased stickiness made it more difficult to return to the task (van Vugt & van der Velde, 2018). Such a model has predicted decreased accuracy on a sustained attention to response task (van Vugt & van der Velde, 2018), decreased ability to remove negative stimuli from working memory (van der Velde & van Vugt, 2018) and increased persistence in recalling negative stimuli in a free recall task (Gupta et al., 2022).

Amir and Berstein (this issue) present an alternative approach to modeling mind-wandering and repetitive negative thinking based on dynamical systems. This model seeks to explain when thought is more freely moving and when it is constrained (Christoff et al., 2016). The model consists of a set of differential equations that describe the dynamics of affect and representations in working memory. The representations in working memory are subject to selection biases and modulation by contextual demands. While selection biases are primarily driven by emotions, contextual demands reflect the idea that in certain contexts, such as a cognitively demanding experiment, attention may be driven more toward the task than to task-irrelevant stimuli. Indeed, they show that in a 2.5-min simulation, negative affect gets more of a chance to grab attention during a period of low task demands than during a period of high task demands. Critically, the negative thoughts become repetitive and "sticky" partially due to the limited capacity of working

CONTACT Marieke van Vugt m.k.van.vugt@rug.nl Bernoulli Institute of Mathematics, Computer Science and Artificial Intelligence, University of Groningen, Groningen, Netherlands.

memory. Assumed to have a constant capacity of five items, the affect is assumed to be the average of the valence of the items in working memory, and therefore, increasing working memory capacity leads to higher chances of repetitive negative thinking. This happens because the occurrence of one negative thought biases the next iterations of attention that have access to the working memory contents (now five items). They also examine the effect of individual differences in cognitive reactivity, where higher cognitive reactivity is associated with an increased tendency for repetitive negative thinking. As such, this model describes how the dynamics of thinking is affected by different variables.

The model proposed by Amir and Bernstein is, as they themselves indicate, a formal model, but not a data model. This means that it is designed to replicate a general pattern of behavior across a range of different contexts and parameters, but not to capture detailed behavioral patterns quantitatively. It also means that compared to models used in quantitative psychology, such as the drift diffusion model (Ratcliff, 1978; Ratcliff, Smith, Brown, & McKoon, 2016) or the generalized context model (Nosofsky, 1991), the model is relatively unconstrained. This has its challenges. It is known that by slightly changing the shape of the equations, the dynamics of the model could be dramatically changed (Borsboom et al., 2021). For instance, Robinaugh, Haslbeck, Ryan, Fried, and Waldorp (2021) showed that changing a linear to a sigmoid function in a dynamical system of panic attacks with only three variables can fundamentally change the response of the model to external and internal stressors. The same applies to the model proposed by Amir and Bernstein. For instance, the distribution from which the selective bias to negative representations is drawn is an ex-Gaussian and is filtered through a non-linear tangent hyperbolic function but changing it into for example a normal distribution would dramatically reduce the variance of the values that are drawn, and this could mean that attention switches much less frequently.

Similar questions could be asked about the mathematical model used to model the interrelationship between context and internal attention, as well as the ratio of negative task-unrelated thinking and attentional bias. As such, it is important to examine how the model's behavior changes across the full parameter space. This will allow us to determine how much of the patterns shown in Amir and Bernstein are the natural behavior of the model, and how much it depends on the specific tuning of parameters. For instance, we notice that across a wide range of parameters and simulations, attentional bias and affect are strongly correlated ($r > 0.9$) which could potentially indicate redundancy in the model. Beyond the considerations regarding the model structure, we notice that the model offers a high level of flexibility due to the large number of parameters involved. Indeed, such a high level of flexibility makes the model in its current form less suitable for providing explanations of existing data. The reason that the model is less useful for explaining existing data is that given the high flexibility of this model, it can generate many different behavioral patterns (Pitt et al., 2006). Together, this means it is at present difficult to falsify the model, apart from using preregistered studies. Below we will make some suggestions for adapting the model itself such that it can be more easily adapted and improved based on experimental data and precise numerical predictions.

An exciting area of improvement to bring the model closer to empirical data, as suggested by the author, is to focus on individual differences. For example, it is known that different people have different working memory capacities (Conway & Engle, 1996), which could impact ruminative thinking (Wanmaker, Geraerts, & Franken, 2015). As discussed above, interestingly, the current model makes the counterintuitive prediction that larger working memory capacity is associated with more ruminative thinking, which is inconsistent with existing evidence (e.g., Pe, Raes, & Kuppens, 2013). Another possible source of data consists of brain data that track (ruminative) mind-wandering over time. For example, Jin, Borst, and van Vugt (2019) have created a machine learning classifier that can predict when a person is mind-wandering, and Kaushik et al. (https://psyarxiv.com/89tx3/) have extended this to "sticky," ruminative thinking. Such data could give a temporal evolution of rumination in different contexts, which could be matched to simulations, such as the one provided by Amir and Bernstein of low *vs.* high task demands.

Apart from examining how the model adapts to individual data, it is important to explore how its behavior develops over different time scales (i.e., seconds through weeks). The current model has only been applied to a period of 300 s (5 min). Within the context of a cognitive task, that is very short, comprising only a few trials. In fact, during mind-wandering experiments, a class of experiments that is very relevant to this model, thoughts are sampled only once every minute or so (Smallwood & Schooler, 2015), which means that the model could only capture five of such thought probes (although obviously, many more thoughts take place)—a very limited period of behavior. Our previous work has demonstrated that over the course of 1 h of doing this task, there are appreciable fluctuations in off-task thinking, with on average an increase in off-task thinking as the task proceeds (Jin et al., 2019). Rumination more broadly tends to change on the time scale of days and weeks (Connolly & Alloy, 2017). The fact that this model is a dynamical system, rather than a task-focused algorithm gives it the possibility to examine its dynamics across a multitude of time scales. This results in the exciting possibility to examine how changes in thinking on one time scale, e.g., across a task, affect the thinking on a different time scale, e.g., across days as measured with ecological momentary assessment.

Another interesting application of the model by Amir and Bernstein is to examine the effects of meditation or other interventions on maladaptive mind-wandering. If these interventions can be claimed to impact specific cognitive-affective operations that are within the scope of the model, corresponding predictions for how it changes ruminative thinking could be made. A particularly exciting prospect is the idea of predicting the occurrence of such ruminative thinking on several time scales. While the model of van Vugt and van der Velde (2018) could make predictions of ruminative thinking on the time scale of a cognitive task, and a meditation model has been created as well (Moye & van Vugt, 2021), it cannot make predictions on the time scale of days or weeks–something which the model by Amir and Bernstein could potentially do.

Furthermore, since the model by Amir and Bernstein is operationalized using the dynamical systems theory, the effect of interventions on the model could be mathematically informed and studied using network control theory (Tang & Bassett, 2018). Specifically, control theory could determine boundaries, conditions, and the extent to which the theory-implied behavior of mind wandering model could be challenged based on an intervention based on a mathematically principled framework (Henry, Robinaugh, & Fried, 2022). Such a possibility to inform and study interventions would provide a unique possibility for improving both the model and the interventions at the same time. Furthermore, one could use such an iterative process to automate the improvement of the model. While little work has been done in this area, recent developments in data-driven non-linear system identification allow to infer the equations that best describe the observations only based on experimental data (Brunton, Proctor, & Kutz, 2016b). Built based on sparsity promoting techniques, these approaches enable learning arbitrary complex interactions based on available data on constrained, unconstrained, and intervention studies to improve the models, enhance the accuracy of the models but also potentially reduce the number of components as they explicitly favor parsimonious interactions (Brunton, Proctor, & Kutz, 2016a).

In short, we believe the model proposed by Amir and Bernstein is a great attempt to turn a descriptive, verbal theory into a computational theory that can describe how repetitive negative thinking arises, and on what factors it depends. It relates major putative cognitive processes engaged in mind-wandering within a dynamical systems framework and can make numerical predictions. Having said that, the model does have substantial flexibility, which means it can be easily adapted to explain many different data patterns in a *post-hoc* manner. We suggest that on the one hand, clearer connections are made between the model and measurable quantities, and on the other hand, that state-of-the-art method are used to parametrize the computational theory. Together, this will ensure that the model can make testable predictions across different time scales, and potentially also for the effect of different interventions to counter repetitive negative thinking. More importantly, such applications could potentially allow this model to be usable in clinical practice.

References

Anderson, J. R., Bothell, D., Byrne, M. D., Douglass, S., Lebiere, C., & Qin, Y. (2004). An integrated theory of the mind. *Psychological Review*, *111*(4), 1036–1060. doi:10.1037/0033-295X.111.4.1036

Borsboom, D., van der Maas, H. L. J., Dalege, J., Kievit, R. A., & Haig, B. D. (2021). Theory construction methodology: A practical framework for building theories in psychology. *Perspectives on Psychological Science*, *16*(4), 756–766. doi:10.1177/1745691620969647

Brunton, S. L., Proctor, J. L., & Kutz, J. N. (2016a). Sparse identification of nonlinear dynamics with control (SINDYc). *IFAC-PapersOnLine*, *49*(18), 710–715. doi:10.1016/j.ifacol.2016.10.249

Brunton, S. L., Proctor, J. L., & Kutz, J. N. (2016b). Discovering governing equations from data by sparse identification of nonlinear dynamical systems. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(15), 3932–3937. doi:10.1073/pnas.1517384113

Christoff, K., Irving, Z. C., Fox, K. C. R., Spreng, R. N., & Andrews-Hanna, J. R. (2016). Mind-wandering as spontaneous thought: A dynamic framework. *Nature Reviews. Neuroscience*, *17*(11), 718–731. doi:10.1038/nrn.2016.113

Ciaramelli, E., & Treves, A. (2019). A mind free to wander: Neural and computational constraints on spontaneous thought. *Frontiers in Psychology*, *10*, 39. doi:10.3389/fpsyg.2019.00039

Connolly, S. L., & Alloy, L. B. (2017). Rumination interacts with life stress to predict depressive symptoms: An ecological momentary assessment study. *Behaviour Research and Therapy*, *97*, 86–95. doi:10.1016/j.brat.2017.07.006

Conway, A. R., & Engle, R. W. (1996). Individual differences in working memory capacity: More evidence for a general capacity theory. *Memory*, *4*(6), 577–590. doi:10.1080/741940997

Faber, M., & Mills, C. (2018). The critical role of the hippocampus in mind wandering. *The Journal of Neuroscience*, *38*(29), 6439–6441. doi:10.1523/JNEUROSCI.0995-18.2018

Fox, K. C. R., Spreng, R. N., Ellamil, M., Andrews-Hanna, J. R., & Christoff, K. (2015). The wandering brain: Meta-analysis of functional neuroimaging studies of mind-wandering and related spontaneous thought processes. *NeuroImage*, *111*, 611–621. doi:10.1016/j.neuroimage.2015.02.039

Fried, E. I. (2020). Lack of theory building and testing impedes progress in the factor and network literature. *Psychological Inquiry*, *31*(4), 271–288. doi:10.1080/1047840X.2020.1853461

Gupta, A., Kaiser, C., Everaert, J., van Vugt, M. K., & Roy, P. P. (2022). Modeling effects of rumination on free recall using ACT-R. *PsyArXiv*. doi:10.31234/osf.io/5qn9h

Henry, T. R., Robinaugh, D. J., & Fried, E. I. (2022). On the control of psychological networks. *Psychometrika*, *87*(1), 188–213. doi:10.1007/s11336-021-09796-9

Hoffmann, F., Banzhaf, C., Kanske, P., Bermpohl, F., & Singer, T. (2016). Where the depressed mind wanders: Self-generated thought patterns as assessed through experience sampling as a state marker of depression. *Journal of Affective Disorders*, *198*, 127–134. doi:10.1016/j.jad.2016.03.005

Jin, C. Y., Borst, J. P., & van Vugt, M. K. (2019). Predicting task-general mind-wandering with EEG. *Cognitive, Affective & Behavioral Neuroscience*, *19*(4), 1059–1073. doi:10.3758/s13415-019-00707-1

Joormann, J., Levens, S. M., & Gotlib, I. H. (2011). Sticky thoughts: Depression and rumination are associated with difficulties manipulating emotional material in working memory. *Psychological Science*, *22*(8), 979–983. doi:10.1177/0956797611415539

Marchetti, I., Koster, E. H. W., Klinger, E., & Alloy, L. B. (2016). Spontaneous thought and vulnerability to mood disorders: The dark side of the wandering mind. *Clinical Psychological Science*, *4*(5), 835–857. doi:10.1177/2167702615622383

Moye, A. J., & van Vugt, M. K. (2021). A computational model of focused attention meditation and its transfer to a sustained attention task. *IEEE Transactions on Affective Computing*, *12*(2), 329–339. doi:10.1109/TAFFC.2019.2908172

Nosofsky, R. M. (1991). Tests of an exemplar model for relating perceptual classification and recognition memory. *Journal of Experimental Psychology. Human Perception and Performance*, *17*(1), 3–27. doi:10.1037/0096-1523.17.1.3

Ottaviani, C., Shahabi, L., Tarvainen, M., Cook, I., Abrams, M., & Shapiro, D. (2014). Cognitive, behavioral, and autonomic correlates of mind wandering and perseverative cognition in major depression. *Frontiers in Neuroscience*, *8*, 433. doi:10.3389/fnins.2014.00433

Pe, M. L., Raes, F., & Kuppens, P. (2013). The cognitive building blocks of emotion regulation: Ability to update working memory moderates the efficacy of rumination and reappraisal on emotion. *PLOS One*, *8*(7), e69071. doi:10.1371/journal.pone.0069071

Pitt, M. A., Kim, W., Navarro, D. J., & Myung, J. I. (2006). Global model analysis by parameter space partitioning. *Psychological Review*, *113*(1), 57.

Poerio, G. L., Sormaz, M., Wang, H.-T., Margulies, D., Jefferies, E., & Smallwood, J. (2017). The role of the default mode network in component processes underlying the wandering mind. *Social Cognitive and Affective Neuroscience*, *12*(7), 1047–1062. doi:10.1093/scan/nsx041

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*(2), 59–108. doi:10.1037/0033-295X.85.2.59

Ratcliff, R., Smith, P. L., Brown, S. D., & McKoon, G. (2016). Diffusion decision model: Current issues and history. *Trends in Cognitive Sciences*, *20*(4), 260–281. doi:10.1016/j.tics.2016.01.007

Robinaugh, D. J., Haslbeck, J. M. B., Ryan, O., Fried, E. I., & Waldorp, L. J. (2021). Invisible hands and fine calipers: A call to use formal theory as a toolkit for theory construction. *Perspectives on Psychological Science*, *16*(4), 725–743. doi:10.1177/1745691620974697

Smallwood, J., Obsonsawin, M., Baracaia, S. F., Reid, H., O'Connor, R., & Heim, D. (2003). The relationship between rumination, dysphoria, and self-referent thinking: Some preliminary findings. *Imagination, Cognition and Personality*, *22*(4), 317–342. doi:10.2190/2N80-AVM3-4A23-LEAJ

Smallwood, J., & Schooler, J. W. (2015). The science of mind wandering: Empirically navigating the stream of consciousness. *Annual Review of Psychology*, *66*(1), 487–518. doi:10.1146/annurev-psych-010814-015331

Taatgen, N. A., van Vugt, M. K., Daamen, J., Katidioti, I., Huijser, S., & Borst, J. P. (2021). The resource-availability model of distraction and mind-wandering. *Cognitive Systems Research*, *68*, 84–104. doi:10.1016/j.cogsys.2021.03.001

Tang, E., & Bassett, D. S. (2018). Colloquium: Control of dynamics in brain networks. *Reviews of Modern Physics*, *90*(3), 031003. doi:10.1103/RevModPhys.90.031003

van der Velde, M., & van Vugt, M. K. (2018). Modeling the effect of depression on working memory. In *Proceedings of the 16 Th International Conference on Cognitive Modeling* (pp. 199–205).

van Rooij, I. (2022). Psychological models and their distractors. *Nature Reviews Psychology*, *1*(3), 127–128. doi:10.1038/s44159-022-00031-5

van Vugt, M. K., & Broers, N. (2016). Self-reported stickiness of mind-wandering affects task performance. *Frontiers in Psychology*, *7*, 732. doi:10.3389/fpsyg.2016.00732

van Vugt, M. K., Taatgen, N. A., Bastian, M., & Sackur, J. (2015). Modeling mind-wandering: A tool to better understand distraction. In *Proceedings of the International Conference in Cognitive Modeling*.

van Vugt, M. K., & van der Velde, M. (2018). How does rumination impact cognition? A first mechanistic model. *Topics in Cognitive Science*, *10*(1), 175–191. doi:10.1111/tops.12318

Wanmaker, S., Geraerts, E., & Franken, I. H. A. (2015). A working memory training to decrease rumination in depressed and anxious individuals: A double-blind randomized controlled trial. *Journal of Affective Disorders*, *175*, 310–319. doi:10.1016/j.jad.2014.12.027

Watts, F. N., & Sharrock, R. (1985). Description and measurement of concentration problems in depressed patients. *Psychological Medicine*, *15*(2), 317–326. doi:10.1017/S003329170002359X

Zhang, M., Bernhardt, B. C., Wang, X., Varga, D., Krieger-Redwood, K., Royer, J., … Jefferies, E. (2022). Perceptual coupling and decoupling of the default mode network during mind-wandering and reading. *eLife*, *11*, e74011. doi:10.7554/eLife.74011