

Title: Computational modelling approaches to meditation research: why should we care?

Short Title: Computational modeling in meditation research

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Abstract

Computational modeling and meditation are not frequently mentioned in the same breath. However, in this article we argue that computational modeling can provide insights into the mechanisms by which meditation produces its effects on cognition. Moreover, computational modeling allows the researcher to make predictions about how effects of meditation will generalize to other contexts such as other tasks, which can be tested in subsequent experiments. In addition, computational theories can help to clarify similarities and differences between meditation practices, which is crucial for mapping out the space of contemplative practices. In short, even though computational modeling has not yet been used extensively, we think this approach can make important contributions to the field of meditation research.

Introduction

As is evident from this special issue, the research on meditation and its effects is burgeoning [1]. An important challenge in the mindfulness and meditation research field is that there is little consensus about the definition of these practices [1–3]. The lack of definitional clarity and the wide range of meditation practices in existence [4] mean that it is exceedingly difficult to build predictive theories about the effects of these practices on emotion, cognition, and general human flourishing.

Despite the lack of consensus on definitions on meditation, there has been substantial theoretical and philosophical effort in trying to define these contemplative practices [3,5,6]. However, an inherent problem with such attempts is that different individuals can mean different things with the same words. A vivid demonstration of such ambiguity in verbal theory was given by Marewski and Mehlhorn [7], who attempted to convert verbal theories of decision making into computational models. They showed that the same verbal theory could be instantiated into many different computer algorithms of the decision process. In

other words, computational modeling could be one approach to arriving at definitional clarity on various meditation practices and their mechanisms. In this review, we will provide an overview of how computational modeling has been used to date in research on meditation. We will critically evaluate its merits and pitfalls, and then outline future perspectives.

Main body

Before reviewing the applications of cognitive modeling in research on meditation it is important to review what is meant by this term. Modeling always describes a theory about a mechanism underlying the phenomenon being modelled [8]. For example, statistical models and machine learning *use* computational tools but *are not* computational models, because they do not provide a mechanistic model of the process they describe.

Computational modeling in the context of meditation research can take several different shapes. On the one hand, modeling can be used to extract the cognitive mechanisms that may be modified by a certain meditation practice, as a kind of data analysis tool that zooms in on the relevant mechanisms. On the other hand, modeling can be used to formally describe the meditation practice itself, and use that to make predictions about how meditation could affect performance on cognitive tasks.

The first modeling work in meditation research focused on extracting information from behavioral tasks. Most cognitive tasks collect response times and accuracies, which are used to extrapolate how cognitive functions such as attention, memory, or decision making work. However, response times and accuracies are determined by many influences, including the participant's attentional fluctuations or their level of response caution [9]. A popular model to disambiguate those influences is the drift diffusion model [10], which decomposes the distributions of correct and error response times into cognitive parameters such as the quality of information (with a model parameter called "drift rate"), the level of caution (a parameter called "decision threshold"), and estimates of time needed for non-decision processes (a model parameter called "non-decision time"). Van Vugt and Jha [11] used the drift diffusion model to examine how an intensive one-month Shamatha meditation practice affected participants' ability to keep in mind complex visual stimuli. They showed that the drift rate parameter increased for the meditation group, but not for an inactive control group, which suggests the meditators improved in their ability to extract information from a stimulus. The drift diffusion model can be applied to many types of tasks, as long as the tasks

consist of two-alternative forced choice decisions that are relatively simple. For example, van Vugt & van den Hurk [12] applied the drift diffusion model to data from a study in which a group of meditators was compared cross-sectionally to a group of age-, gender- and education-matched controls in their performance on the Attention Network Task [13]. They showed that meditators adapted their level of caution more to the task conditions than controls, although the effect of meditation practice was not very strong. A critical note here is that the drift diffusion model they used was not adapted specifically to the Attention Network Task [14], which may have resulted in inaccuracies in the parameter estimates. While drift diffusion modeling approach allows the researchers to extract more detailed information about the effects of meditation on cognition, it does not explain how these effects come about.

Measurement models are not restricted to behavioral data but can also be applied to neuroscience data. For example, Sagar et al. [15] used a model of EEG to investigate what neural changes could have resulted in meditation-related differences in EEG activity. Specifically, they used a mean-field EEG model with ten parameters to reproduce a decrease in beta power in posterior and anterior-central channels and a decrease in the alpha frequency of meditators. This data pattern could be reproduced by changing only two parameters: an intrathalamic gain parameter, and a corticothalamic delay parameter. They suggested that the intrathalamic gain parameter reflected increased alertness, while the corticothalamic delay parameter caused the decrease in the individual's alpha frequency, which has no specific cognitive interpretation. While this approach elegantly describes the specific neural changes resulting from meditation practice, it says little about how the meditation practice effected those changes.

Instead of using models as measurement tools for quantifying the effect of meditation on cognition, another approach is to use models to describe the meditation process itself and/or to predict its effects on cognition and emotion. A neural network model describing the thought processes involved in meditation was developed by Edalat and Lin [16], who used attractor states in a Hopfield network to model how a meditator gets less stuck in their negative emotions. By using reinforcement learning, they showed that the model's negative emotions reduced when it practiced its mindful state, which competes with the negative emotion attractor states. While this is an interesting model, it did not get validated with empirical data.

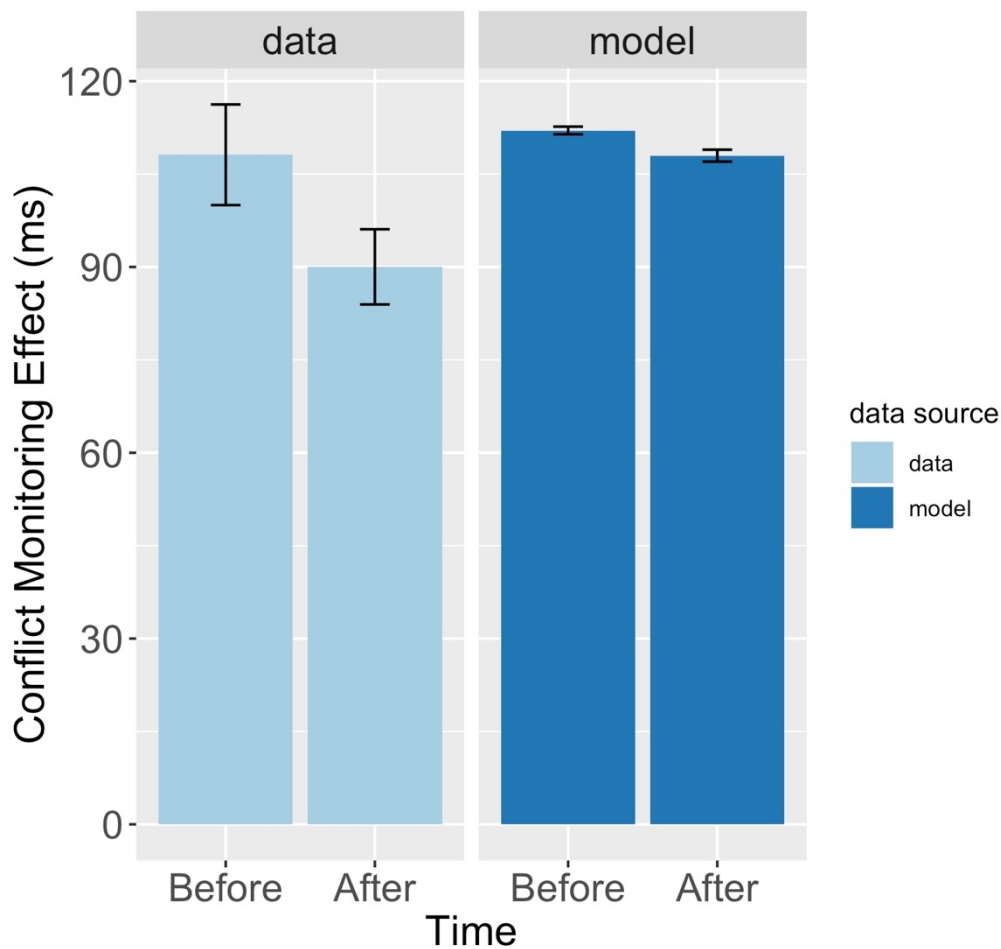
Yet another modeling study focused on the neural mechanisms. Raffone and Srinivasan [17] built their model in the global workspace framework, which states that all conscious processing takes place in a single global workspace in the brain [18]. This global workspace is relevant because key brain areas of this global workspace, such as anterior cingulate cortex (ACC) and insula, have been shown to be altered by meditation practice. Raffone and Srinivasan [19] proposed that meditation is associated with changes in the mode of processing in this global workspace, which is becoming more parallel, linking multiple brain areas, and simultaneously less goal-directed. While during open monitoring meditation, the processing is completely parallel, in focused attention meditation there is still a single attentional focus, but with a stronger meta-cognitive focus by the ACC than in most other cognitive tasks. However, while a general computational implementation of the global workspace has been developed [20], there is no computational model yet for meditation.

We ourselves developed a model of the process of doing focused attention meditation using the ACT-R cognitive architecture [21] and its extensions for modeling cognitive transfer [22]. In contrast to the just-discussed models that emphasized only specific components of the meditation process, we tried to describe the complete sequence of steps involved in the practice [23]. Focused attention meditation is conceptualized as a competition between paying attention and a mind-wandering. The model starts out with a strong tendency to mind-wander. Mind-wandering is counteracted by an ongoing effort to pay attention, which over time leads a habituation of this process. This habituation makes the goal of paying attention and its associated actions more active in memory and thereby easier to for the model to do. Habituation happens because the reinforcement of actions is confined to a small amount of memories in the case of the paying attention process, whereas the mind-wandering process' reinforcement is dispersed between many different mind-wandering topics, which slows down the process of learning.

Transfer is modelled as a re-use of model mechanisms and actions by other tasks [22]. By transferring the mind-wandering process with its enhanced focus, it is possible to assess how the acquired enhancement of focus affects performance on different tasks. We demonstrated that performance on a sustained attention task was improved after the simulated meditation practice, in line with empirical data from MacLean and colleagues [24]. Although the modelled data were quantitatively similar to those published results, the quantitative fit was lacking, which will need to be addressed in future work. Moreover, this

model only captures concentration, and does not capture other aspects of meditation such as decentering [5].

More recently we have extended this focused attention meditation model to the Attention Network Task. Previous research demonstrated that performance on this task improved after meditation practice [25]. In an Attention Network task participants have to indicate the direction of an arrow in the middle of the screen. When this arrow is flanked by arrows pointing in the opposite direction (e.g., <><<), this increases the participant's response time, but this cost has been shown to be reduced in meditators. Our model assumes that participants scan the row of arrows from left to right, start preparing a response, and then have to backtrack once they find the center arrow is in the opposite direction of its flankers. In our model, the metacognitive checking trained in meditation allows the participant to detect the opposite direction in the flankers sooner, which reduces the cost of the incongruent flankers (Figure 1).



This demonstrates how a single model of focused attention meditation can make quantitative predictions for performance on two different tasks (a sustained attention task and an Attention Network Task). The model's predictions depend on the details of the meditation practice that has been implemented, which underscores the importance of having detailed models of meditation practices.

Conclusions

On the basis of the results discussed above, we think that computational modeling is providing interesting perspectives to the field of meditation research. Modeling allows researchers to go beyond simple descriptions of empirical results and instead make quantitative predictions that can be tested in follow-up experiments. When using models as

measurement tools, they can give deeper insights into the specific mental operations that are being changed by meditation processes. When models describe the meditation process itself, they are more constrained than theories of meditation that have not been implemented as computational models. While computational modeling approaches thus far have been quite scarce, continued efforts in this direction may help us to make differences between different meditation practices more explicit. While such classification efforts do exist [3], those cannot make quantitative predictions. Of course it is likely that not all aspects of the meditative state can be captured by computational modeling, and this is where careful phenomenology is important [3]. When the limitations of computational modeling of cognition become clear in this way, this in turn can help push the boundaries of cognitive modeling.

A particularly interesting direction in which modeling could push forward is predictive coding [26], which is notable in that it does not only say what an organism does in goal-directed tasks, but rather how an organism continually interprets the world and makes models of it. Such predictions affect subsequent perceptions, and in this way an organism's perception continually interacts with the world. This cycle between perception, the outside world, and the corresponding representations in the internal world is not incorporated into any of the existing models of meditation—in fact—those leave the world of thoughts mostly abstract. Yet, verbal theories of meditation in the predictive coding framework have been proposed [27,28]. Computational implementations of such theories could help to make important predictions about how meditation practices could affect psychiatric diseases such as depression and schizophrenia, diseases for which predictive coding accounts have been developed [29].

In short, computational modeling will help us to develop more constrained and detailed theories about the nature of different meditation practices and their effects on meditation and cognition. They will push the boundaries of meditation research and cognitive modeling alike, and they will constrain predictions about the effects of different types of meditation practices.

References

- [1] N.T. Van Dam, M.K. van Vugt, D.R. Vago, L. Schmalzl, C.D. Saron, A. Olendzki, T. Meissner, S.W. Lazar, C.E. Kerr, J. Gorchov, K.C.R. Fox, B.A. Field, W.B. Britton, J.A.

Brefczynski-Lewis, D.E. Meyer, Mind the Hype: A Critical Evaluation and Prescriptive Agenda for Research on Mindfulness and Meditation, *Perspect. Psychol. Sci.* 13 (2018) 36–61. doi:10.1177/1745691617709589.

- [2] R.J. Davidson, A.W. Kaszniak, Conceptual and methodological issues in research on mindfulness and meditation, *Am. Psychol.* 70 (2015) 581–592. doi:10.1037/a0039512.
- [3] A. Lutz, A.P. Jha, J.D. Dunne, C.D. Saron, Investigating the Phenomenological Matrix of Mindfulness-related Practices from a Neurocognitive Perspective, *Am. Psychol.* 70 (2015) 632–658. doi:10.1037/a0039585.
- [4] C.J. Dahl, A. Lutz, R.J. Davidson, Reconstructing and deconstructing the self: cognitive mechanisms in meditation practice, *Trends Cogn. Sci.* 19 (2015) 515–523. doi:10.1016/j.tics.2015.07.001.
- [5] G. Desbordes Gard, T...Hoge, E...Holzel, B...Kerr, C...Lazar, S...Olendzski, A...Vago, D.R., Moving beyond Mindfulness: Defining Equanimity as an Outcome Measure in Meditation Research, *Mindfulness.* 6 (2014) 356–372. doi:10.1007/s12671-013-0269-8.
- [6] D.R. Vago, D.A. Silbersweig, Self-awareness, self-regulation, and self-transcendence (S-ART): a framework for understanding the neurobiological mechanisms of mindfulness, *Front. Hum. Neurosci.* 6 (2012) 296.

An important mechanistic model of three different types of meditation: focused attention meditation, open monitoring, and ethical enhancement meditation. This mechanistic model provides a good basis for subsequent computational modeling.

- [7] J.N. Marewski, K. Mehlhorn, Using the ACT-R architecture to specify 39 quantitative process models of decision making, *Judgm. Decis. Mak.* 6 (2011) 439–519.
- [8] S. Palminteri, V. Wyart, E. Koechlin, The Importance of Falsification in Computational Cognitive Modeling, *Trends Cogn. Sci.* 21 (2017) 425–433. doi:10.1016/j.tics.2017.03.011.
- [9] E.-J. Wagenmakers, H.L.J.V.D. Maas, R.P.P.P. Grasman, An EZ-diffusion model for response time and accuracy, *Psychon. Bull. Rev.* 14 (2007) 3–22. doi:10.3758/BF03194023.
- [10] R. Ratcliff, A theory of memory retrieval, *Psychol. Rev.* 85 (1978) 59–108. doi:10.1037/0033-295X.85.2.59.
- [11] M.K. van Vugt, A.P. Jha, Investigating the Impact of Mindfulness Meditation Training on Working Memory: A Mathematical Modeling Approach, *Cogn. Affect. Behav. Neurosci.* 11 (2011) 344–353.

First application of computational modeling as a measurement model for the cognitive mechanisms that were being trained by meditation practice.

- [12] M.K. Van Vugt, P.A.M. van den Hurk, Modeling the effects of attentional cueing on meditators, *Mindfulness.* 8 (2017) 38–45. doi:10.1007/s12671-015-0464-x.
- [13] J. Fan, B.D. McCandliss, R. Sommer, A. Raz, M.I. Posner, Testing the efficiency and independence of attentional networks, *J. Cogn. Neurosci.* 14 (2002) 340–347.
- [14] C.N. White, R. Curl, Cueing Effects in the Attentional Network Test: a Spotlight Diffusion Model Analysis, *Comput. Brain Behav.* (2018). doi:10.1007/s42113-018-0004-6.
- [15] M. Saggar, A.P. Zanesco, B.G. King, D.A. Bridwell, K.A. MacLean, S.R. Aichele, T.L. Jacobs, B.A. Wallace, C.D. Saron, R. Miikkulainen, Mean-field thalamocortical modeling of longitudinal EEG acquired during intensive meditation training, *NeuroImage.* 114 (2015) 88–104. doi:10.1016/j.neuroimage.2015.03.073.

First detailed neural measurement model that explained how the EEG changes observed after intensive meditation practice could have come about.

- [16] A. Edalat, Z. Lin, A neural model of mentalization/mindfulness based psychotherapy, in: 2014 Int. Jt. Conf. Neural Netw. IJCNN, 2014: pp. 2743–2751. doi:10.1109/IJCNN.2014.6889896.
- [17] A. Raffone, N. Srinivasan, Mindfulness and Cognitive Functions: Toward a Unifying Neurocognitive Framework, *Mindfulness*. 8 (2017) 1–9. doi:10.1007/s12671-016-0654-1.
- [18] B.J. Baars, Global workspace theory of consciousness: toward a cognitive neuroscience of human experience, in: S. Laureys (Ed.), *Prog. Brain Res.*, Elsevier, 2005: pp. 45–53. doi:10.1016/S0079-6123(05)50004-9.
- [19] A. Raffone, N. Srinivasan, An adaptive workspace hypothesis about the neural correlates of consciousness: insights from neuroscience and meditation studies, in: N. Srinivasan (Ed.), *Prog. Brain Res.*, Elsevier, 2009: pp. 161–180. doi:10.1016/S0079-6123(09)17620-3.
- [20] L. Simione, A. Raffone, G. Wolters, P. Salmas, C. Nakatani, M.O. Belardinelli, C. van Leeuwen, ViSA: a neurodynamic model for visuo-spatial working memory, attentional blink, and conscious access, *Psychol. Rev.* 119 (2012) 745–769. doi:10.1037/a0029345.
- [21] J.R. Anderson, *How Can the Human Mind Occur in the Physical Universe?*, Oxford University Press, 2007.
- [22] N.A. Taatgen, The nature and transfer of cognitive skills, *Psychol. Rev.* 120 (2013) 439–471.
- [23] A. Moye, M.K. Van Vugt, A computational model of focused attention meditation and its transfer to a sustained attention task, in: *Proc. 15th Int. Conf. Cogn. Model.*, University of Warwick, Coventry, UK., 2017: pp. 43–48.

First computational model of the meditation process itself that could explain changes in performance on a sustained attention task.

- [24] K.A. MacLean, E. Ferrer, S.R. Aichele, D.A. Bridwell, A.P. Zanesco, T.L. Jacobs, B.G. King, E.L. Rosenberg, B.K. Sahdra, P.R. Shaver, B.A. Wallace, G.R. Mangun, C.D. Saron, Intensive meditation training improves perceptual discrimination and sustained attention, *Psychol. Sci.* 21 (2010) 829–839.
- [25] B. Ainsworth, R. Eddershaw, D. Meron, D.S. Baldwin, M. Garner, The effect of focused attention and open monitoring meditation on attention network function in healthy volunteers, *Psychiatry Res.* 210 (2013) 1226–1231. doi:10.1016/j.psychres.2013.09.002.
- [26] K. Friston, S. Kiebel, Predictive coding under the free-energy principle, *Philos. Trans. R. Soc. Lond. B Biol. Sci.* 364 (2009) 1211–1221. doi:10.1098/rstb.2008.0300.
- [27] G. Pagnoni, F.T. Guareschi, Remembrance of things to come: a conversation between Zen and neuroscience on the predictive nature of the mind, *Mindfulness*. 8 (2017) 27–37. doi:10.1007/s12671-015-0438-z.
- [28] W. Hasenkamp, G. Pagnoni, Remembrance of things to come: the predictive nature of the mind and contemplative practices - Mind & Life Institute Blog, *Mind Life Inst.* (2014). <https://www.mindandlife.org/remembrance-things-come-predictive-nature-mind-contemplative-practices/> (accessed August 7, 2018).
- [29] K.J. Friston, K.E. Stephan, R. Montague, R.J. Dolan, Computational psychiatry: the brain as a phantastic organ, *Lancet Psychiatry*. 1 (2014) 148–158. doi:10.1016/S2215-0366(14)70275-5.

