A Computational Model of Unintentional Mind Wandering in Focused Attention Meditation

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Abstract

Why does the mind wander? Recent theoretical models suggest mental content depends on a calculation that measures the expected rewards gained from the current task compared to other cognitive tasks and procedures. In Focused Attention Meditation (FA), participants practice attentional control by maintaining attention to an internal stimulus. Throughout the task, attentional lapses occur, in which there is an abrupt shift to mind wandering. We propose a model that formalizes attentional lapses as the interaction between a controller that boosts attentional resources to a target according to expected value calculations and a metacognitive monitoring procedure that stochastically observes internal contents. The model is applied to explain individual variation in button press data on an FA meditation task.

Keywords: mind wandering; sustained attention; meditation; control; metacognitive monitoring; lapse; computational model

Introduction

Minds tend to wander. These meanderings can be positive, as in the case when a particular train of thought synthesizes disparate concepts and produces a burst of creative insight. At other times, they can be negative, like when the occurrence of mind wandering during a lecture prevents a critical piece of information from being understood. Sometimes it feels like we can direct thought, and sometimes it feels like the mind rambles on its own accord. Recently, mind wandering has been studied in an effort to distinguish cognition that can be controlled versus cognition that seemingly occurs without intention (Seli, Risko, Smilek, & Schacter, 2016).

Mind wandering is operationalized in a lab setting as task-unrelated thought (TUT), where internal contents of mind are subjectively determined to be unrelated to task stimuli (Murray, Krasich, Schooler, & Seli, 2020). To identify the frequency of TUTs, two methods are commonly employed. The first technique involves thought probes, in which participants perform a task and report what they are thinking about when intermittently probed (i.e. the probe-caught method). In the second technique, the self-caught method, participants continuously monitor their own minds for off-task episodes and indicate when they believe these events have occurred. The self-caught method requires that participants keep track of the contents of their mind for the entire duration of the task, while the probe-caught method only necessitates an introspective query at the onset of the probe.

Focused attention meditation (FA) is a subset of meditation tasks that evoke the self-caught method. FA encourages practitioners to train an awareness of internal contents as well as effective control of their own minds (Lutz, Slagter, Dunne, & Davidson, 2008). Participants are directed to pay attention to a target object, often their breath, and indicate via a response (e.g. button press) when they notice attention is no longer on the correct target. Once noted, participants reorient attention away from the off-task stimuli back to the target of FA. The button press indicates the moment at which participants become aware of the internal contents of their mind after a period of unawareness. This period before the button press is often described as an attentional lapse, in which participants experience a shift in attention away from the target without volition. Thus, mind wandering during FA is characterized by an unintentional shift from on-task to off-task internal content.

Unintentional mind wandering has been conceptualized as a failure of cognitive control (Mcvay & Kane, 2010). Cognitive control can be defined as a method for manipulating behavior to achieve some end (Botvinick, Braver, Barch, Carter, & Cohen, 2001; Miller & Cohen, 2001), particularly ends with adaptive benefit beyond simple reinforcement. The process that determines how control signals are implemented has been debated (Esterman & Rothlein, 2019). One prominent theory (Shenhav, Botvinick, & Cohen, 2013) suggests that control signal specification is the result of a cost benefit analysis that weighs the costs of implementing various signals and intensities against their predicted rewards. According to this framework, the opportunity cost of applying control to the task at hand is compared to the value of engaging in nearby available tasks. A mind wandering event is initiated when the value of another task / thought exceeds the rewards generated from control in the current task (e.g. Agrawal, Mattar, Cohen, & Daw, 2021; Kurzban, Duckworth, Kable, & Myers, 2013; Shepherd, 2019).

Considering these perspectives, we outline a model in which the transition to mind wandering, specifically during tasks where mind wandering is undesirable, results from the functional lapse of a top-down supervisory attention network according to expected value calculations. To remain on task, this supervisory system executes a particular subset of control signals, which include selecting the appropriate task schema (a set of input/output rules), suppling necessary activation to them, inhibiting irrelevant schemas, and monitoring overall task performance (Shallice & Burgess, 1996; Stuss, Shallice, Alexander, & Picton, 1995). In FA, this corresponds to coordinating attentional shifts that maintain the meditation schema through the continuous assignment of salience to the target stimulus, inhibiting mind wandering, and monitoring internal contents to ensure that attention is sufficiently on breath. In the absence of these supervisory control signals, mental content transitions to internal representations and procedures that potentially yield more reward. A lapse can therefore be defined as a certain period of time without supervisory attentional control. The present model incorporates this perspective with previous models of attentional lapses.

Previous Models of Attentional Lapses

Attentional lapses and mind wandering have been commonly explored when monitoring external stimuli (Dux & Marois, 2009; Langner & Eickhoff, 2013). In one such task, the SART, attentional lapses are defined as the frequency of misses, or when participants fail to identify a target stimulus (e.g. the number 3) presented in a sequence of non-targets (e.g. random numbers from 1-10; Robertson, Manly, Andrade, Baddeley, & Yiend, 1997). Previous models focus on replicating response time and accuracy of target vs. non-target stimuli (Gunzelmann, Gross, Gluck, & Dinges, 2009; Vugt, Taatgen, Sackur, & Bastian, 2015).

While theoretical aspects of these models are transferable to meditation, models based on external stimuli may not entirely represent mind wandering when performance depends on meta-perceptions and continuous monitoring of internal stimuli. Despite the recent call advocating for computational models of meditation (van Vugt, Moye, & Sivakumar, 2019), only one model exists (Moye & van Vugt, 2021), although theoretical process models of FA have been previously proposed (Vago & Silbersweig, 2012). In Moye and van Vugt (2021), the authors suggest four processes during FA: continuously remembering to meditate, maintaining breath stimuli in working memory, recalling task-unrelated stimuli that conflict with task stimuli, and remembering to reorient to task when off task. These processes occur through the interaction of 'modules' that represent distinct brain functions.

Here, we present a computational model that incorporates this theoretical perspective and builds off of it by further explaining the computations and attentional processes behind an attentional lapse. First, we explicitly define control signals that depend on rational, expected utility calculations. These calculations predict how much control signal intensity should be applied on each timestep based on the error produced through observations of the internal state of the system. Second, we define the metacognitive monitoring process as a probability function that samples internal contents according to the availability of attentional resources. Lastly, we use our model to predict individual variation on an FA task.

Model Components

In this section we describe the components of a process model representing an FA task.

The System, *D*

Control theory proposes a general framework for mapping dynamical systems to desired states, typically balancing error against an optimal solution. We consider the brain to be a dynamical system, *D*, with a supervisory attention system functioning as a controller that can manipulate internal cognitive processes. While the application of control theory is prevalent in many models of cognition (Madhav & Cowan, 2020; Pezzulo & Castelfranchi, 2009; Wolpert & Ghahramani, 2004), it has only recently been discussed in models of attentional control (Wilterson & Graziano, 2021). Importantly, the control we discuss here is metacognitive control, dissociable from other automatic correction procedures (e.g. eye saccades to task-relevant stimuli) that operate without the explicit representation of internal mental contents (Lyons & Zelazo, 2011; Schooler, 2002).

We suggest that there are two continuous states during FA meditation, one in which participants are on task, associated with attention to a target (e.g. breath), and another where they are off task, a state in which attention is not on the target. The off-task state is described as mind wandering, an exploratory, default function that initiates in the absence of an explicit task goal. We propose that, during meditation, internal contents are always pulled towards mind wandering, which functions as an attractor state, due to an implicit calculation that considers the value of maintaining attention on breath against the value of exploring some new internal or external stimulus.

We codify this interaction in the form of a drift diffusion model, in which participants begin on task, but gradually evolve towards a mind wandering, off-task state. At any moment during an FA task, the state of the system, s_t, can be defined as the amount of resources allocated to the target of attention, or a value that corresponds to the level to which a participant is on task:

$$s_{t+1} = \lambda(s_t - s_\varepsilon) + \eta(0, \sigma) \qquad (1)$$

Off task is defined as s_ε, the system equilibrium, or a state of mind wandering. s_t is largest at the onset of the task and following a button press, but proceeds to decay towards a state of mind wandering s_ε according to the drift rate λ. The drift rate depicts how quickly the system transitions from on task to off task. Random Gaussian noise [$\eta(0, \sigma)$] produces stochastic variation on each timestep.

Controller Action

To remain on task, the system exerts a control signal, b, which we define as a top-down boost of attentional resources on the target of attention. A larger signal intensity produces larger values of s_t, corresponding to a state that is more on task and further away from mind wandering. In the absence of these boosts, the target of attention will recede according to the rate of decay, consistent with accounts that implicate control when trying to remain in a meditative state (Tang, Holzel, & Posner, 2015).

However, *how* the brain computes the amount of control to exert throughout an FA task has remained unexplained. We propose that the brain conducts a value-based decision to determine whether more attention should be allocated to the target of attention on any given timestep (e.g. Shenhav et al., 2013). At each timestep, the controller calculates the error by comparing the current state s_t to an optimal state in which there is perfect attention to breath, ${s^*}_t$.

$$E_t = {s^*}_t - s_t \tag{2}$$

We define the intensity of the control signal, b_t, as a scaled sigmoid, in which the error term determines the amount of attentional boost to be applied on the next timestep (Figure 1A).

$$b_t = b_{min} + \frac{(b_{max} - b_{min})}{1 + (e^{-a(E_t - c)})} \tag{3}$$

Thus, as error increases, a larger control signal should be applied. b_{max} and b_{min} correspond to the respective upper and lower bounds of signal intensity the system can exert. For the purposes of the present design, we set b_{min} as 0 and b_{max} to a signal intensity that boosts s_t from the mind wandering equilibrium s_ε to a state of optimal performance ${s^*}_t$.

Larger values of a correspond to a steeper slope of the sigmoid function and the value of c changes the point at which it is determined valuable to begin increasing control intensity. Larger values of c therefore allow greater error to occur before boosting.

With the additional capability of boosting attention, participants no longer necessarily drift to a state of mind wandering, but instead to a state that is subjectively determined to be on task, given by their unique boost function. This creates a second equilibrium s_θ in which the value of control signal intensity is equal to the drift towards mind wandering:

$$s_\theta : b_t = \lambda(s_t - s_\varepsilon) \tag{4}$$

Participants hover around the mean on-task equilibrium for a majority of the FA task, a state in which task performance is suboptimal and less than maximum control is applied continuously. Deviations below this threshold correspond to distracting external events or memories that interfere with attention to the target and diminish task performance (Holzel et al., 2011).

Meta-cognitive monitoring

According to the current model, participants can maintain attention on the target indefinitely. However, sustaining consistent attention to a target in FA meditation paradigms is implausible; participants naturally mind wander.

We hypothesize that an attentional lapse during meditation, behaviorally indicated as a button press, is due to the failure of a metacognitive monitoring process to properly observe the state and then apply the necessary control.

Previous work suggests that metacognitive monitoring is intermittent (Lyons & Zelazo, 2011; Schooler et al., 2011), but the details of this internal sampling procedure are left unspecified. We propose that the probability of sampling is a function of attentional resources, s_t, and can be defined as:

$$p(sample_t) = p_{low} + \frac{(p_{up} - p_{low})}{1 + (e^{-\omega(s_t - d)})} \tag{5}$$

According to our model, larger values of s_t correspond to more attentional resources supplied to the target, which in turn produces better task performance. Similarly, the metacognitive monitoring function also depends on the availability of attentional resources, in which larger values of s_t result in a greater probability of sampling (Figure 1B).

When the system reaches mean on-task equilibrium s_θ, the probability of sampling on the next timestep is lower than during periods of optimal performance. A missed sample here causes the state to drift further off task, and simultaneously reduces the sampling probability $p(sample_t)$ on the subsequent timestep. A rapid decrease in sampling probability can therefore account for abrupt transitions to mind wandering.

Parameter ω defines the slope and d expresses the offset of the sigmoid. In order for participants to indicate that an attentional lapse has occurred, there must be a non-zero probability of sampling during mind wandering, supported by the idea that the supervisory system automatically 'refreshes' or samples according to some reoccurring cyclical process (Robertson et al., 1997). Thus, for all values of s_t, the probability of sampling is bounded between p_{low} and p_{up} to ensure a non-zero probability even when mind wandering.

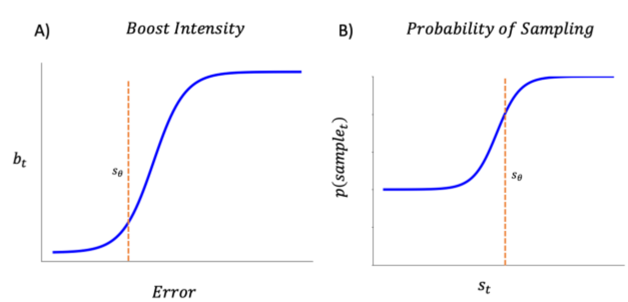

Figure 1: A) The relationship between the value of boosting and error; B) the relationship between probability of sampling and attention resources allocated to monitoring.

Model Simulation and Behavioral Comparison

The current model proposes that attentional lapses, indicated by button presses, can be explained by the relationship between a metacognitive monitoring procedure and a controller that boosts attentional resources on a target representation. In this section, we report an FA experiment in which we collected button press data from twenty-two participants and then compare these results to model simulations. Notably, the behavioral data reported here was part of a larger fMRI session, but we only discuss the behavioral data for the purposes of the present paper.

Sustained Attention Monitoring Task

Participants Twenty-two subjects were recruited from the Princeton University subject pool and the surrounding Princeton area to participate in a fMRI study investigating the mechanisms of attention monitoring. Informed consent was obtained according to procedures approved by the IRB. Participants were compensated with either course credit or $40 for their participation, depending on the recruitment source.

Task Procedure Participants completed a 1-hour scanning session consisting of four conditions. Each condition was a 306 second (~5 minute) block interleaved throughout the experiment. In meditation blocks, participants viewed a blank screen and were instructed to stare at a fixation cross. Participants were then told to attend to their breath and press a button if they noticed their mind to have wandered away from attending to breath. Once noted via button press, participants were instructed to reorient attention back to breath. To help remain on task, participants nonverbally recited "breathe in, breath out," in sync with their breath. Instructions and procedures were developed from previous focused attention meditation tasks (Hasenkamp, Wilson-Mendenhall, Duncan, & Barsalou, 2012).

All subjects were given a chance to ask questions and confirmed their understanding before beginning the experiment. Following the scan, participants answered a post-task questionnaire in which they evaluated their own task performance and effort. All participants reported that they were able to complete the task. Additionally, eye movement was monitored to ensure wakefulness of all participants.

Behavioral Results The button press data for twenty-two subjects was collected over the two 306 second meditation runs. We considered the time interval between button presses to be an approximate measure of the time course of attentional lapses, and thus the total number of presses to correspond to the frequency of lapses. Across all participants, we computed the average time interval (M=37.13, SD = 43.54) and number of button presses (M=11.27, SD=4.96). Figure 3 reports the data for each subject.

	Button Press Mean	Button Press StD	Int Mean	Int StD
Behavioral	11.27	4.96	37.13	43.54
Simulation	11.91	2.74	25.00	17.73

Figure 2: Figure shows group mean and standard deviations of button press counts and intervals for behavioral and simulated subjects.

A)

	Button Press Count	Interval Mean	Interval StD
sub-0	9.5	29.9	20.2
sub-1	13.5	20.9	11.2
sub-2	8.0	38.0	21.4
sub-3	9.0	32.6	13.2
sub-4	10.0	29.8	20.3
sub-5	8.5	34.5	14.3
sub-6	20.5	14.8	9.7
sub-7	16.0	18.6	6.7
sub-8	13.0	23.0	10.6
sub-9	1.0	225.7	98.9
sub-10	14.5	20.5	17.8
sub-11	13.5	22.4	18.8
sub-12	11.5	23.8	15.5
sub-13	11.5	25.6	13.8
sub-14	4.5	46.6	33.0
sub-15	13.5	22.3	11.6
sub-16	12.5	24.0	9.5
sub-17	12.5	24.1	18.1
sub-18	4.0	59.8	17.4
sub-19	6.0	44.3	22.9
sub-20	13.0	22.3	16.0
sub-21	22.0	13.3	5.9

B)

	Button Press Count	Interval Mean	Interval StD
simsub-0	9.0	31.6	19.7
simsub-1	9.0	32.7	14.2
simsub-2	15.0	17.0	10.5
simsub-3	12.0	21.3	14.0
simsub-4	9.0	33.7	25.3
simsub-5	13.0	22.9	10.2
simsub-6	12.0	25.0	19.3
simsub-7	9.0	31.1	34.1
simsub-8	11.0	26.4	26.4
simsub-9	16.0	18.4	13.6
simsub-10	11.0	27.0	20.9
simsub-11	12.0	23.8	10.8
simsub-12	16.0	18.4	13.9
simsub-13	10.0	25.9	17.5
simsub-14	11.0	27.0	23.2
simsub-15	16.0	18.7	7.2
simsub-16	16.0	18.4	8.9
simsub-17	10.0	27.1	20.8
simsub-18	10.0	24.4	24.6
simsub-19	14.0	20.9	13.9
simsub-20	14.0	21.3	9.7
simsub-21	7.0	37.0	31.1

Figure 3: Behavioral (A) and simulated (B) button press data for twenty-two subjects. Button press counts as well as the means and standard deviations of intervals between button presses are displayed.

Model Simulation

The goal of model simulations is to explore relationships that capture comparable statistics of button press count and intervals recorded in the behavioral data. The model defines a button press as an event where s_t is sampled and the value of s_t is three standard deviations below mean on-task performance s_θ. We also condition that the previous timestep s_{t-1} not be sampled in order to mimic a mind wandering event that occurs due to a lapse in metacognitive monitoring. Mean on-task performance s_θ is calculated by averaging s_t over 1000 timesteps with perfect monitoring (100%). The standard deviation of s_θ therefore represents the natural variation in task performance about the mean in the absence of attentional lapses.

We simulated 306 timesteps of data, analogous to the 306 second meditation blocks in the FA task design. Figure 4 displays a sample run, whereas Figure 3B reports summary statistics for twenty-two simulated 'subjects.' Parameters of meta-cognitive monitoring, attentional boost, and the drift diffusion model were systematically manipulated until simulated data mimicked the group means and standard deviations of button press counts and intervals.

The focus of the comparison between behavioral data and model simulation was not to identify precise relationships between monitoring and the value of boosting, but instead to explore how adjusting model parameters could explain variations in subject behavioral data. Notably, many combinations of parameter values can potentially yield these means and standard deviations.

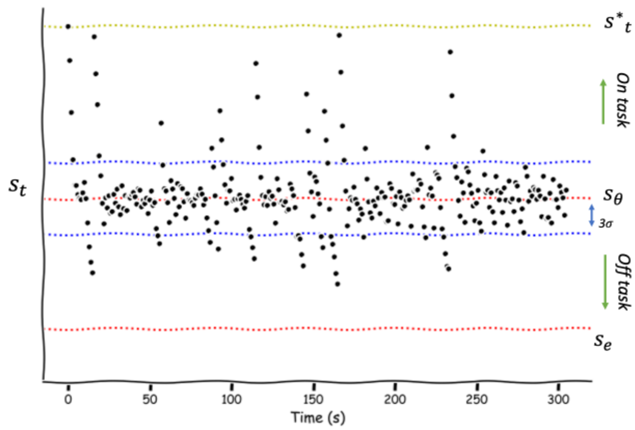

Figure 4: One 306 second simulated run of an FA task. s_t represents the amount of attentional resources allocated to breath, providing a measure of the extent to which a subject is on task. Following task onset and subsequent button presses, s_t decays to a mind wandering state, s_ε. A control signal is applied to remain on task, creating a mean on-task equilibrium s_θ. In the absence of metacognitive monitoring, no control is applied, and s_t drifts towards mind wandering. Once mind wandering is observed, a corrective control signal is applied to reorient attention back to the target.

Behavioral Predictions

To identify the effect of each free parameter (c, d, λ) on button press counts and intervals, one parameter was manipulated while the others held constant (Figure 5). Free parameters were selected to maximize the interpretability of the model, such that smaller parameter values of c, d, λ, correspond to increased monitoring, increased boosting, and greater propensity to drift towards mind wandering, respectively. Button press counts and time intervals were observed for each parameter manipulation, and we interpret the relationships below.

Button Presses The model proposes a couple of potential explanations for a high number of button presses during a five minute meditation run. The first is that participants who rarely press the button monitor internal contents less frequently, and as a result drift towards mind wandering more often. Our model accounts for this by increasing the value of the monitoring parameter d, or decreasing the probability of sampling at larger values of s_t. Similarly, more button presses are generated when less control is applied. By moderately increasing parameter c of the control function, more error is incurred before applying larger control signal intensities, resulting in a lower mean on-task equilibrium, and values of s_t that are generally closer to mind wandering. If both control and monitoring functions are constant, and instead the drift rate λ is decreased, s_t will drift towards mind wandering at a quicker rate. A timestep without metacognitive monitoring is more detrimental in this case, as there is a greater chance it will result in an attentional lapse, ultimately producing more button presses throughout the meditation run.

We can then apply the same logic to explain *fewer* button presses. Smaller values of metacognitive monitoring parameter d correspond to timesteps in which the state is sampled and consequently, control applied. Better monitoring here suggests that there is greater probability of internally sampling, even as mental contents drift further towards mind wandering. As a result, fewer lapse events occur and more time is spent on task. Applying more control by decreasing c will also result in fewer button presses, as little error is allowed before applying more attentional boost, moving the on-task equilibrium closer to optimal performance. Additionally, fewer button presses can be observed if c is drastically increased in the opposite direction. That is, if participants don't care to apply any control, essentially deciding not to engage with the task, they will remain in a mind wandering state for the majority of the task, producing few or no button presses. Lastly, less propensity to drift towards mind wandering, denoted as an increase in λ may also explain fewer button presses.

		Button Press Mean	Button Press StD	Interval Mean	Interval StD	Δ Param
	Behavioral	11.27	4.96	37.13	43.54	NA
	Simulation	11.91	2.74	25.0	17.73	NA
More button presses	**Less Monitoring, d**	15.18	2.36	19.78	13.09	-.5
	Less Control, c	14.18	1.92	20.38	11.97	+2
	More Drift, l	17.18	2.99	17.34	11.49	-.05
Less button presses	**More Monitoring, d**	8.59	1.89	33.98	26.67	-.5
	More Control, c	4.95	1.76	57.41	43.55	-2
	Less Control, c	1.64	0.85	126.73	68.64	+6
	Less Drift, l	4.91	2.07	55.44	39.66	+.05

Figure 5: Figure compares mean and standard deviation button press counts and intervals across 22 simulated subjects when each free parameter (c, d, λ) is manipulated independently. Δ Param describes the amount each parameter was manipulated. Parameter values for model simulation: c=9.7, d=10, ω=1, a=1, b_{min}=0, b_{max}=17, p_{low}=.4, p_{up}=1, λ=.85, s_ε=3, s^*_t=20, s_θ=10.25, σ=.5

Other model predictions Besides button press and interval data, the model affords other theoretical predictions.

Thought probe experiments report that participants mind wander at rates up to 50% (Seli, Carriere, Levene, & Smilek, 2013). However, such tasks typically do not require monitoring of internal contents, and instead only induce an internal sample at the time of the probe. When remaining on task is an explicit goal, as in self caught methodologies, we would expect participants to remain on task for nearly the entire duration, with off-task periods only occurring during lapses. Our model calculates the on-task percentage as the amount of time s_t is above the mind wandering threshold ($s_\theta - 3\sigma$). On average, simulated subjects are on task for 92% of the 5-minute run, and are therefore mind wandering due to an attentional lapse 8% of the time. Additionally, we can examine the percentage of time spent monitoring by extracting number of timesteps where s_t is sampled. According to our model, to produce an average of 92% on-task performance across simulated subjects, sampling must occur 81% of the 5-minute run. Notably, a missed sample can happen while on task, without necessarily inducing a lapse. A percentage of 81% therefore represents general fluctuations in the monitoring procedure in addition the failed monitoring sequences that produce lapses.

Our model can also predict the number of timesteps that a subject spends mind wandering prior to a button press. Behavioral evidence supports that this time period is brief, with subjects almost immediately recognizing when mind wandering has occurred. We calculate this value by summing the number of timesteps greater than three standard deviations prior to an attentional lapse event. Simulations yielded an average of 2.18 timesteps spent mind wandering before button press.

Lastly, our model predicts how participants recover from mind wandering as well as the degree to which participants adjust attention following a lapse event. This re-initiation or reorienting to the task following mind wandering cannot be explored through behavioral data, but may be observable in neural control regions that adjust control based on error calculations.

Discussion

This paper outlines a model that aims to explain subject-level variation in button press data. We propose that subjective determinations of mind wandering are a result of (1) control that boosts attentional resources to a target and (2) a metacognitive monitoring procedure that stochastically observes internal contents. Button presses indicate self-reported attentional lapses, which are modeled as a metacognitive sample of the state following consecutive timesteps of mind wandering.

The model provides theoretical insight onto button press variation in FA tasks. More button presses can be explained by worse metacognitive monitoring or less control applied to maintain an on-task state. It's also possible that more attentional lapses are not due to the interaction of top down control network functions, but instead due to a high value for exploratory cognition, or more drift toward mind wandering. Conversely, less button presses may be due to better monitoring of internal contents or a result of inadequate task engagement, such that participants apply little control and instead mind wander for a majority of the meditation run.

The previous model of FA (Moye & van Vugt, 2021) did not model meditation data, yet did speculate on how meditation performance might improve with training of attention control. Through simulations of their model, they found that after 18 hours of 5-minute meditation runs, near optimal on-task performance could be achieved. Extensions of our model can also test predictions about meditation ability through examining how metacognitive monitoring and unique control functions contribute to better performance. A hallmark of meditation expertise is the phenomenological experience of less effort needed in order to remain focused for long durations (Lutz et al., 2008). One possible explanation for this finding is that expert meditators train their minds to remain in a meditative state. In our framework, this is analogous to increasing λ, or decreasing the rate at which participants drift off task. To increase meditation performance, increased monitoring may initially be required to ensure that the automatic procedure, mind wandering, is not employed. Over time though, it is possible that less supervisory monitoring and control are required to achieve equal levels of task performance. The initial effortful experience may be the result of the large amount of continuous control initially required by the top down system, which decreases as meditators train a new a default brain state in the meditative context.

A previous work by Shepherd (2019) suggests that shifts to mind wandering are initiated by an executive control system, contrary to the hypothesis that mind wandering is a failure of executive control. While our model proposes lapses are due to a supervisory system, it's possible that these accounts can be tested by comparing activations of our model to activations of networks and regions implicated in control during meditation. For example, empirical evidence supports two anti-correlated networks in the brain: one 'default mode' network (DMN) active during mind wandering, and a group of task positive attention networks that execute task related procedures (Corbetta and Shulman 2002, Fox, Snyder et al. 2005). Given these relationships, we would expect to see a decrease in activation of attention networks related to supervisory attention and increased activation of the DMN immediately prior to a button press (Malinowski, 2013; Tops, Boksem, Quirin, IJzerman, & Koole, 2014). We can observe these relationships by comparing extracted activations from different manipulations of model parameters. Our model will ideally contribute to testing predictions of the neural mechanisms responsible for shifts in brain states during FA in addition to providing unique hypotheses about meditation training and individual button press variation.

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