Short Interventions During Sustained Attention Tasks Preserve Performance Without Reducing Mind-Wandering

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Abstract

Despite extensive evidence that performance declines over time in sustained attention tasks, questions remain about whether interventions such as short breaks can address this issue. This study investigated the effects of a rest-break vs. task-switch during the Sustained Attention to Response Task (SART) on task performance and mind-wandering (MW) frequency. In addition to measuring performance via accuracy and reaction time (RT), drift-diffusion modeling (DDM) was implemented to assess performance, and the effectiveness of the interventions was evaluated across different mental states (on-task vs. off-task). Results showed that both interventions preserved accuracy compared to the no-break group. The rest-break intervention maintained stable no-go drift rates, while the task-switch intervention showed an increase in boundary separation. However, neither intervention reduced rates of MW. Additionally, the effects of interventions were more pronounced when participants reported being on-task. These findings suggest that short breaks can help sustain performance, yet do not necessarily halt MW.

Keywords: Mind Wandering; Sustained Attention; Intervention; Drift-Diffusion Modeling (DDM)

Introduction

In vigilance tasks—i.e., sustained attention tasks requiring ongoing detection of critical signals—performance often declines over time, a phenomenon known as the vigilance decrement (Langner & Eickhoff, 2013; Mackworth, 1948). This decline in vigilance often also results in increased mind wandering (MW) and fatigue (Warm et al., 2008). One common approach to mitigate the vigilance decrement is to introduce rest breaks during the task or to temporarily switch to an unrelated task (Ariga & Lleras, 2011; Helton & Russell, 2015; Ralph et al., 2017). Although research suggests that breaks like these can mitigate performance decline, the specific conditions under which they are beneficial, whether they can also mitigate the often-associated increases in MW frequency, and the mechanisms underlying their effectiveness remain under-specified.

Research on the potential effectiveness of breaks in mitigating performance decline has centered primarily on two classes of theories. *Overload theories*, also known as resource theories, suggest that performance decline is due to the gradual exhaustion of attentional resources needed for vigilance (Warm et al., 2008; Helton & Russell, 2015). Extending this theory to MW contexts, some researchers have hypothesized that the frequency of MW should similarly decrease over time, as MW also consumes attentional resources (Thomson et al., 2015). Under this class of theories, a rest break, which will restore depleted attentional resources, should then improve performance but may also increase MW frequency after the break. Temporarily switching to a different demanding task, on the other hand, should further deplete information-processing resources, thus resulting in larger performance decrements while simultaneously disrupting the allocation of resources to MW, thereby reducing its frequency. In contrast, *underload theories* suggest that monotony and lack of stimulation in sustained attention tasks leads to disengagement, resulting in individuals withdrawing their attention from the task (Manly et al., 1999; Pattyn et al., 2008) and, consequently, increasing MW frequency (Thomson et al., 2015). Consistent with this account, research suggests that *both* rest breaks and switching to a different task can help re-engage cognitive resources and lead to smaller performance decrements over time (Ralph et al., 2017). While not as well established in prior research, according to this account, MW frequency should also decrease following both types of interventions as individuals become more engaged with their primary task.

Despite a conceptual link between vigilance decrements and MW during sustained attention tasks (Zanesco et al., 2024), it remains unclear from an empirical perspective whether break interventions can simultaneously mitigate performance decrements and MW frequency, or whether they disproportionately impact one outcome over the other. According to overload theories, break interventions should inversely affect performance decrements and MW frequency, for example, decreasing one while increasing the other, respectively. Whereas underload theories suggest that break interventions should mutually reduce both performance decrements and MW frequency.

This study aimed to directly investigate the impact of inserting interventions (rest-break and task-switch) at the midpoint of a sustained attention task on both task performance and MW frequency. And further, whether this

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impact was influenced by participants' current mental state (on-task vs. off-task). To explore these questions, analyses were conducted with both traditional accuracy and speed outcome measures from the sustained attention task. In addition, previous research has suggested that for the tasks like the one implemented in this study, integrated measures of speed and accuracy offer more sensitive indicators of performance (Mueller et al., 2020). Thus, the current study also employed a sequential sampling model. Specifically, a drift-diffusion model (DDM), which simultaneously considers speed and accuracy on decision making tasks involving many trials to estimate latent cognitive parameters associated with task performance, was used thereby enhancing the interpretation of the behavioral data (Myers et al., 2022; Ratcliff et al., 2018; Ratcliff & McKoon, 2008).

Methods

Participants

Forty-eight healthy adults (M_{age} = 20.39 years, 63.6% females) were recruited from the University of Washington undergraduate subject pool. All participants were provided with extra credit compensation for their time. Participants were randomly assigned to one of the three conditions: no-break, task-switch, or rest-break. Three participants were excluded from the final analysis. Two were excluded due to accuracy lower than 60% and the other one due to not providing any responses during the second half of the task. Therefore, the final sample included 45 participants ($N_{\text{no-break}}$= 13, $N_{\text{rest-break}}$ = 15, $N_{\text{task-switch}}$= 17). All procedures were approved by the local institutional review board.

Experiment Design and Procedure

The present experiment was a 3 (no-break, rest-break, task-switch) × 2 (pre-intervention vs. post-intervention) experimental design. All participants consented and completed a demographic survey before doing the primary experimental task, which took about 30 minutes to complete.

For the primary task, participants performed a fast-paced Sustained Attention to Response Task (SART; Robertson et al., 1997), programmed using PsychoPy3. SART is a go/no-go based task wherein participants are asked to withhold responses to an infrequently presented target (the digit 3) and press the spacebar for the frequently presented non-targets (digits 0-2 and 4-9). Each digit was displayed for 250ms followed by a fixation for 900 ms (see Figure 1). Overall, the task included 1,120 stimuli, comprising 960 targets and 160 non-targets (14.3% of trials). Participants were instructed to respond as quickly and accurately as possible.

The intervention tasks lasted approximately 3-minutes and were inserted into the middle of the SART task. Participants in the rest-break group were asked to watch a 3-minute landscape movie. Participants in the task-switch group performed a computerized version of the Stroop task (Stroop, 1935). In the no-break group, participants continued with the primary SART task for an additional 3-minutes. Following each intervention, participants were notified that "The main task will start in 5 seconds." and then completed the second half of the SART task.

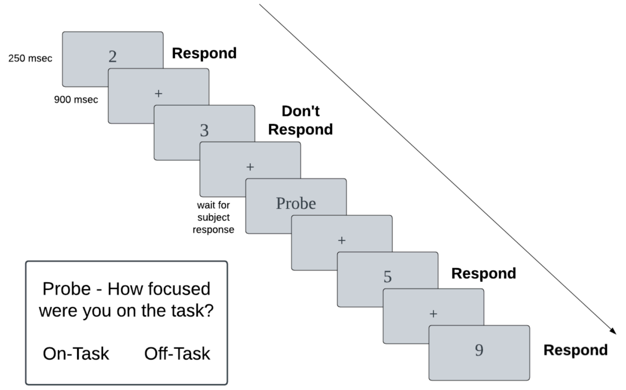

Figure 1: Sustained Attention to Response Task (SART) with probe.

Throughout the experiment, participants responded to 34 thought probes (17 pre-intervention and 17 post-intervention). Probe trials were pseudo-randomly dispersed within the task with a minimum of 30 and a maximum of 45 SART trials between successive probes. Within the 30–45 trial window, the trial on which a thought probe would appear was uniformly sampled. During the interventions no thought probes were given. Each probe consisted of the question, "How focused were you on the task?" with answer options being "On-task" and "Off-task." Participants used the “F” and “J” keys to select one of the two options. Before starting the task, participants were briefed on the definitions of “On-Task” and “Off-Task” and completed 28 practice trials, with one thought probe inserted.

Behavioral Analyses

Dependent Variables. Overall accuracy and reaction time (RT) were included in the behavioral analysis. RTs were computed from the onset of the stimulus presentation only for correct trials (given the nature of the task, by focusing on correct trials, this RT outcome measure only captures reaction times on Go trials). Trials with RTs below 150 ms (3.12 % of trials) were excluded from all analysis.

Pre-probe Analysis. Consistent with previous work in this area (Andrillon et al., 2021), to capture performance under different mental states, a secondary analysis was conducted focusing specifically on the 15 trials that occurred within 20s before each thought probe. The choice of a 15 trials window allowed for the inclusion of 1-3 No-Go trials for each probe, while focusing on trials that are relatively close to the probe onset and therefore are most likely to align with the subsequent subjective report of being on or off task. One participant's data was dropped from the off-task condition for low accuracy (< 60%, in line with the general exclusion criteria).

Drift Diffusion Modeling (DDM)

In addition to the behavioral data analyses, a drift-diffusion model (DDM) was used to estimate two key parameters: drift rate (v) and boundary separation (a). The drift rate quantifies the rate at which evidence for a particular response accumulates over time during a trial. A higher drift rate indicates faster and more confident decision-making, reflecting stronger evidence in favor of one option. The boundary separation represents the distance between the decision boundaries. A larger boundary separation requires more evidence before making a response, favoring accuracy but slowing down decision speed, while a smaller boundary separation speeds up decisions at the cost of accuracy, reflecting the individual's speed-accuracy trade-off approach (Huang-Pollock et al., 2020). Changes in DDM parameters before and after break interventions can serve as indicators of intervention effectiveness and help identify which underlying cognitive processes are affected.

Task performance was modeled by fitting a DDM to participant accuracy and RT data using the Dynamic Models of Choice (DMC) package for R (Heathcote et al., 2019). The model was a modified version of the standard DDM that specified that crossing the upper boundary indicates a Go (response) decision, whereas crossing the lower boundary indicates a No-Go (withhold) decision, by integrating the diffusion density across time to obtain the probability of hitting the withhold boundary. Bayesian estimation in DMC was used for the DDM, with all models fitted to individual participants' data via Markov Chain Monte Carlo (MCMC) sampling. For each individual participant, separate drift rates were fitted for the Go (v_G) and No-Go trials (v_{NG}), and other parameters, included boundary separation (a), starting point (z), and non-decision time (t_0), were allowed to vary freely across trials.

Data Pre-processing. Prior to model estimation, and in line with recommendations for DDM analyses, RTs less than 200 ms were removed. Both correct and error trials were included in the analyses, as typically done with DDM. Following preprocessing, trial-by-trial accuracy and RTs for each participant were inputted into the DDM.

Model Specifications and Fit. Priors were specified as truncated normal distributions for each parameter. Model convergence was checked by inspecting traces of model parameters, Gelman-Rubin diagnostics, and effective sample sizes (Gelman & Rubin, 1992). Posterior predictive checks confirmed adequate model fits.

Results

Mind Wandering Frequency

A total of 34 thought-probes were divided into four blocks (8 or 9 probes pre block), with two blocks before intervention and two blocks after intervention (see Figure 2). This allowed us to examine how MW frequency changed over time and in response to the interventions. An ANOVA revealed a significant main effect of block on mean proportion of MW [$F(3,123)= 14.96$, $p < .001$] but no significant effect of intervention or intervention × block interaction. Overall, MW was lowest in the first block and then increased over time, consistent with recent meta-analytic findings (Zanesco, Denkova, & Jha, 2024). Neither intervention mitigated this increase in MW frequency.

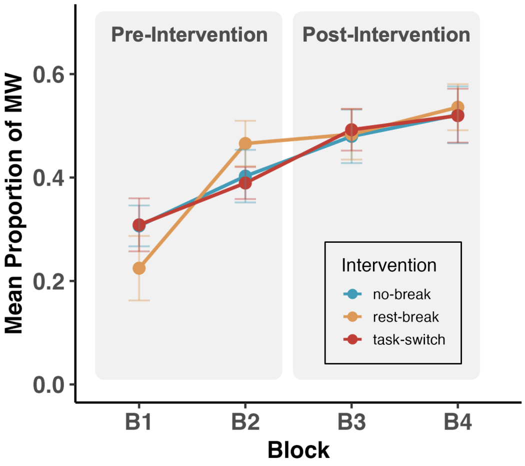

Figure 2: Proportion of mind-wandering (MW), as reflected by reported off-task responses, by intervention group, across blocks pre- and post-intervention.

Effects of Breaks on Task Performance

Accuracy. We fit a generalized linear mixed-effects model predicting accuracy (binary: correct/incorrect) from intervention phase (pre vs. post) and break intervention condition (no-break, rest-break, task-switch) using a binomial (logit) link. The final model included both random intercepts and random slopes for phase by participant. To determine the optimal model structure, we compared a model with only random intercepts to a model that included both random intercepts and random slopes using ANOVA. The results confirmed that the latter structure was optimal. We then conducted pairwise comparisons to assess changes in accuracy pre- and post-intervention within each condition (see Table 1).

Analyses revealed that only the no-break group showed a significant drop in accuracy from pre- to post-intervention. The predicted probability of a correct response was lower post-intervention compared to pre-intervention for the no-break group (see Table 1). Neither the rest-break nor the task-switch group showed a significant change (*ps* > .10). Follow-up analyses showed that the difference in accuracy from post to pre intervention was significant between the task-switch group and the no-break group ($\beta = 0.29$, 95 % CI [0.01, 0.58], $z = 2.03$, $p = .042$), indicating that compared to the no-break group, participants in the task-switch group exhibited smaller decreases in accuracy. In addition, the difference in post-to-pre intervention accuracy was marginally significant between the rest-break group and the no-break group ($\beta = 0.25$, 95 % CI [-0.05, 0.54], $z = 1.64$, $p = .10$), indicating a trend toward the rest break mitigating the vigilance decrement in terms of accuracy.

Table 1: Within-group pairwise comparisons of estimated marginal means of dependent variables.

Condition	Pre	Post	SE (Pre; Post)	$M_{\text{difference}}$	*p*
Accuracy					
No-Break	0.934	0.914	0.008; 0.012	0.020	**0.007**
Rest-Break	0.935	0.932	0.007; 0.009	0.003	0.622
Task-Switch	0.923	0.923	0.008; 0.009	0.000	0.980
Response time (s)					
No-Break	0.354	0.368	0.016; 0.019	-0.014	0.126
Rest-Break	0.363	0.365	0.015; 0.017	-0.002	0.848
Task-Switch	0.350	0.352	0.014; 0.016	-0.002	0.845

Note. SE = standard error of estimates. $p < .05$ were bold.

RTs. A linear mixed-effects model was used to predict correct trial RTs. The same procedure and model selection process was used for the RT model as was used for the accuracy model. The analysis revealed no significant main effect of intervention phase ($\beta = 0.05$, 95 % CI [-0.17, 0.28], $t(41.78) = 1.53$, $p = .134$). Additionally, the difference in RT post to pre intervention was not significantly different between the other two groups and the no-break group (task-switch: $\beta = 0.15$, 95 % CI [-0.15, 0.45], $t(41.86) = 1.02$, $p = .313$; rest-break: $\beta = -0.01$, 95 % CI [-0.32, 0.30], $t(41.79) = -0.99$, $p = .329$). Further, no significant differences were found in pairwise comparisons within each group (see Table 1).

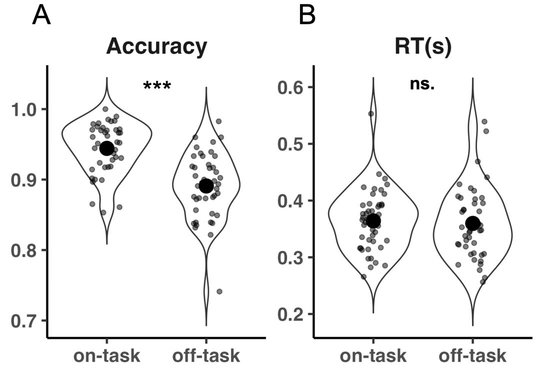

Figure 3: Comparison of behavioral metrics across on-task and off-task mental states using pre-probe data. ***$p < .001$.

Behavioral Performance in Pre-Probe Trials

Performance On and Off Task. Two-sample *t*-tests were conducted to compare performance metrics (Accuracy and RT) between the 'On-Task' and 'Off-Task' states across all data, without grouping by break condition (see Figure 3). Consistent with previous work (Andrillon et al., 2021), results revealed a significant difference in average accuracy, with greater accuracy in the on-task trials ($M = 0.94$) than in the off-task trials ($M = 0.89$), $t(80.67) = 6.12$, $p < .001$, 95% CI [0.04, 0.07]. However, no significant difference was found in RTs between the sets of trials, $t(84.39) = 0.36$, $p = .717$, with comparable means for the on-task trials ($M = 0.36$) and the off-task trials ($M = 0.36$), 95% CI [-0.02, 0.03].

Interventions under On-Task state. The same analytic methods and model selection process that was used in the full trial behavioral analysis were also used in the two pre-probe analyses. First, pre-probe data associated with "On-Task" probe reports was fit into a generalized linear mixed-effects model predicting accuracy. Analyses revealed a significant main effect of intervention phase ($\beta = -0.40$, 95 % CI [-0.75, -0.06], $z = -2.28$, $p = .023$). Additionally, the change in accuracy from post to pre intervention differed significantly for the no-break group compared to both the rest-break ($\beta = 0.59$, 95 % CI [0.10, 1.08], $z = 3.22$, $p = .018$) and task-switch ($\beta = 0.56$, 95 % CI [0.12, 1.01], $z = 3.22$, $p = .014$) groups. These interactions suggest that, compared to the no-break group, both interventions resulted in smaller decreases in post-intervention accuracy when people report they were on-task (see Figure 4). There were no significant main effects or interactions when RTs were examined (all *ps* > .05).

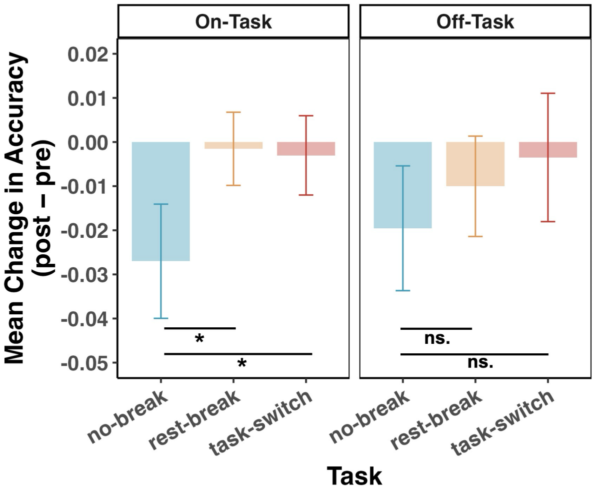

Figure 4: Effects of intervention on mean change in accuracy across on-task and off-task mental states. *$p < .05$.

Interventions under Off-Task state. Pre-probe data associated with "Off-Task" probe reports was fit into a generalized linear mixed-effects model predicting accuracy

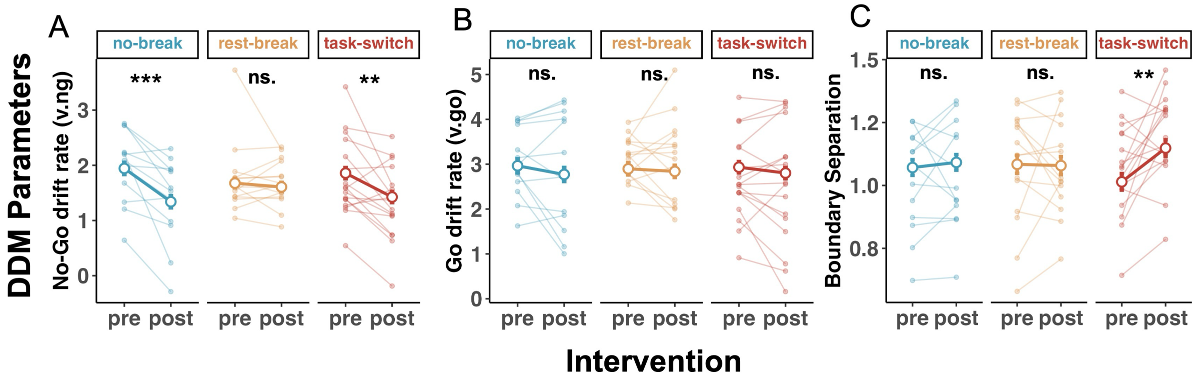

Figure 5: Effects of intervention on DDM parameters across no-break, rest-break, and task-switch conditions. ****p* < .001; ***p* < .01.

and RT. No significant main effects or interactions were found (all *p*s > .05).

DDM Analyses

DDM parameters (v_{NG}, v_G, a) were estimated using both full and pre-probe data for each individual, across pre-/post-intervention and on-/off-task states. Linear mixed-effects models were used to separately analyze each parameter.

No-Go Drift Rate (v_{NG}). Results from the linear mixed model revealed a significant main effect of intervention phase (β = -0.91, 95% CI [-1.37, -0.46], $t(42) = -4.02$, $p < .001$). Furthermore, the difference in post to pre intervention v_{NG} was significant between the rest-break group and the no-break group (β = 0.81, 95% CI [0.19, 1.43], $t(42) = 2.61$, $p = .013$) but not significantly different between the task-switch group and the no-break group (β = 0.26, 95% CI [-0.34, 0.86], $t(42) = 0.85$, $p = .397$). Pairwise comparisons within each group indicated that no-go drift rate was significantly slower in the post-intervention period in the no-break group ($M_{\text{difference}}$ = 0.60, 95% CI [0.30, 0.91], $t(42) = 4.02$, $p < .001$) and the task-switch group ($M_{\text{difference}}$ = 0.43, 95% CI [0.17, 0.70], $t(42) = 3.30$, $p = .002$). By contrast, in the rest-break group, the difference was non-significant ($M_{\text{difference}}$ = 0.07, 95% CI [0.17, 0.70], $t(42) = 0.49$, $p = .624$), indicating that the rest-break intervention mitigates the decline of the no-go drift rate (see Figure 5A). This same pattern was found for the “On-Task” trials, but not for the “Off-Task” trials. That is, when on-task pre-probe data was used to estimate the DDM parameters, the rest-break group showed a significant change in no-go drift rate pre- and post-intervention as compared to the no-break group (β = 0.90, 95% CI [0.14, 1.67], $t(41) = 0.62$, $p = .023$).

Go Drift Rate (v_G). Results from the linear mixed model showed no significant main effects or interactions (all *p*s > .05). Within group comparisons indicated no significant differences between the pre and post intervention go drifts rates across the no-break ($M_{\text{difference}}$ = 0.19, 95% CI [-0.23, 0.62], $t(42) = 0.93$, $p = .360$), rest-break ($M_{\text{difference}}$ = 0.06, 95% CI [-0.34, 0.45], $t(42) = 0.29$, $p = .771$), and task-switch ($M_{\text{difference}}$ = 0.13, 95% CI [-0.24, 0.50], $t(42) = 0.71$, $p = .481$) groups (see Figure 5B).

Boundary Separation (a). Results from the linear mixed model revealed no significant main effects of intervention phase (β = 0.10, 95% CI [-0.41, 0.62], $t(42) = 0.40$, $p = .691$) or break condition (rest-break: β = 0.29, 95% CI [-0.46, 1.03], $t(64.2) = 0.77$; task-switch: β = 0.19, 95% CI [-0.54, 0.91], $t(64.2) = 0.72$, all *p*s > .10). The difference in boundary separation after intervention was marginally significant between the task-switch group and the no-break group (β = 0.57, 95% CI [-0.11, 1.26], $t(42) = 0.11$, $p = .10$) but not significantly different between the rest-break group and the no-break group (β = -0.13, $t(42) = -0.03$, 95% CI [-0.83, 0.57], $p = .717$). Pairwise comparisons indicated that boundary separation did not significantly differ pre and post interventions in the no-break group ($M_{\text{difference}}$ = -0.02, 95% CI [0.08, -0.40], $t(42) = -0.40$, $p = .691$) or the rest-break group ($M_{\text{difference}}$ = 0.01, 95% CI [-0.09, 0.10], $t(42) = 0.11$, $p = .916$). However, in the task-switch group, boundary separation was significantly higher in post intervention compared to pre intervention ($M_{\text{difference}}$ = −0.13, 95% CI [-0.22, -0.04], $t(42) = -3.00$, $p = .005$), suggesting that after the task-switch intervention, participants shifted their strategy toward a more cautious approach to decision-making (see Figure 5C).

Parameters estimated from the pre-probe trials showed the same pattern was found for the “On-Task” trials, but not for the “Off-Task” trials. This indicates that, compared to the no-break condition, the change in boundary separation increased after switching to another unrelated task, but only when participants were on-task with marginal significance (β = 0.57, 95% CI [-0.07, 1.21], $t(41) = 0.13$, $p = .083$). No interactions were observed in the rest-break condition (β = -0.25, 95% CI [-0.92, 0.41], $t(41) = -0.05$, $p = .453$), or when people were off-task (all *p*s > .05).

General Discussion

This study set out to examine whether two types of break interventions—rest-break and task-switch—could mitigate vigilance decrement and reduce MW frequency in a sustained attention task.

Performance outcomes under intervention and DDM insights. Analyses revealed that the no-break group exhibited a significant decline in overall accuracy, whereas both the rest-break and task-switch group maintained accuracy over time. In terms of task performance, this pattern of results is most consistent with the underload theories' predictions that both interventions lead to smaller performance decrements over time. Consistent with Ralph et al. (2017), our results also challenge the idea that vigilance decrements arise solely from the depletion of information-processing resources and instead highlight the importance of considering other explanations, such as engagement levels, as described by underload theories.

Interestingly, the DDM analyses provided a more nuanced interpretation of how each intervention preserved accuracy. Specifically, for the rest-break group, although there was only a marginal interaction in the accuracy change compared to the no-break group, rest-break participants demonstrated relatively stable no-go drift rates (v_{NG}) across the pre- and post-intervention phases. This suggests that their capacity to accumulate evidence for successfully withholding responses remained intact. In contrast, participants in the task-switch condition did experience a decrement in no-go drift rate. However, they appeared to compensate by adopting a more conservative response strategy (marginally increased boundary separation). This shift effectively offset the drift-rate decline and help to maintain overall accuracy. These distinct DDM patterns highlight that mitigating declined performance can manifest through different pathways: preserving the underlying evidence-accumulation processes (rest-break) or shifting decision thresholds (task-switch). The precise mechanisms underlying the changes in the latent DDM parameters stand for future investigation.

Effects of breaks on mind-wandering frequency. Although numerous studies have linked time-on-task with increased MW (Randall et al., 2014; Zanesco, Denkova, & Jha, 2024), the key question examined in this study was whether a short mid-task break or a switch to a different task could stop this rise. Our results indicated that mind-wandering continued to climb across blocks in all groups, with no significant differences among break conditions—findings not predicted by either account. This pattern suggests that performance outcomes and MW frequency could be dissociated under certain conditions, which potentially support recent finding that the processes leading to vigilance decrement should be differentiated from those responsible for MW (Martínez-Pérez et al., 2023). This pattern also resonates with theories suggesting that MW arises predominantly from internally driven processes, such as personal concerns and spontaneous thoughts (Smallwood & Schooler, 2006), and MW is not just the result of mindless disengagement but occurs in response to failures in effortful cognitive control (Thomson et al., 2015). Therefore, even though both the rest-break and task-switch may temporarily disrupt monotony (Ralph et al., 2017; Ross et al., 2014), they may not directly impact the underlying drivers of MW. While the rest-break and task-switch interventions succeeded in sustaining performance in accuracy, they did not interrupt the build-up of off-task thoughts as time-on-task increased.

Effects of breaks on On-and Off-Task states. Our pre-probe analysis demonstrated that participants accuracy was lower when they reported being off task, mirroring prior findings (Andrillon et al., 2021). Notably, the beneficial effects of the rest-break and task-switch interventions emerged only when participants reported being on-task, rather than off-task, in terms of accuracy. This result suggests that break interventions might help participants maintain or reestablish a more focused state, but only when individuals are already predisposed to engaging with the task. Once participants slip into an off-task state, short breaks may not suffice to pull them back to the same level of attentional engagement.

The current study showed accuracy effects but not RT effects and this may in part have been due to how we operationalized mind-wandering. First, we used a binary state classification (on-task vs. off-task). Studies that separate *mind-wandering*, *mind-blanking*, and *on-task* responses report RT slowing only for mind-blanking, not for mind-wandering (Andrillon et al., 2021); collapsing those categories in the present study may have therefore washed-out subtle differences. Second, we focused on mean RT, while other studies have employed variability-based RT metrics as indicators of sustain attention task performance. In these studies, RT measures have been shown to distinguish between brain states during the sustained attention tasks (Cheyne et al., 2009; Bastian & Sackur, 2013; Yamashita et al., 2021).

Taken together, our results underscore the complexity of addressing both performance and MW outcomes in sustained attention tasks. Short breaks in the middle of the task do not always reduce MW, yet they can still preserve performance by either preserving efficiency of evidence accumulation or encouraging compensatory adjustments in decision-making processes, specifically when people report they are on-task. To further refine these findings, future studies could 1) replicate the study, perhaps with a larger sample, to investigate whether the pattern of marginal results remain, 2) investigate different forms of MW (e.g., spontaneous vs. deliberate) for a more nuanced understanding of off-task thoughts (Wong et al., 2022), 3) incorporate RT-variability indices alongside mean RT, as these metrics are more sensitive to subtle changes in attentional stability, and 4) explore varied break strategies (Blasche et al., 2018), such as unstructured breaks, to determine which approach most effectively mitigates vigilance decrement. Understanding these nuances will be crucial for designing more effective protocols in real-world settings, such as educational contexts, monitoring tasks, and in operational domains, where sustained attention is needed.

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