Cognitive, Motivational, and Contextual Factors Implicated in the Dynamics of Time-on-Task Effects and Attentional Fluctuations During Sustained Attention

By

Deanna L. Strayer

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Dissertation Committee:

Nash Unsworth, Advisor

Elliot Berkman, Core Member

Benjamin Hutchinson, Core Member

Jenefer Husman, Institutional Representative

University of Oregon

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DISSERTATION ABSTRACT

Deanna L. Strayer

Doctor of Philosophy in Psychology

Title: Cognitive, Motivational, and Contextual Factors Implicated in the Dynamics of Time-on-Task Effects and Attentional Fluctuations During Sustained Attention

The ability to sustain attention during prolonged tasks is a vital part of our attentional system and is necessary for everyday activities ranging from driving to maintaining focus during a boring meeting. However, even if we perform well in general, performance tends to decline with time-on-task in the form of slowing, greater response variability, more frequent attention lapses, and increased mind-wandering. This dissertation investigated why and under what circumstances attention lapses occur and ways to reduce their frequency and severity. This was done by examining cognitive, motivational, and contextual factors across three experiments that combined behavioral, subjective, and pupillometric measures and interpreting the results through a general resource allocation framework. Experiment 1 tested whether specific goals that become progressively harder-over-time (HOT) reduce lapses by enhancing meta-awareness of task-unrelated thoughts during a four-choice reaction time task. HOT goals replicated previously established behavioral and pupillary benefits (faster, less variable RTs, fewer lapses, and greater preparatory attentional effort), but showed no effect on meta-awareness, which remained stable across condition and time. Experiment 2 tested whether tailoring HOT goals to individual ability would preserve these behavioral benefits while improving the subjective task experience, using motivational measures collected repeatedly throughout the task. Tailored and group-level HOT goals produced equivalent behavioral gains over a vague-goal control, but tailoring did not broadly improve subjective experience. Goal-acceptance, commitment, and motivation began high in both HOT goal conditions and diminished as difficulty escalated, with tailoring locally protecting self-

efficacy when goal-difficulty diverged between groups in the final block of the task. Experiment 3 shifted from manipulating the goal to manipulating task structure, testing how differentially segmenting a fixed amount of passive break time affects the vigilance decrement during a psychomotor vigilance task. Mandated breaks led to a shallower vigilance decrement, fewer behavioral lapses, and sustained anticipatory attentional effort relative to a self-paced control, but the two break schedules did not significantly differ. Across all three experiments, manipulations reliably improved behavioral performance yet left rising task-unrelated thought and declining pupillary responses untouched. Overall, findings indicated that the most effective strategy for reducing attention lapses likely requires coordinated interventions that target distinct components of a dynamic, multiply-determined attentional system based on task circumstances and individual differences.

CURRICULUM VITAE

NAME OF AUTHOR: Deanna L. Strayer

GRADUATE AND UNDERGRADUATE SCHOOLS ATTENDED:

University of Oregon, Eugene
Arizona State University, Tempe

DEGREES AWARDED:

Master of Science, Psychology, 2021, University of Oregon
Bachelor of Science, Psychology, 2020, Arizona State University

AREAS OF SPECIAL INTEREST:

Attention
Goal-Setting
Motivation
Pupillometry and Eye-Tracking

PUBLICATIONS:

Unsworth, N., Miller, A. L., **Strayer, D. L.,** & Grudzien, A. M. (in press). Individual differences in attention and learning: A latent variable analysis. *Journal of Experimental Psychology: Learning, Memory, and Cognition.* https://doi.org/10.1037/xlm0001541

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CHAPTER I

INTRODUCTION

The ability to sustain attention is a critical component of our attentional system which entails maintaining focus on a task for periods of time spanning seconds to hours. Every day we encounter situations where sustaining attention is necessary, such as driving a car, taking notes during class, or making sure you are listening during a very long meeting so that if you are asked a question you are able to respond. Note that this capacity to steadily maintain focus is its own distinct aspect of attention control; sustaining attention is different from both the shifting and dividing of attention, as well as the control of attention selectivity (Posner & Boies, 1971; Posner & Peterson, 1990; Raz & Buhle, 2006; Robertson & O'Connell, 2010, 2014). While we are generally competent at sustaining attention, over time our performance tends to decline (Robertson & O'Connell, 2010; Esterman & Rothlein, 2019). Especially when the current task is repetitive/tedious/undemanding as opposed to more cognitively demanding tasks (Langner & Eickhoff, 2013; Robertson et al., 1997; Robertson & O'Connell, 2010). This is commonly referred to as the vigilance decrement, or in more contemporary work, the term time-on-task (TOT) effect is often used interchangeably (Parasuraman, 1986; Parasuraman & Davies, 1977; Mackworth, 1948; Robison et al., 2021; Oken et al., 2006; see also, See et al., 1995). Some ways these TOT effects can manifest include diminished behavioral performance (increasing response time/variability), decreased self-reported alertness/arousal/task-engagement, increased reports of mind-wandering, and more frequent attention lapses (Mackworth, 1948; Parasuraman & Davies, 1977; Unsworth & Robison, 2016; Robison et al., 2021; Strayer et al., 2024). Attention lapses reflect an unintended shift of focus away from the task at hand towards unrelated thoughts and can

lead to failures in completing intended actions (Casner & Schooler, 2014; Lindquist & McLean, 2011; Unsworth et al., 2021a; Unsworth & McMillan, 2017). Consequences of these lapses can range from the relatively benign (e.g., forgetting the attachment in an email you just sent) to disastrous (e.g., unintentionally running a red light and causing a car accident; Galera et al., 2012). Relatedly, we all experience periods of mind-wandering to different degrees. This can take the form of daydreaming or even intentionally thinking of other things such as planning what you are going to make for dinner later while you are in the middle of your current task. An ever-growing body of research has found mind-wandering to be detrimental in common settings like learning environments (Smallwood, Fishman, & Schooler, 2007; Unsworth & McMillan, 2017; Lindquist & McLean, 2011), driving (Yanko & Spalek, 2014), and even just general day-to-day life (McVay, Kane, & Kwapil, 2009; Williamson et al., 2011). Despite nearly a century of research, the cognitive and motivational mechanisms underlying attention lapses and mind-wandering remain incompletely understood. Not to mention the ongoing contention about how best to conceptualize, measure, and mitigate these attentional fluctuations.

Historically, theories of sustained attention have emphasized resource-based accounts, which suggest that cognitive performance deteriorates because individuals have a limited pool of attentional resources that becomes depleted over time (Kahneman, 1973; Mackworth, 1948; Grier et al., 2003; Warm et al., 2008; see Fortenbaugh et al., 2017 for review). Foundational vigilance research by Mackworth (1948) was inspired by questions that arose during World War II concerning prolonged visual search due to the widespread use of radar technology. The findings indicated a decline in monitoring efficiency over the course of a two-hour task, particularly after the first thirty minutes. Mackworth (1948) dubbed this decline the "vigilance decrement" (see

Broadbent, 1958). Though these early findings were consistent with the notion of diminishing resources, more work quickly followed that indicated effective ways to combat the vigilance decrement, like: providing feedback, enhancing visibility/contrast of the target signal, telephoning the research subject halfway through and asking them to perform even better on the second half, short rests, and increasing the amount of time the signal is shown (Mackworth, 1948; Fraser, 1950, 1953).

Over several decades, newer frameworks have emerged that attempt to account for these follow-up findings, and challenge explanations based purely on resource depletion. These frameworks support more nuanced, dynamic accounts that emphasize fluctuation in arousal (Aston-Jones & Cohen, 2005; Unsworth & Robison, 2017), cognitive control (Braver, 2012), motivational trade-offs (Inzlicht et al., 2018), and meta-awareness processes (Schooler et al., 2011). Rather, some accounts no longer view sustained attention as a simple decline, but as a process scattered with brief episodes of disengagement or off-task thought (Christoff et al., 2009; Rosenberg et al., 2016). These lapses in attention occur even under ideal conditions (i.e., highly motivated, well-rested, and physically alert) which suggests that they arise from some fundamental limitation of cognitive control, motivation, and arousal systems and their interactions, and not just fatigue or general disinterest (Unsworth & Robison, 2016; van den Brink et al., 2016).

Advancement and integration of research methodologies has fueled further interest in attention lapses. Behavioral measurement techniques, like capturing reaction time variability during computerized sustained attention tasks, have allowed researchers to inspect dynamics of attentional fluctuations over time in a highly detailed manner (Esterman et al., 2014; Reteig et al., 2019). The use of subjective experience-sampling methods to assess the prevalence of task-

unrelated thoughts during sustained attention tasks has facilitated insight that indicates a dissociation between deliberate disengagement and involuntary, spontaneous attention lapses (Seli et al., 2016; Robison & Unsworth, 2018). Finally, neuroimaging techniques and physiological measures have been able to reliably link attention lapses to fluctuations in brain activity and general arousal, like: increased default mode network activity (Christoff et al., 2009), reduced amplitude of the P300 event-related potential (EEG; Martel et al., 2014), and smaller baseline pupil diameter indicating reduced locus coeruleus-norepinephrine system activity (Unsworth & Robison, 2016, 2017a). Collectively, these advancements have led to prioritization of integrative, multi-level models of attention control that incorporate cognitive, motivational, and neural mechanisms.

Relatedly, there is an ever-growing interest in identifying factors and interventions that can help mitigate time-on-task-effects and reduce the occurrence of attention lapses. Sustained attention work (borrowing goal-setting theory from industrial-organizational psychology) has shown that setting specific, difficult goals can improve general motivation and task engagement while reducing attentional fluctuations (Locke & Latham, 2002, 2019; Robison et al., 2021; Strayer et al., 2024; Strayer & Unsworth, 2026; Garner et al., 2024). Short implementations of mindfulness techniques can reduce mind-wandering during a sustained attention task (Mrazek et al., 2012). Additionally, incorporating strategic breaks into a task can help restore attentional resources and maintain performance over time (Ariga & Lleras, 2011; Ralph et al., 2017).

The Present Study

In spite of the collective advances in methodology and previous research conducted, there remain many gaps in our understanding of attention lapses and sustained attention dynamics.

Cognitive and neurophysiological factors and their respective roles in time-on-task effects are not fully explored. Additionally, more research is needed on the fluctuations of subjective, motivational factors (e.g., goal-difficulty, goal-commitment, goal-acceptance, self-efficacy, motivation) in response to motivational interventions and as a function of time-on-task.

Broadly, the present study aimed to advance our understanding of why and under what circumstances attention lapses occur, how they relate to performance outcomes, and techniques that can be implemented to reduce the frequency of their occurrence and/or severity. These aims were addressed by conducting a set of three experiments, each designed to explore an aspect of different factors pertaining to attention lapses, including: meta-awareness (cognitive factor), individually tailoring task goals (motivational factor), and differential allocation of the same amount of break time (contextual factor). I also discuss how the findings in each experiment can be explained under a general resource allocation framework (Unsworth, under review; Kahneman, 1973; Kanfer & Ackerman, 1989; Thomson et al., 2015).

According to a general resource allocation framework proposed by Unsworth (under review) which builds on Kahneman's (1973) capacity model of attention and the elaborated version proposed by Kanfer and Ackerman (1989), the amount of currently available resources depends on arousal. Factors such as sleep deprivation, illness, and stress lower arousal and thereby shrink the pool of resources that can be devoted to the task (Anderson & Horne, 2006). However, even when resources are plentiful, individuals typically hold some capacity in reserve rather than committing everything to the task at hand (Hockey, 1997; Kahneman, 1973; Kalsbeek, 1968; Kanfer & Ackerman, 1989). The proportion that is actually invested is shaped by conative and motivational factors: greater task motivation, specific and difficult (yet achievable) goals, and

higher self-efficacy all tend to encourage the investment of additional resources, whereas low levels of these same factors lead to under-investment (Bandura, 1977; Kanfer & Ackerman, 1989; Locke & Latham, 1990). Allocation decisions are further guided by cost-benefit considerations regarding the value of performing well and the likelihood of actually doing so (Kanfer, 1987, 2011; Kurzban et al., 2013; Shenhav et al., 2017).

Whatever resources are invested must then be divided among competing demands: the current task, off-task thoughts, and self-regulatory processes (Kanfer & Ackerman, 1989). Performing well requires that the task goal be activated and continuously maintained above other goals, such as personal concerns and biological needs, that are often far more meaningful to the individual than an assigned task (Altmann & Trafton, 2002; Hockey, 2013; Klinger, 1999; McVay & Kane, 2010; Unsworth & Robison, 2020). If the task goal activation wanes, one of these competing goals can capture the focus of attention towards internal or external distraction. Concurrently, some resources are directed toward self-regulation: monitoring ongoing performance, comparing it against internal or external standards, and feeding that evaluation back into the allocation process to reorient attention and adjust overall engagement (Hockey, 2013; Kahneman, 1973; Kanfer & Ackerman, 1989; Unsworth & Robison, 2016). Explicit performance feedback lightens this self-evaluative burden and frees resources for the task itself. Alternatively, lack of feedback forces individuals to expend resources toward gauging how well they are doing (Ackerman, 2011). In this way, self-regulatory demands, much like task-unrelated thoughts (TUTs), can siphon attention away from the current task and open the door to lapses.

Viewed through this lens, lapses of attention are not a unitary phenomenon. They take different forms and arise for different reasons (Kahneman, 1973; Randall et al., 2014; Thomson et

al., 2015; Unsworth & Robison, 2020). A lapse may reflect too few resources reaching the task in the first place, either because low arousal has limited what is available or because low motivation or vague goals have left the primary task goal weakly activated despite ample capacity. Alternatively, resources may be diverted elsewhere (e.g., personal concerns that fuel mind-wandering, salient external distractors, deliberate/intentional mind-wandering or task disengagement; Seli et al., 2016; Unsworth & McMillan, 2017) or to the self-regulatory processes mentioned above. Excessively high arousal carries its own risks, such as producing erratic or unstable allocation of attention (Kahneman, 1973; Lenartowicz et al., 2013). Overall, this general resource allocation framework accommodates the heterogeneity of attention lapses, identifies factors that make their occurrence more or less frequent, and points towards strategies for reducing them. It provides the theoretical lens through which the findings of the three experiments reported here are interpreted.

CHAPTER II

EXPERIMENT 1: THE ROLE OF META-AWARENESS IN GOAL-SETTING TECHNIQUES

Meta-awareness reflects the ability to monitor the contents of one's own consciousness and recognize attentional shifts away from task-relevant goals (Schooler, 2002; Smallwood & Schooler, 2015). The concept of meta-awareness is an extension of previous research on meta-cognition, or, how individuals reflect on and regulate their own cognitive processes (Flavell, 1979). Theoretically, if attention lapses result from failures of control and self-monitoring, then strategies designed to elevate meta-awareness of task-unrelated thoughts should also work to enhance overall sustained attention performance by minimizing time spent off-task. In my previous work, I found that setting specific goals that became progressively harder-over-time (HOT) resulted in improved task performance and fewer attention lapses (Strayer et al., 2024). Further exploration revealed that attentional effort was a key mechanism in the efficacy of the HOT goal-setting (Strayer & Unsworth, 2026). Experiment 1 utilized pupillometry, thought-probes, and self-caught TUT measures during a 4-choice reaction time task (4CRT) in order to: 1) replicate the findings that HOT goals enhance attentional effort and reduce attention lapses during sustained attention, and 2) test the hypothesis that meta-awareness of task-unrelated thoughts is another mechanism behind this effect. As far as I am aware, no study currently exists that directly tests the influence of this goal-setting technique on meta-awareness and attention lapses, particularly with combined behavioral, dual-experience-sampling, and pupillometric methodology.

Meta-Awareness in Sustained Attention

Meta-awareness has become a prominent construct for explaining the variable nature of attention during extended tasks (Schooler, 2002; Schooler et al., 2011). Classic vigilance studies (e.g., Mackworth, 1948) recorded attention decrements behaviorally, but lacked the ability to

connect those behaviors to concurrent mental states (See et al., 1995; Warm et al., 2008). However, modern work has been able to demonstrate that time-on-task decrements are often accompanied by internally oriented thoughts and failures in noticing unintentional off-task thoughts, possibly until externally cued to take stock of your own thoughts (i.e., a lack of meta-awareness; Christoff et al., 2009; Smallwood et al., 2009; Smallwood & Schooler, 2015; Seli, Carriere, & Smilek, 2015; Thomson et al., 2014; Zanesco et al., 2025). Findings from experience-sampling studies separate spontaneous mind-wandering (which tends to fly under the radar of meta-awareness) from deliberate mind-wandering (where disengagement from the task is intentional; Seli et al., 2015; Seli, Carriere, & Smilek, 2015). Of these, spontaneous mind-wandering (probe-caught) is more strongly predictive of time-on-task decrements (McVay & Kane, 2010; Smallwood et al., 2007; Neigel et al., 2019; Unsworth & McMillan, 2013). This implies that temporary lapses of meta-awareness play a role in time-on-task effects. Additionally, the distinction between an individual detecting their own lapse (self-caught) or whether it remains unnoticed (probe-caught) makes a difference (McVay & Kane, 2010; Seli et al., 2016). Paradigms with both probe-caught and self-caught measures have shown that self-caught instances of mind-wandering are followed by quicker reorienting and limited downstream performance costs compared to their probe-caught counterparts (Smallwood & Schooler, 2006; Seli et al., 2016). This difference implicates meta-awareness as a recovery mechanism and supports its role in reducing time-on-task effects. Without meta-awareness, attention failures may drag on for extended periods, thereby perpetuating task disengagement.

Physiological and Neural Correlates of Meta-Awareness

Evidence from physiological and neural paradigms suggests that meta-awareness plays a meaningful role in monitoring, control, and arousal systems. fMRI studies indicate that episodes of off-task thought are associated with both increased default mode network activity and decreased frontoparietal control engagement (Mason et al., 2007; Christoff et al., 2009). Conversely, self-caught attentional drift and subsequent re-engagement were associated with salience and control networks related to performance monitoring (Langner & Eickhoff, 2013). Two key EEG indices, increased posterior alpha power (reduced external awareness) and reduced P300 amplitude (orienting response), both precede performance errors and reports of off-task thoughts, which indicates perceptual decoupling and diminished attentional allocation toward external events (O'Connell et al., 2009; Smallwood et al., 2008; Polich, 2007; Jin et al., 2020). Pupillometric indices link these dynamics to the LC-NE system. Diminished baseline pupil diameter and attenuated phasic responses typically precede probe-caught task-unrelated thoughts, while higher phasic responses align with self-correction and renewed engagement (Kahneman & Beatty, 1966; Laeng et al., 2012; Unsworth & Robison, 2016, 2018; van den Brink et al., 2016; Martin et al., 2022). These dynamics coincide with adaptive-gain accounts, wherein the LC-NE system modulates the balance of tonic (general arousal) and phasic (response bursts for salient events) norepinephrine projections and enables rapid state shifts necessary for

noticing lapses and course-correcting (Aston-Jones & Cohen, 2005; Gilzenrat et al., 2010; Berridge et al., 1993; Robison et al., 2023).

Meta-Awareness Interventions

Not only is meta-awareness a construct related to the occurrence of time-on-task effects, but it is likely an explanatory factor behind the effectiveness of some interventions that aim to mitigate time-on-task effects during sustained attention. Several researchers have found evidence that meta-awareness is not a set cognitive ability, but a malleable one. For example, one of the most popular methods of enhancing meta-awareness is mindfulness meditation training (Vago & Zeidan, 2016; Brandmeyer & Delorme, 2021). Mrazek et al. (2012) found that just 8 minutes of a mindful breathing exercise resulted in diminished mind-wandering (compared to passive relaxation and reading conditions) over the course of a Sustained Attention to Response Task (Robertson et al., 1997). Mrazek et al. (2013) later found that a two-week mindfulness-training procedure led to reduced frequency of off-task thoughts while completing the GRE reading-comprehension section and a working memory task, resulting in boosted scores for both. Both of these studies are consistent with the notion of training-induced gains in monitoring one's attentional state and indicate that even relatively brief interventions can improve recognition of moment-to-moment attentional shifts (Brandmeyer & Delorme, 2021).

Meta-awareness can also be improved by including break periods or other contextual manipulations that aim to prevent goal representations from diminishing with time-on-task. For example, Ariga and Lleras (2011) found that providing brief and rare breaks, in the form of a task-switch, throughout a visual vigilance task attenuated typical time-on-task effects. They argued that this effect was due to the breaks reactivating goal representations, thereby increasing

attentional monitoring after each break (Ariga & Lleras, 2011). Similarly, Ralph et al. (2017) demonstrated that groups that received either a rest break or a demanding visuospatial task in the middle of a boring visuospatial vigilance task both performed better and displayed an attenuated vigilance decrement compared to a control group that did the task straight-through. This was interpreted as evidence that these interventions periodically reset individuals' attentional priorities and helped them reengage in the monotonous task (Ralph et al., 2017). Overall, these findings align with theories of vigilance decrements that argue time-on-task effects are partially due to the progressive loss of goal salience and indicate that occasionally refreshing goals (even with a more demanding task) bolsters sustained attention and meta-awareness.

Goal-Setting and Meta-Awareness

A growing set of research provides evidence that goal-setting and other motivational manipulations are effective interventions for reducing or even eliminating time-on-task effects, in particular, specific goals that become progressively harder-over-time (HOT; Strayer et al., 2024; Strayer & Unsworth, 2026). Goal-setting theory states that setting specific, difficult (but attainable) goals helps mobilize effort, sustain persistence, and direct attention toward goal-relevant cues. In the context of sustained attention, these mechanisms have the potential to facilitate higher monitoring of one's own mental state, leading to speeded detection and correction of attention lapses and mitigating their effect on overall performance. Here, I argue that several findings in the meta-awareness literature, in conjunction with central aspects of goal-setting theory, lend support to the idea that goal-setting techniques work not only due to effects on motivation and effort, but also partially through their effect on meta-awareness (Locke & Latham, 2019; Smallwood & Schooler, 2015).

During sustained attention tasks, attention lapses can go unnoticed for considerable periods of time (McVay & Kane, 2010). This indicates that meta-awareness (i.e., the conscious recognition of one's own thoughts), or a lack thereof, plays a role in their occurrence (Schooler et al., 2011; Smallwood & Schooler, 2015). Studies by Robison et al. (2021) and Strayer et al. (2024) demonstrated that setting specific, difficult goals during sustained attention tasks (PVT and 4-choice reaction time) reduced behaviorally captured attention lapses in the response time distribution and mitigated time-on-task effects. Critically, feedback was necessary for these effects. The combination of goal-specificity and timely feedback works to enhance the salience of performance standards, which may increase the odds of consciously detecting unintentional off-task thoughts, in turn providing a chance for attentional control mechanisms to reorient focus back toward the task (Thomson et al., 2015). Strayer et al. (2024) further found that setting specific goals that progress in difficulty over the course of three task blocks led to more pronounced results and even eliminated time-on-task effects on response time. This could relate back to the effect of contextual manipulations found by Ariga and Lleras (2011) and Ralph et al. (2017), wherein the inclusion of brief breaks (in the form of task-switching) led to attenuated vigilance decrements, presumably due to combating the loss of goal salience. Since each block was preceded by the presentation of a new, specific goal, goal salience was preserved over time. The salience of the goal in conjunction with feedback on every trial could facilitate a higher likelihood of meta-awareness on trials displaying response times that do not reach the goal. This is in contrast to the control condition that received a standard, vague ("do your best") goal (Strayer et al., 2024). Though the control condition also received a goal before each block instructing them to try their best, the lack of specificity gave little meaning to the feedback. The lack of connection between

the given goal and feedback likely allowed slow responses (i.e., attention lapses) to pass by inconspicuously.

Beyond behavioral and subjective findings, Strayer & Unsworth (2026) utilized pupillometric methods and demonstrated evidence that HOT goals increased attentional effort, reduced attention lapses and off-task thoughts, and even caused those in the HOT goal condition to respond faster as the task went on, reversing the typical decrement. This mobilization of effort by goal-setting may also gear attentional control processes toward monitoring for and correcting attentional fluctuations, which is a process mediated by meta-awareness.

Overall, the theoretical integration of HOT goal techniques fits within a general resource allocation framework which holds that a limited pool of attentional resources is distributed between the primary task, off-task thoughts, and self-regulatory processes, with successful task performance depending on activating and maintaining the primary task goal above competing goals. Under this framework, attention lapses may occur due to insufficient resources initially allocated to the task, or when the task goal loses saliency and resources are captured by opposing goals or distractors. HOT goals may guard against these lapses on two fronts. Motivationally, setting specific goals that become progressively more difficult over time may encourage the investment of additional attentional resources and help keep the task goal activated above other conflicting goals (Locke & Latham, 1990). At the same time, HOT goals may strengthen the self-regulatory component of the framework by making attentional shifts more explicit and actionable, thereby enhancing meta-awareness and enabling faster detection and correction of off-task episodes. Thus, meta-awareness potentially represents an important mechanism linking

HOT goal-setting to improved performance outcomes and reduced frequency of attention lapses and off-task episodes in sustained attention tasks.

Current Study

In Experiment 1, I replicated the methods used in Strayer & Unsworth (2026) with the addition of a self-caught mind-wandering measure (Chu et al., 2023). In this HOT goal-setting scenario, self-caught mind-wandering alone is not particularly indicative of any divergence in meta-awareness rates between groups. The goal manipulation has already shown effects on the overall proportion of time spent mind-wandering using the probe-caught method, which limits interpretation of self-caught TUTs as an isolated measure. However, recent studies have operationalized meta-awareness as the ratio of self-caught mind-wandering to probe-caught mind-wandering (Scheibner et al., 2016; Meier, 2019; see Chu et al., 2023, and Weinstein, 2018, for meta-analytic review on self-caught and probe-caught methodologies). The probe-caught method is considered to be indicative of "true" time spent off-task (Meier, 2019; Chu et al., 2023). By comparing the proportion of trials where individuals catch themselves mind-wandering to true overall time spent mind-wandering, we can capture a more accurate view of any group-level differences in meta-awareness. We can also look at the effect of time-on-task on meta-awareness, including the effect of increasingly difficult goals.

Method

Participants and Procedure

Eighty students between the ages of 18 and 35 were recruited from the University of Oregon human subjects pool and were compensated with partial course credit (40 Control vs. 40 HOT goal condition). We aimed to collect a minimum of 40 participants per condition. This sample

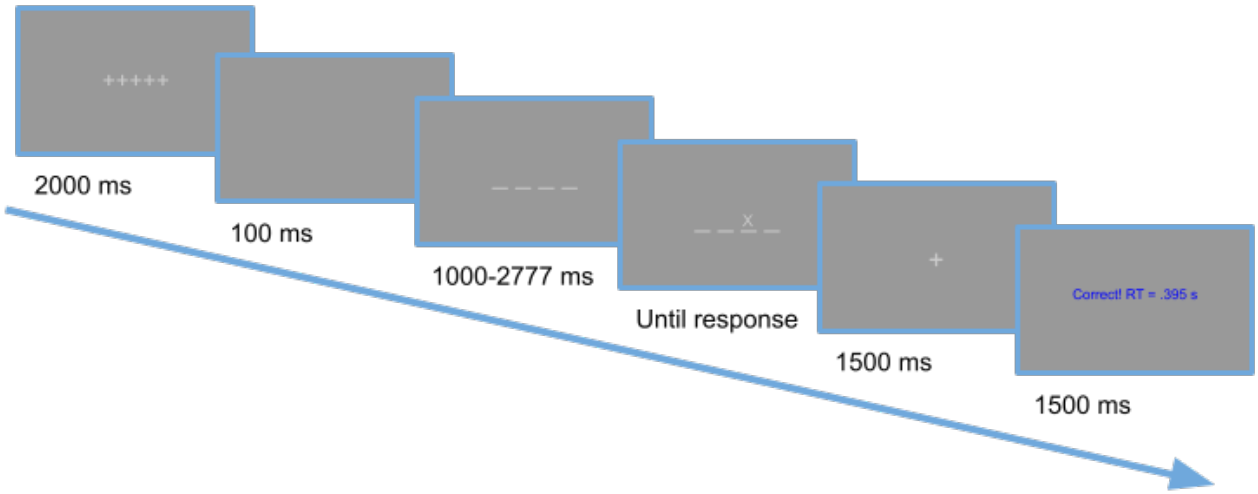
size provided adequate statistical power to identify medium to large effects ($\eta_p^2 \geq .06$) both within- and between-subject. Consistent with prior work, criteria for exclusion included any of the following: 1) less than 80% overall task accuracy, 2) less than 50% accuracy in any single block, or 3) excessive missing pupil data. Based on these criteria, no subjects were excluded from this study. The task lasted approximately 40 minutes. Participants provided informed consent and completed a brief demographic survey prior to beginning the task.

Task

Participants completed a 4-choice reaction time task consisting of 180 trials (3 blocks with 60 trials each) programmed via E-Prime 2.0 (see *Fig. 1*). Each trial began on a gray screen with a 2000 ms light-gray fixation (+++++), followed by a brief blank gray screen for 100 ms, then four light-gray lines appeared in a row in the center of the screen. Following a random time interval (between 1000-2777 ms), a light-gray target (X) appeared above one of the four lines. Participants responded with a key press corresponding to the location of the target ('f','g','h','j') and then saw a 1500 ms fixation screen. Finally, a 1500 ms feedback screen appeared indicating whether they answered correctly (in blue) or incorrectly (in red). If correct, the response time for that trial and accuracy for the current block were also shown. At 5 random points in each block, the participant responded to a thought-probe and then saw a 3000 ms goal-reminder before continuing.

Figure 1

4-Choice Reaction Time Task Paradigm: Sequence of Events Within a Single Trial



Note. The same paradigm was used in both Experiments 1 and 2.

Thought-Probes

Participants were randomly presented with 15 thought-probes (5 per block) that assessed their attentional state just prior to the probe appearing. The display read:

"Press the key that best describes what you were thinking about just prior to this screen appearing.

1) I was totally focused on the current task

2) I was thinking about my performance on the task

3) I was distracted by sights/sounds in my environment

4) I was thinking about things unrelated to the task

5) My mind was blank."

Participants responded using the numbers at the top of the keyboard (1-5) corresponding to their answer**.** Response 1 was coded as on-task, response 2 as task-related, and responses 3-5 as task-unrelated thoughts (TUTs).

Self-Caught Mind-Wandering

Prior to beginning the task, the participants saw an instruction screen telling them how to report their self-caught task-unrelated thoughts. It read:

"At any time during this task that you catch yourself mind-wandering, please press one of the SHIFT keys. It doesn't matter which, just whichever side is easier. For the purposes of this task, mind-wandering refers to shifts of attention away from the task. This can be day-dreaming about dinner, being distracted by outside noise, or purposefully thinking about other things. Whenever you notice mind-wandering, please press the SHIFT key."

The task recorded presses of the SHIFT key during the trial blocks at any time other than the brief period where the actual target appeared (because if the target was on-screen, their priority was to respond to that first).

Goal-Setting Instructions

There were two conditions for this experiment: Control (vague goal) and Harder-Over-Time (HOT). The Control condition first received the instruction: "GOAL: Your goal on this task is to respond as quickly as possible while keeping your accuracy above 95%. Your reaction time and accuracy will be recorded." Before blocks 2 and 3 they saw: "GOAL REMINDER: Remember, your goal on this task is to respond as quickly as possible while keeping your accuracy above 95%." The same reminder was given after each thought-probe as well. In the HOT condition, the participants were initially instructed: "GOAL: Your goal on this task is to keep your response times under .450 s while keeping your accuracy above 95%. Your reaction time and accuracy will be recorded." Before block 2, they saw: "NEW GOAL: Your goal on this task is to keep your response times under .400 s while keeping your accuracy above 95%. Your reaction time and accuracy will be recorded." Finally, prior to block 3, they saw: "NEW GOAL: Your goal

on this task is to keep your response times under .350 s while keeping your accuracy above 95%. Your reaction time and accuracy will be recorded." After each thought-probe, the HOT condition was reminded: "Remember, your goal on this task is to keep your reaction times under [.450, .400, or .350 s] while keeping your accuracy above 95%."

After completing the task, participants rated their goal commitment. The question for the Control condition asked: "How committed were you to the goal of responding as quickly and accurately as possible?" The HOT condition was asked: "How committed were you to the goals of keeping your response time under .450 s, .400 s, and .350 s while staying as accurate as possible?" Subjects provided their response with a keypress between 1-7 indicating their goal commitment (anchors: 1 = "Not committed at all", 4 = "Somewhat committed", 7 = "Totally committed").

Pupil Measurement

Participants were individually tested in a dark room lit only with ambient screen light. Pupil diameter was continuously binocularly recorded at 120 Hz using a Tobii T300 eye tracker, integrated with a 23-inch monitor (1920x1080 screen resolution). Subjects were seated approximately 60 cm from the screen with their chin seated in a chin-rest. Data from the left eye was used for analyses. Any data points missing due to blinks, off-screen fixations, and/or eye-tracker malfunction were removed. We did not eliminate full trials for missing data points.

Analyses

Behavioral Analyses

RTs outside the range of 150 ms – 10 s were excluded from analysis to prevent anticipatory responses and abnormally long RTs from skewing the results (for consistency with prior work; Strayer et al., 2024; Strayer & Unsworth, 2026). Only RTs from correct trials were included.

The primary measure for behavioral attention lapses was the RT distribution. RTs were ranked from fastest to slowest within-participant and then split into 5 equal bins (Bin 1 = 20% fastest, Bin 5 = 20% slowest). It is important to consider the entire RT distribution because experimental manipulations can affect different parts of the distribution (i.e., among the slowest RTs; Balota & Yap, 2011). In this case, we expected the largest difference between conditions to occur in Bin 5. The distributions were analyzed with a 2 (condition: Control vs. HOT) × 5 (bin) mixed ANOVA. The # of lapses measure was computed as the number of responses more than 2x the mean RT within-subject. Though it is a more simplistic and less-than-ideal measure, it was included for the sake of comparison with historical work (e.g., Bertelson & Joffe, 1963; Bills, 1931, 1935; Broadbent, 1958; Unsworth et al., 2021; Williams et al., 1959). We also assessed response time percent coefficient of variation (RT CoV%) as another measure of RT dispersion.

RT, # of lapses, RT CoV%, and accuracy were each analyzed as a function of time using 2 (condition: Control vs. HOT) × 3 (time block) mixed ANOVAs. Goal-commitment was analyzed using a one-way ANOVA between conditions.

Pupil Analyses

The two primary pupil measures were preparatory pupil responses (i.e., prior to target onset) and phasic responses (after target onset). Only trials with a correct response were included in analyses. Preparatory pupil responses were measured as the change from baseline (baseline = average of the first 100 ms in the preparatory period) during the ISI period (i.e., from when the 4 lines appeared until the "X" pops up). The data was split into 70 bins of 40 ms each. Since the ISI varied between 1000-2777 ms, the later bins contain fewer data. The data was analyzed using a 2 (condition: Control vs. HOT Goal) × 70 (time bin) mixed ANOVA. Phasic pupillary responses were measured as a change from baseline (average of the first 100 ms after the target appeared)

after the target ("X") appeared. The data was split into 80 bins of 20 ms (1800 ms total), and then analyzed using a 2 (condition: Control vs. HOT Goal) × 80 (time bin) mixed ANOVA. Pupil measures were also examined as a function of time using 2 (condition: Control vs. HOT Goal) × 3 (time block) mixed ANOVAs.

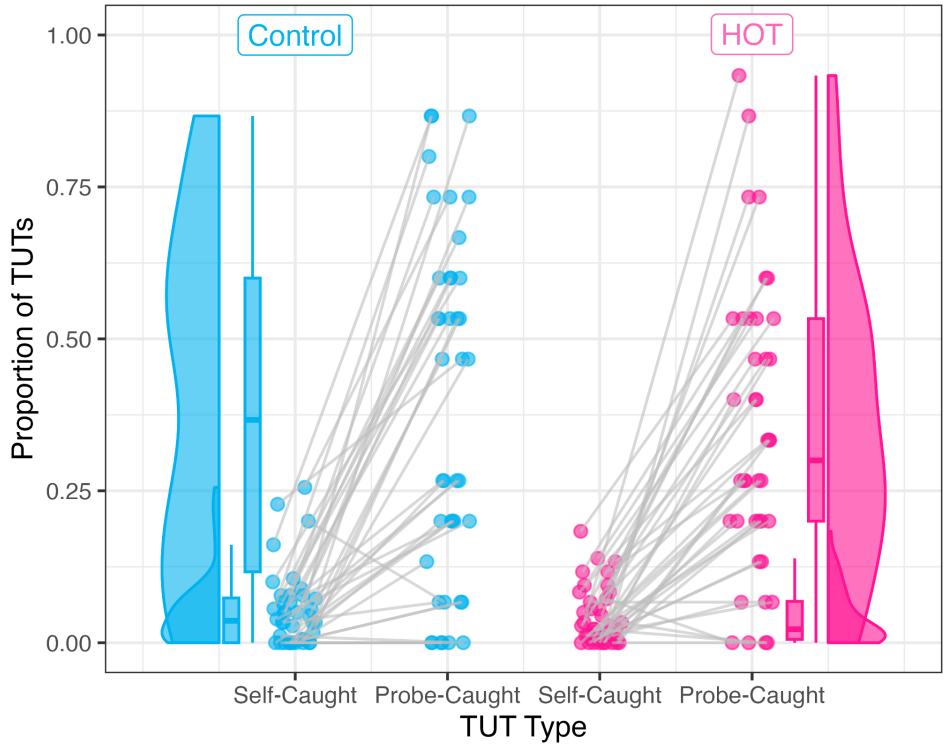
Meta-Awareness Analyses

Both the proportion of probe-caught (PC) TUTs and self-caught (SC) TUTs, are analyzed over time using 2 (condition: Control vs. HOT) × 3 (time block) mixed ANOVAs as measures of general task-unrelated thought. Meta-awareness is operationalized and analyzed in two different ways. The first is the ratio method of using the proportion of SC TUTs to PC TUTs (SC/PC; instances where PC equals zero are coded as 1) that has been reported in past literature with the same 2 × 3 ANOVA as above (see Chu et al., 2023; Meier, 2019). However, this measure is sensitive to the number of TUT instances contributing to each subject's score. This means that participants who report very few TUTs overall can generate extreme ratio values (e.g., 1.0 based on a single SC TUT) that are less statistically stable than ratios calculated with larger denominators but are nonetheless treated as equivalent data points in a typical ANOVA. Additionally, since proportions are constrained between 0 and 1, these extreme ratio values may lead to violations of key ANOVA assumptions: normality and homoscedasticity (see *Fig. 2* for visual of the TUT distributions). In an attempt to address these limitations, I added a second analytic method in which I modeled catch-type (self vs. probe) at the level of individual TUT events using mixed-effects logistic regression, with condition, time block, and their interaction as fixed effects and a random intercept for subject. This method models each TUT event as a Bernoulli trial nested within-subject, better capturing the unequally-sampled nature of the data and allowing subjects who report more TUT events to carry more weight in the estimation of condition and block effects

without necessitating further correction for subjects with sparse or zero-denominator ratios. Both the ANOVA and the mixed-effects regression model results are reported to facilitate comparison with other works and explore a potentially more robust measure of meta-awareness.

Figure 2

Visualization of Self-Caught and Probe-Caught TUTs by Condition



Note. Lines connect the self-caught and probe-caught TUT reports for each subject.

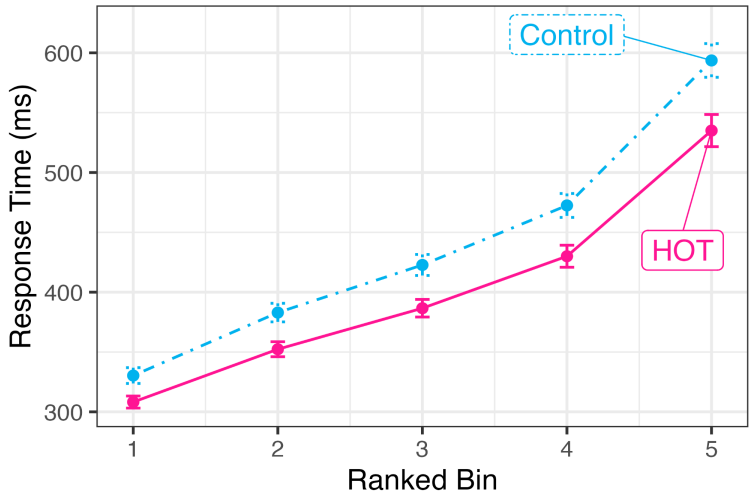
Results

Behavioral

The RT distribution, as expected due to the ranking procedure, exhibited a main effect of bin, $F(4, 312) = 852.522$, $p < .001$, $\eta_p^2 = .916$. Additionally, there was a main effect of condition on response time, $F(1, 78) = 10.315$, $p = .002$, $\eta_p^2 = .117$ (Control $M = 440.418$, $SD = 8.363$ vs. HOT $M = 402.433$, $SD = 8.363$), indicating those in the HOT condition were faster overall. Most importantly, there was a significant bin × condition interaction, $F(4, 312) = 4.605$, $p = .001$, $\eta_p^2 = .056$ (Bin 1: Control $M = 330.331$, $SD = 41.728$ vs. HOT $M = 308.207$, $SD = 31.91$; Bin 5: Control $M = 593.622$, $SD = 89.065$ vs. HOT $M = 535.015$, $SD = 85.044$). This interaction indicates that the largest difference in RTs occurred amongst the slowest RTs (Bin 5; see *Fig. 3*). This is consistent with our prior findings and aligns with the notion that subjects given the HOT goals experience fewer and/or less severe lapses in attention throughout the task.

Figure 3

Response Time Distribution by Condition for Experiment 1

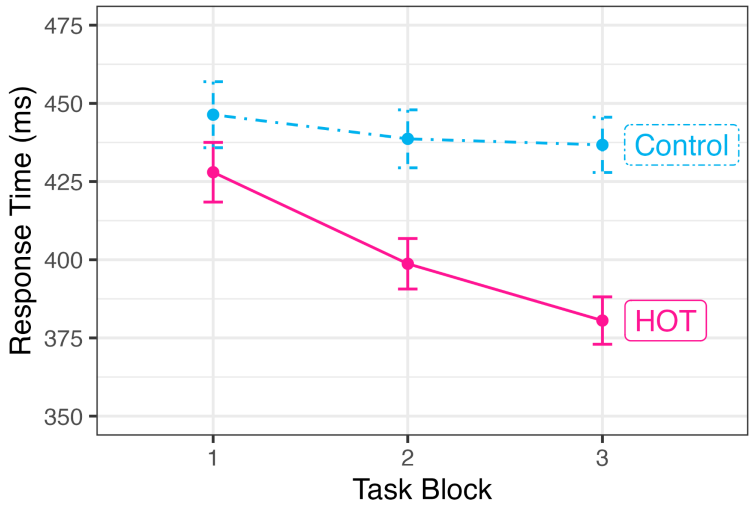


Note. Bars represent one standard error. Response times by condition and ranked bin. Bin = RTs rank-ordered fastest to slowest (1 = fastest, 5 = slowest). Results showed that those in the Control condition had significantly longer slow RTs (bin 5; indicates more attention lapses) and were slower overall.

RT, RT CoV%, # of lapses, and accuracy were analyzed as a function of time. The ANOVA for RT found a significant main effect for both condition, $F(1, 78) = 10.431$, $p = .002$, $\eta_p^2 = .118$, and block, $F(2, 156) = 23.896$, $p < .001$, $\eta_p^2 = .235$. Importantly, there was also a condition × block interaction, $F(2, 156) = 10.241$, $p < .001$, $\eta_p^2 = .116$. As illustrated in *Fig. 4*, the HOT condition became significantly faster over the course of the task, while the Control group stayed relatively stable (Block 1: Control $M = 446.376$, $SD = 66.783$ vs. HOT $M = 427.979$, $SD = 60.376$; Block 3: Control $M = 436.729$, $SD = 55.880$ vs. HOT $M = 380.554$, $SD = 47.965$).

Figure 4

Response Times as a Function of Time-on-Task (Task Block) by Condition for Experiment 1



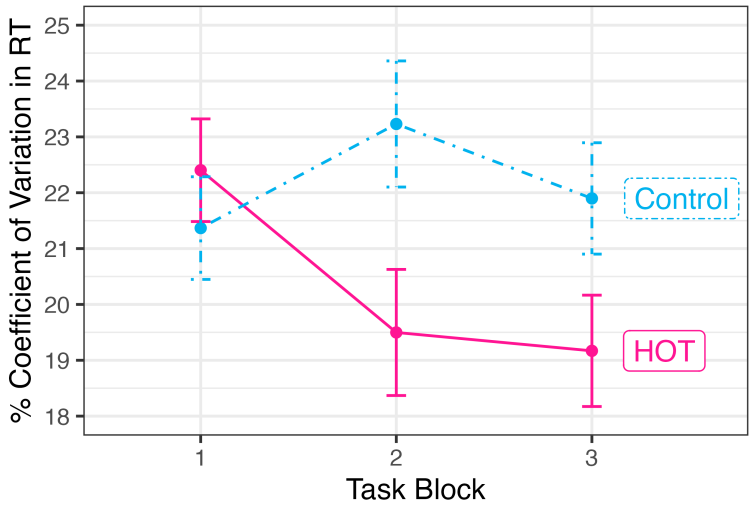
Note. Bars represent one standard error. Response times by condition and block. Results showed that the Control group maintained their RTs over time, while the HOT group was faster overall and actually became faster over time as the goal became more difficult.

The ANOVA for RT CoV% did not find a main effect of condition, $F(1, 78) = 2.508$, $p = .117$, $\eta_p^2 = .032$, or block, $F(2, 156) = 1.608$, $p = .204$, $\eta_p^2 = .02$. However, there was a significant condition × block interaction, $F(2, 156) = 5.471$, $p = .005$, $\eta_p^2 = .066$. *Fig. 5* shows that as the task progresses the HOT group becomes less variable, while the Control group stays relatively

consistent (Block 1: Control M = 21.367%, SD = .919% vs. HOT M = 22.403%, SD = .919%; Block 3: Control M = 21.898%, SD = .997% vs. HOT M = 19.169%, SD = .997%).

Figure 5

Coefficient of Variation in Response Times as a Function of Time-on-Task (Task Block) by Condition for Experiment 1

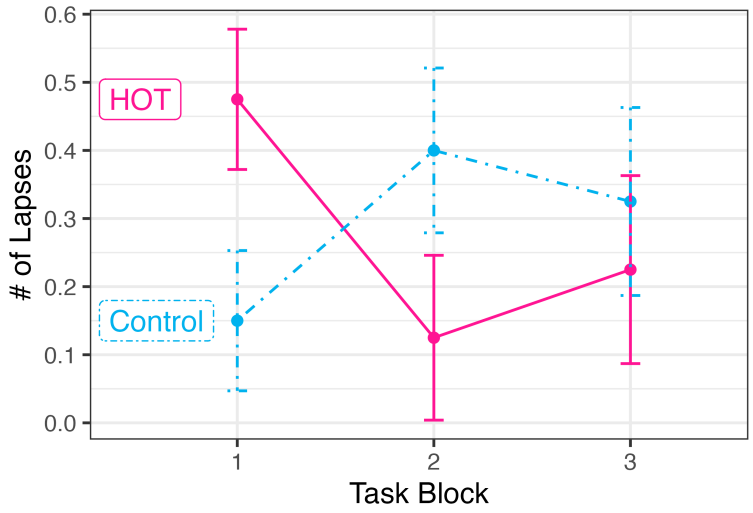


Note. Bars represent one standard error. CoV % by condition and task block. Results indicated a significant condition × block interaction, in which the Control group remained relatively stable in their RT CoV% overtime while the HOT group became less variable.

The ANOVA for # of lapses did not indicate a main effect of either condition, $F(1, 78)$ = .026, p = .873, η_p^2 = .000, or block, $F(2, 156)$ = .096, p = .909, η_p^2 = .001. However, there was a condition × block interaction, $F(2, 156)$ = 3.372, p = .037, η_p^2 = .041. Looking at *Fig. 6*, the HOT condition started with a higher # of lapses in the first block relative to Control (Block 1: Control M = .15, SD = .427 vs. HOT M = .48, SD = .816). This flips in the second block where Control exhibits a larger # of lapses. Then in the third block the two conditions meet in the middle (Block 3: Control M = .33, SD = 1.163 vs. HOT M = .23, SD = .423).

Figure 6

Number of Lapses as a Function of Time-on-Task (Task Block) by Condition for Experiment 1

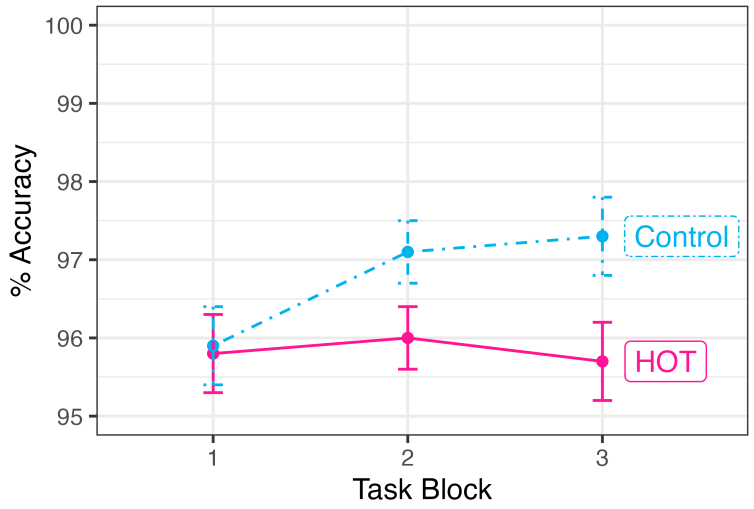


Note. Bars represent one standard error. # of Lapses by condition and task block. Results showed a significant condition × block interaction where the HOT group initially displays more lapses compared to Control in the first block, then flips in the second block.

The accuracy ANOVA did not indicate a significant main effect of either condition, $F(1, 78) = 2.795$, $p = .099$, $\eta_p^2 = .035$, or block, $F(2, 156) = 2.488$, $p = .086$, $\eta_p^2 = .031$. The condition × block interaction was also non-significant, $F(2, 156) = 2.787$, $p = .065$, $\eta_p^2 = .034$. Overall, both conditions performed with a similar accuracy percentage and stayed consistent over the course of the task (Block 1: Control $M = 95.9\%$, $SD = 3.6\%$ vs. HOT $M = 95.8\%$, $SD = 3.0\%$; Block 3: Control $M = 97.3\%$, $SD = 2.2\%$ vs. HOT $M = 95.7\%$, $SD = 3.8\%$; see *Fig. 7*).

Figure 7

Response Accuracy as a Function of Time-on-Task (Task Block) by Condition for Experiment 1



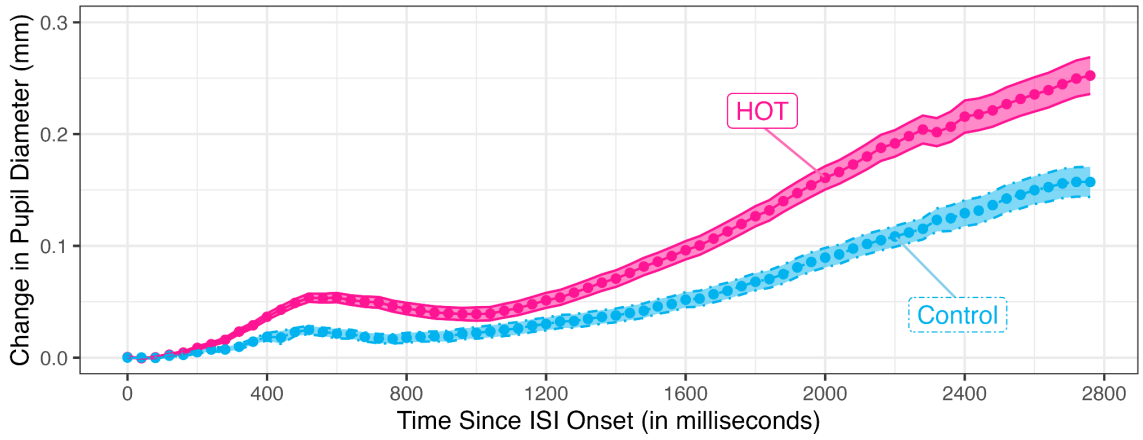
Note. Bars represent one standard error. Response accuracy by condition and task block. Results indicate no significant difference between conditions.

Pupil

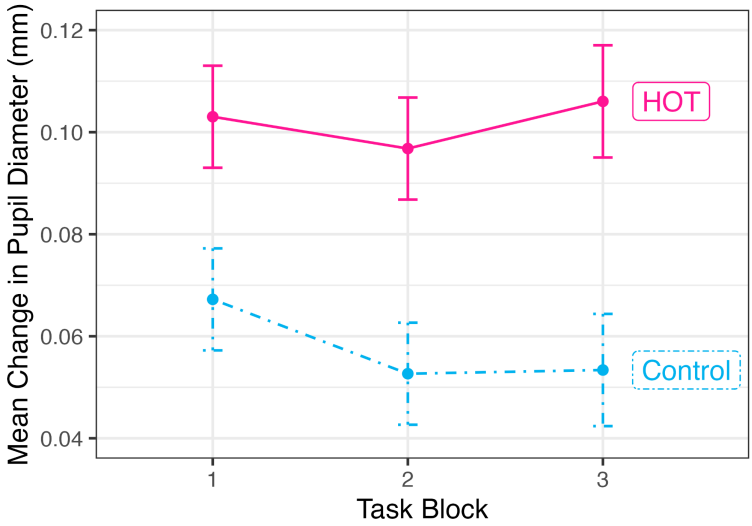
The ANOVA for preparatory pupil revealed a main effect of condition, $F(1, 78) = 11.247$, $p = .001$, $\eta_p^2 = .126$, and bin, $F(69, 5382) = 118.378$, $p < .001$, $\eta_p^2 = .603$, as well as a condition × bin interaction, $F(69, 5382) = 6.499$, $p < .001$, $\eta_p^2 = .077$. Additionally, there was a significant bin × block interaction, $F(138, 10764) = 2.573$, $p < .001$, $\eta_p^2 = .032$. These results indicate that subjects in the HOT goal group generally ramped up their attentional effort more during the ISI period compared to the Control group (See *Fig. 8a*). However, there was no significant main effect of block, $F(2, 156) = 1.456$, $p = .236$, or condition × block interaction, $F(2, 156) = .955$, $p = .387$. Both groups stayed relatively consistent in their preparatory attentional effort over time (Block 1: Control $M = .067$, $SD = .063$ vs. HOT $M = .103$, $SD = .063$; Block 3: Control $M = .053$, $SD = .07$ vs. HOT $M = .106$, $SD = .07$; See *Fig. 8b*).

Figure 8

Visualizations for Preparatory Pupil Dynamics in Experiment 1



a)



b)

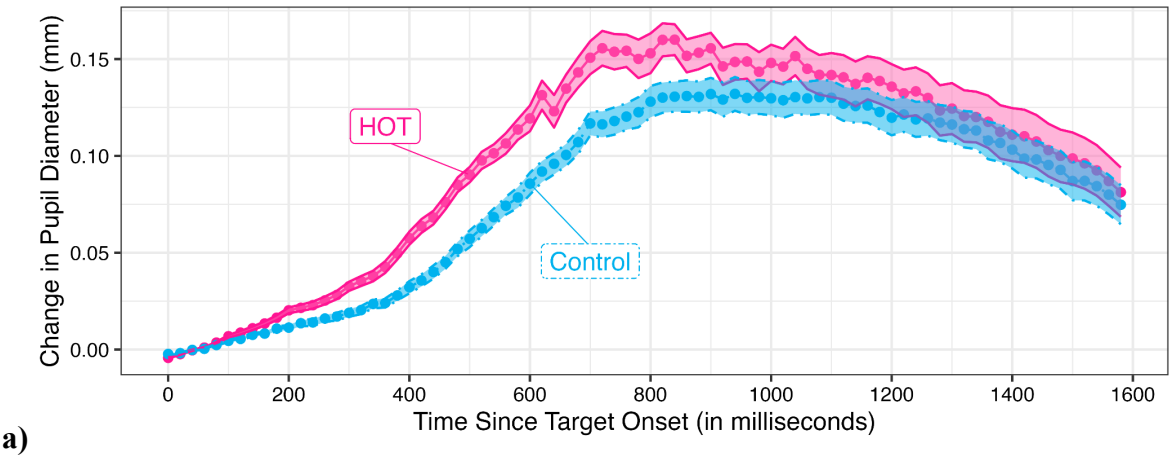
Note. Bars represent one standard error. (**a**) Change in pupil diameter over the ISI period. Results indicated the HOT condition exerted more preparatory attentional effort compared to Control. (**b**) Mean change in pupil diameter over the ISI period by task block. Results showed the HOT group maintained a significantly higher level of preparatory effort throughout the task.

The ANOVA for phasic pupil found a main effect of bin, $F(79, 6162) = 55.781$, $p < .001$, $\eta_p^2 = .417$, but did not find a main effect of condition, $F(1, 78) = 1.959$, $p = .166$, or a condition × bin interaction, $F(79, 6162) = .717$, $p = .973$. This indicates that both conditions had similar phasic responses to the target stimuli (see *Fig. 9a*). However, there was a significant main effect of block,

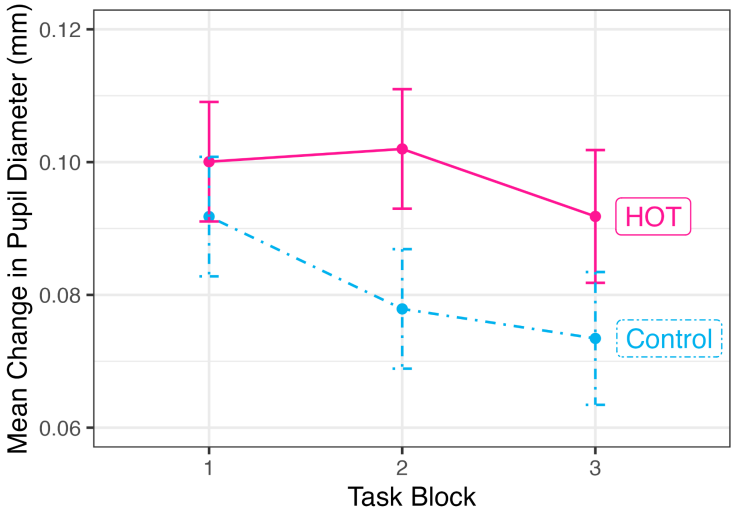
$F(2, 156) = 5.510$, $p = .005$, $\eta_p^2 = .066$, and a bin × block interaction, $F(158, 12324) = 5.179$, $p < .001$, $\eta_p^2 = .062$. As seen in *Fig. 9b*, both conditions showed diminished phasic pupil responses over time (Block 1: Control $M = .092$, $SD = .057$ vs. HOT $M = .100$, $SD = .057$; Block 3: Control $M = .073$, $SD = .063$ vs. HOT $M = .092$, $SD = .063$).

Figure 9

Visualizations for Phasic Pupil Dynamics in Experiment 1



a)



b)

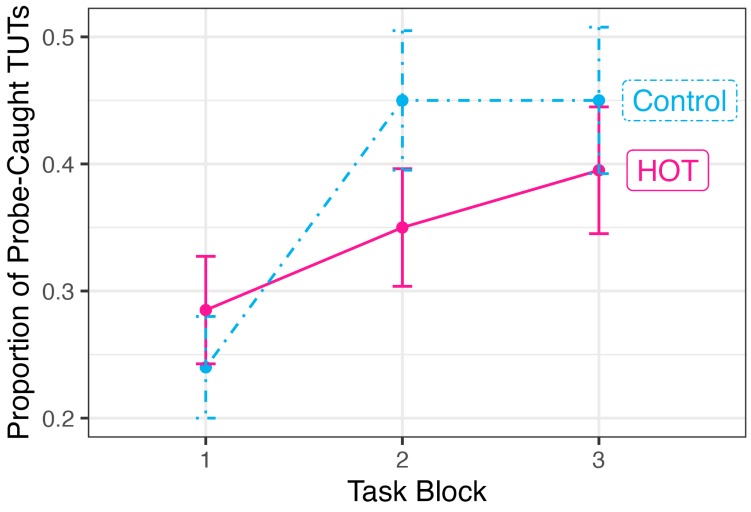
Note. Bars represent one standard error. (**a**) Change in pupil diameter after the target appears. Results indicated that both conditions displayed similar phasic pupillary responses. (**b**) Mean change in pupil diameter after the target appears by task block. Results indicated a significant main effect of block wherein both groups showed diminished responses as the task went on.

TUTs & Meta-Awareness

The ANOVA for proportion of probe-caught TUTs as a function of time found a significant main effect of block, $F(2, 156) = 15.486$, $p < .001$, $\eta_p^2 = .166$, but the main effect of condition was nonsignificant, $F(1, 78) = .385$, $p = .537$, $\eta_p^2 = .005$. The condition × block interaction only approached significance, $F(2, 156) = 2.843$, $p = .061$, $\eta_p^2 = .035$, suggesting that both conditions experienced an increase in probe-caught TUTs over time (Block 1: Control $M = .24$, $SD = .253$ vs. HOT $M = .285$, $SD = .268$; Block 3: Control $M = .45$, $SD = .364$ vs. HOT $M = .395$, $SD = .315$; See *Fig. 10*).

Figure 10

Proportion of Probe-Caught Task-Unrelated Thoughts as a Function of Time-on-Task (Task Block) by Condition for Experiment 1



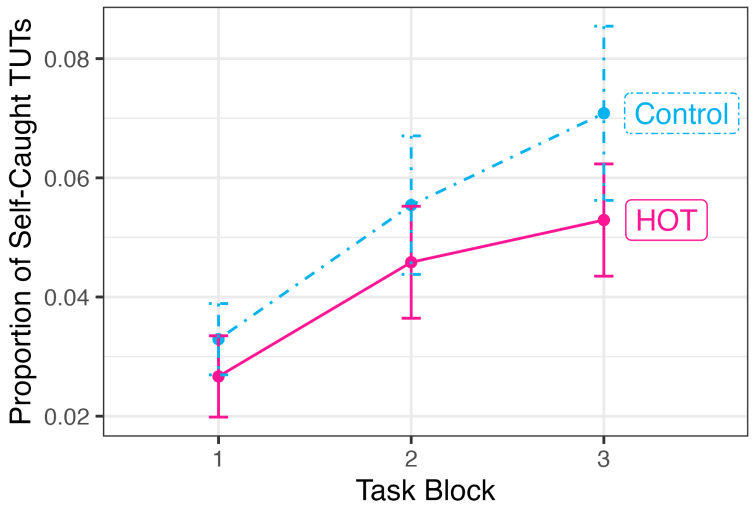
Note. Bars represent one standard error. Proportion of probe-caught TUTs by condition and task block. Results showed a main effect of block; both conditions reported a similar proportion of probe-caught TUTs that rose over time.

The ANOVA for proportion of self-caught TUTs as a function of time found a significant main effect of block, $F(2, 156) = 14.695$, $p < .001$, $\eta_p^2 = .159$, but the main effect of condition was nonsignificant, $F(1, 78) = .819$, $p = .368$, $\eta_p^2 = .01$. Additionally, the condition × block interaction

was not significant, $F(2, 156) = .501$, $p = .607$, $\eta_p^2 = .006$, suggesting that both conditions experienced an increase in self-caught TUTs over time (Block 1: Control $M = .0329$, $SD = .0378$ vs. HOT $M = .0267$, $SD = .0432$; Block 3: Control $M = .0708$, $SD = .0924$ vs. HOT $M = .0529$, $SD = .0595$; See *Fig. 11*).

Figure 11

Proportion of Self-Caught Task-Unrelated Thoughts as a Function of Time-on-Task (Task Block) by Condition for Experiment 1



Note. Bars represent one standard error. Proportion of self-caught TUTs by condition and task block. Results showed both conditions reported a similar proportion of self-caught TUTs that rose over time.

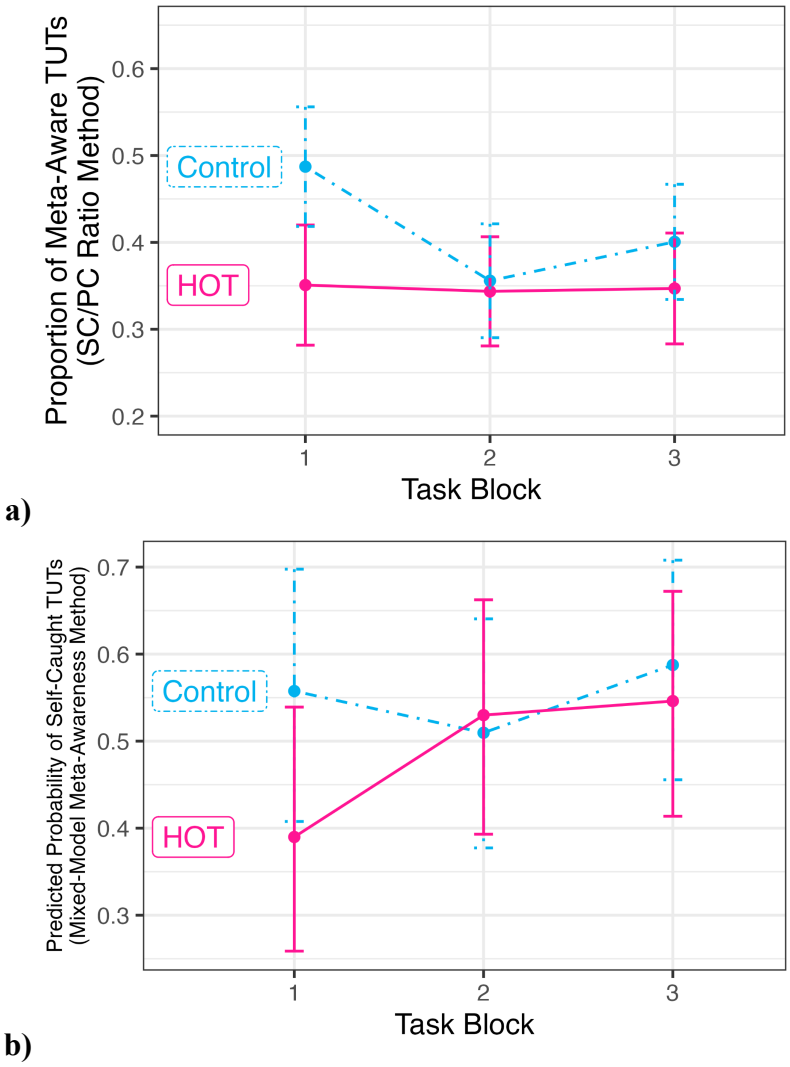
The first key experimental analysis for meta-awareness using the ratio measurement and a 2 (condition) × 3 (block) ANOVA for proportion of meta-aware TUTs as a function of time failed to find significant main effects of condition, $F(1, 78) = .824$, $p = .367$, $\eta_p^2 = .01$, and block, $F(2, 156) = 1.021$, $p = .363$, $\eta_p^2 = .013$. As well as a non-significant condition × block interaction, $F(2, 156) = .824$, $p = .441$, $\eta_p^2 = .01$. This ratio measurement method indicates that both the Control

and HOT group displayed similar levels of meta-awareness of their own TUTs that remained relatively stable over the course of the task.

Since the ratio measure is sensitive to instability from small/zero denominators within-subject, I included a second analytic approach for meta-awareness in which catch-type (self vs. probe) was modeled at the trial level using a mixed-effects logistic regression, with condition, block, and their interaction as fixed effects and a random intercept for subject. The results from this second approach are consistent with the ANOVA. The model found no significant condition × block interaction, $\chi^2(2) = 4.06$, $p = .130$, and estimated marginal means confirmed no significant simple effect of condition within any block (Block 1: OR = 1.97, 95% CI [0.85, 4.60], $p = .116$; Block 2: OR = 0.92, 95% CI [0.43, 1.99], $p = .836$; Block 3: OR = 1.18, 95% CI [0.56, 2.51], $p = .659$; see *Fig. 12*). The convergence of these two analytic approaches lends evidence to the conclusion that the null effect of goal condition on meta-awareness is not an artifact of the ratio measure's limitations.

Figure 12

Proportion of Meta-Aware Task-Unrelated Thoughts as a Function of Time-on-Task (Task Block) by Condition for Experiment 1



Note. Bars represent one standard error. (**a**) Proportion of meta-aware TUTs measured with the ratio method by condition and task block. Results showed no significant effects. (**b**) Proportion of meta-aware TUTs with the GLMM method by condition and task block. Results showed no significant effects.

Goal-Commitment

Goal-commitment scores were significantly higher in the Control condition compared to the HOT group, $F(1, 78) = 16.021$, $p < .001$, $\eta^2 = .170$ (Control $M = 6.075$, $SD = .888$; HOT $M = 5.250$, $SD = .954$). See *Table 1* below for a comparison of the core E1 analyses with and without

goal-commitment as a covariable. The addition of goal-commitment did not meaningfully alter the interpretation of results. However, five results that were already significant increased in effect size and three results that were not statistically significant without the goal-commitment covariable became significant with its inclusion. One significant result, the block × condition interaction for # of Lapses, became nonsignificant with the goal-commitment covariable. This indicates that some amount of variance in the # of Lapses measurement can be attributed to the subject's commitment to achieving the goal.

Table 1

Table Comparing Results With/Without Goal-Commitment as a Covariable in Experiment 1

DV	Without Goal-Commitment Covariable	With Goal-Commitment Covariable
RT × Condition	$p = .002$, $\eta p^2 = .117$	$p < .001$, $\eta p^2 = .205$*
RT Distribution (Bin × Condition interaction)	$p < .001$, $\eta p^2 = .056$	$p < .001$, $\eta p^2 = .132$*
RT Block (Block × Condition interaction)	$p < .001$, $\eta p^2 = .116$	$p < .001$, $\eta p^2 = .112$
RT CoV % × Condition	$p = .117$, $\eta p^2 = .032$	$p = .014$, $\eta p^2 = .076$*
RT CoV % × Block	$p = .204$, $\eta p^2 = .020$	$p = .800$, $\eta p^2 = .003$
RT CoV % (Block × Condition interaction)	$p = .005$, $\eta p^2 = .066$	$p = .004$, $\eta p^2 = .068$*
# of Lapses × Condition	$p = .873$, $\eta p^2 = .000$	$p = .342$, $\eta p^2 = .012$
# of Lapses (Block × Condition interaction)	$p = .037$, $\eta p^2 = .041$	$p = .074$, $\eta p^2 = .033^+$
Prop. of TUTs × Condition	$p = .537$, $\eta p^2 = .005$	$p = .148$, $\eta p^2 = .027$
Prop. of TUTs × Block	$p < .001$, $\eta p^2 = .166$	$p = .015$, $\eta p^2 = .053$
Prop. of TUTs (Block × Condition interaction)	$p = .061$, $\eta p^2 = .035$	$p = .010$, $\eta p^2 = .058$*
MA Ratio × Condition	$p = .367$, $\eta p^2 = .010$	$p = .998$, $\eta p^2 = .000$
MA Ratio × Block	$p = .363$, $\eta p^2 = .013$	$p = .294$, $\eta p^2 = .016$
MA Ratio (Block × Condition interaction)	$p = .441$, $\eta p^2 = .010$	$p = .233$, $\eta p^2 = .019$
Prep. Pupil × Condition	$p = .001$, $\eta p^2 = .126$	$p < .001$, $\eta p^2 = .133$*
Prep. Pupil × Block	$p = .236$, $\eta p^2 = .018$	$p = .886$, $\eta p^2 = .002$
Prep. Pupil (Bin × Condition interaction)	$p < .001$, $\eta p^2 = .077$	$p < .001$, $\eta p^2 = .103$*
Phasic Pupil × Condition	$p = .166$, $\eta p^2 = .025$	$p = .054$, $\eta p^2 = .047$
Phasic Pupil (Bin × Condition interaction)	$p = .973$, $\eta p^2 = .009$	$p = .517$, $\eta p^2 = .013$
Phasic Pupil (Block × Condition interaction)	$p = .139$, $\eta p^2 = .025$	$p = .478$, $\eta p^2 = .010$
Accuracy × Condition	$p = .099$, $\eta p^2 = .035$	$p = .293$, $\eta p^2 = .014$
Accuracy (Block × Condition interaction)	$p = .065$, $\eta p^2 = .034$	$p = .014$, $\eta p^2 = .054$*

Note. * = Analyses where including the goal-commitment covariable either increased an already statistically significant effect size, or the result became statistically significant when it was previously not significant. $^+$ = Analyses that became statistically nonsignificant when including the goal commitment covariable when they were previously significant.
RT response time, *Prop.* proportion, *TUTs* task-unrelated thoughts, *MA* meta-awareness, *Prep.* preparatory, *CoV %* percent coefficient of variation

Discussion

Experiment 1 investigated the effect of goal-setting, harder-over-time (HOT) goals in particular, on meta-awareness of task-unrelated thoughts. Participants were assigned to either the Control condition, which received a vague goal to do their best, or the HOT goal condition, which assigned specific goals that increased in difficulty over the three task blocks (450 ms, 400 ms, 350 ms). Both conditions received feedback on their accuracy and response time after each trial. Based on a combination of goal-setting principles regarding specificity and feedback, previous findings that HOT goals enhanced attentional effort and mitigated time-on-task effects, and a resource allocation framework, I had hypothesized that the HOT goal condition would report higher meta-awareness of TUTs and replicate past behavioral and pupil findings (Strayer et al., 2024; Strayer & Unsworth, 2026). My hypothesis with regard to the behavioral effects was supported by the data. The HOT condition exhibited notably enhanced overall behavioral performance and, in some cases, actually improved over time. Pupil results further indicated that the HOT condition exerted more attentional effort than the Control group and maintained that effort over time. Interestingly, despite the HOT goal demonstrating a clear effect on these observable performance metrics, both conditions reported a very similar proportion of TUTs that increased over time in both the probe-caught and self-caught measure. Most importantly, I found no significant evidence for any effect on meta-awareness in this study. Both conditions exhibited similar levels of meta-awareness regarding TUTs, with that level staying consistent over time.

One interpretation of the null meta-awareness results hinges on the finding that even though the proportion of TUTs experienced showed a clear increase over time in both catch types, meta-awareness of those TUTs was consistent throughout the task. This suggests that perhaps meta-awareness is more of a stable, individual differences component that was not swayed by the HOT

goal. While it is entirely possible, and supported by the current data, that the HOT goal simply had no effect on meta-awareness, one potential reason for the null findings could be due to smaller effect sizes than anticipated and a lack of power to detect them in this study. Interestingly though, in opposition to my hypothesis that meta-awareness would be enhanced by the HOT goals, is the trend visible in *Figure 12*. It appears that, if anything, the HOT condition reported worse meta-awareness compared to Control during the first block of the task before converging in the second block. With respect to the resource allocation framework, one possible explanation is that the HOT goal initially led to the majority of the attentional resources that were being allocated to the task towards behavioral task performance, leaving fewer resources for self-monitoring processes. In block one, the HOT group achieved the accuracy goal and mean RT fell well under the goal, so as the task progressed, they may have felt more confident in their ability to perform well and freed up a portion of their task-allocated resources that allowed self-monitoring to improve.

Another reason for the non-existent effect on meta-awareness may simply be that meta-awareness is an inherently difficult construct to reliably measure. It is one thing to quantify a person's heartbeat or speed, and quite another to untangle the inner machinations of their conscious and unconscious thoughts. The relevant meta-awareness literature is relatively young and has substantial variation in definition and operationalization of the construct (see Chu et al., 2023). Few studies have used a similar dual-catch TUT paradigm to quantify meta-awareness (e.g., Scheibner et al., 2016; Meier, 2019; Rummel & Nied, 2017), and to my knowledge, none have used it in conjunction with behavioral indices of attention lapses and/or pupillary effort measures in the same sustained attention context as the current study. As reported in the Method section, there are several statistical drawbacks of trying to quantify meta-awareness in this manner. The

present null findings are nonetheless an informative contribution for the evolving methodology of measuring meta-awareness of TUTs.

Results regarding the one motivational measure in Experiment 1, goal-commitment, highlight a pattern found in my previous research and supported by the broader principles of goal-setting theory (Strayer et al., 2024; Strayer & Unsworth, 2026; Locke & Latham, 2019). Namely, that goal-commitment ratings tend to be lower in the HOT goal condition compared to Control and, when included in key analyses as a covariable, the HOT goal effects tend to become more prominent. In some cases, the effect size increases and in others, results that were previously non-significant became significant (see *Table 1* for comparison of Experiment 1 outcomes with vs. without goal-commitment included as a covariable). However, the goal-commitment measure in Experiment 1 is limited due to it being a single, retrospective rating. It is impossible to decipher from the single data point whether the low goal-commitment scores of the HOT group are due to a more global difference brought on by the general goal-specificity, or if there is any sort of interactive effect wherein the participants become less committed to the goal as it becomes more difficult. Additionally, there are several other conative/motivational elements proposed by general goal-setting theory that have potential explanatory power with regard to the HOT goals (e.g., goal-acceptance, self-efficacy, perceived goal-difficulty; Locke & Latham, 2019). Under a general resource allocation framework, these conative elements are partially responsible for determining the amount of available resources allocated toward any given task (Kahneman, 1973; Kanfer & Ackerman, 1989). Collectively, these ideas drove one of the key aims of Experiment 2, which was to more thoroughly explore the temporal dynamics of goal-commitment and other motivational factors that may help explain time-on-task effects that occur in sustained attention scenarios.

CHAPTER III

EXPERIMENT 2: THE IMPACT OF INDIVIDUALLY TAILORED GOALS ON MOTIVATIONAL FACTORS IN SUSTAINED ATTENTION

In his work *Mental Fatigue*, Thorndike (1900) gave a warning that is perpetually relevant in the discussion of factors related to mental abilities: do not mistake unwillingness for inability. It is important to keep in mind that differences found in behavior may manifest due to fluid motivational factors, rather than simple static mental ability or limited resources. Modern motivational control theories of cognitive fatigue highlight the limitations of pure resource-depletion accounts and posit that time-on-task effects occur due to a lack of adequate motivation, leaving individuals unwilling to pursue a high level of performance (Kurzban et al., 2013; Inzlicht et al., 2018). Numerous findings that show how different manipulations can mitigate time-on-task effects support this assertion (Massar et al., 2016; Robison et al., 2021; Strayer et al., 2024; Garner et al., 2024). My previous work has demonstrated that harder-over-time goals can reduce attention lapses that manifest behaviorally, but the mechanisms behind that effect and the limits of this goal-setting method require further investigation. Experiment 2 explored a variety of motivational factors implicated in goal-setting theory that are often neglected in sustained attention and attention lapse work, and I posed the idea that individually tailoring HOT goals to each person's ability level will improve subjective ratings of those motivational factors.

Goal-Setting in Sustained Attention

Though classic goal-setting interventions focus on the importance of specific and challenging goals (Locke & Latham, 2002, 2019), integration with sustained attention presents challenges due to time-on-task effects. Goal-setting theory stresses the idea that setting these specific, challenging, and attainable goals boosts motivation and performance outcomes (Locke &

Latham, 2019). However, when applied to sustained/vigilant attention scenarios, static goals may begin to fail over time as fatigue or boredom builds up (Hockey, 2013; Warm et al., 2008). Strayer et al. (2024), Strayer & Unsworth (2026), and Experiment 1 of the present study demonstrated that this concern could be attenuated by setting specific goals that become progressively harder-over-time (HOT) during a 4-choice reaction time task. Although the HOT goal technique proved useful in these cases, it remains unclear where the limits of this strategy lie. A key element missing from these studies is a lack of subjective motivational measures, especially across time (Strayer et al., 2024; Strayer & Unsworth, 2026). The one motivational measure they share is a single goal-commitment scale at the end of the task asking subjects to rate how committed they were to achieving the given goals (1 - Not committed at all, 7 - Totally committed; Strayer et al, 2024; Strayer & Unsworth, 2026; Klein et al., 1999). Even so, the results from that single measure, wherein the HOT goal groups report lower goal-commitment than the vague-goal control, lead to a number of questions. The most obvious question is: how is goal-commitment changing over the course of the task? This is especially important due to the nature of the HOT goals and how the goals themselves change over time. It could be that those in the HOT goal group have the same or even higher goal-commitment than the control initially, but as the goal becomes more/too difficult, self-efficacy is impacted and overall goal-commitment drops (Phillips & Gully, 1997). Since the measure is at the end of the task, there is no way to determine if that is the case with those datasets. This is not unusual; a large number of studies tend to measure these factors with a post-experiment questionnaire, pointing to a need for more research with these ratings integrated throughout the task. Relatedly, the vagueness of the control goal makes the goal-commitment measure difficult to compare between groups. Since the goal itself is so nebulous ("do your best") and there is no way for the participant to anchor their performance or know if they are doing well,

goal-commitment ratings may be inflated. The lack of information on the degree of acceptance of the HOT/control goals to start with is another aspect to address, as the participants may have failed to find the goals personally relevant or worth pursuing in the first place (Strayer et al., 2024; Strayer & Unsworth, 2026).

Motivational Factors in Goal-Setting Theory

Goal-difficulty has long been a core factor of goal-setting theory (Locke & Latham, 2002, 2019). In the realm of sustained attention research, the difficulty of a given goal facilitates a balance between arousal, engagement, and fatigue. The best performance is found when a goal is difficult, but achievable; moderate goals lead to optimum performance. These moderate goals help maintain peak arousal and task engagement (Aston-Jones & Cohen, 2005; Locke & Latham, 2019).

Self-efficacy is tightly connected to goal difficulty and refers to an individual's belief in their own ability to satisfy task demands (Phillips & Gully, 1997; Bandura & Locke, 2003). Individuals holding high self-efficacy beliefs about performance on a task tend to exhibit shallower time-on-task effects, possibly due to a greater allocation of resources towards achieving task goals (Bandura & Locke, 2003; Hopstaken et al., 2015). Findings from Erez (1977) demonstrate that incorporating performance feedback can improve self-efficacy, initiating a loop wherein self-efficacy enhances attentional control and success reinforces self-efficacy. This is corroborated by neurocognitive studies showing a connection between self-efficacy and brain networks implicated in motivation (e.g., dopaminergic midbrain, cortico-striatal-thalamic circuits) that modulate the cost/benefit evaluation of mental/attentional effort (Krebs et al., 2012; Westbrook & Braver, 2015).

Goal-acceptance and goal-commitment are similar yet distinct factors in goal-setting. While self-efficacy refers to one's belief in their own ability to achieve a goal, goal-

acceptance reflects the degree to which one endorses and considers a goal as meaningful and actually worth pursuing (Erez & Zidon, 1984; Meyer & Gellatly, 1988). This is a key distinction; just because an individual believes they could do something does not mean they are actually inclined to do so. Goal-acceptance can be positively influenced by providing autonomy-supportive instructions, the chance to self-set goals, and framing goals in ways that highlight personal relevance (Elliot & Harackiewicz, 1994; Seli, Carriere, & Smilek, 2015). Essentially, individuals like to be involved in the goal-setting process in some way, whether directly or indirectly. Moreover, while goal-acceptance reflects an initial interest in pursuing a goal, goal-commitment reflects the persistence and effort necessary to sustain attention across time in the face of growing fatigue, boredom, or distraction (Hollenbeck et al., 1989). Some factors shown to impact goal-commitment and the continuation of effort throughout a task are goal-difficulty, self-efficacy, and feedback (Locke & Latham, 2019; Robison et al., 2021). Participants that report high goal-commitment during sustained attention tasks tend to experience fewer lapses in attention and higher resistance to time-on-task effects (Robison & Unsworth, 2018; Schooler et al., 2011).

The more broad, overarching concept of motivation is entangled with the above factors and modulates how attentional effort is allocated over time (Inzlicht et al., 2018; Kurzban et al., 2013; Unsworth, under review). Under the general attention allocation framework, individuals are continuously evaluating the worth of their current task against the cost of mental effort in order to determine if that effort should continue to be allocated to that task, or if there is a more enticing alternative use of those resources (Kurzban et al., 2013; Westbrook & Braver, 2015; Varazzani et al., 2015). That cost-benefit appraisal can be influenced by feedback, incentives, and goal-setting factors, leading to better task engagement and reduced instances of mind-wandering and attention lapses (Esterman et al., 2014; Venables & Fairclough, 2009).

Overall, motivational factors like goal-difficulty, self-efficacy, goal-acceptance/commitment (among others) contribute to a dynamic process during sustained attention tasks; goal-difficulty determines the demands of a task, that difficulty impacts self-efficacy and whether or not an individual feels that goal is achievable, these determinations affect whether an individual chooses to accept the goal, goal-commitment determines how invested in doing well an individual stays over time, and general motivation plays among all these factors.

Self-Set Goals in Sustained Attention

Several researchers have explored the possibility of having participants self-set their own goals in order to improve subjective ratings of motivational factors based on the assumption that self-set goals promote intrinsic motivation (Erez et al., 1990; Garner et al., 2025). For example, Erez et al. (1990) used a dual-task paradigm with a 2 (goal-source: experimenter, self-set) x 2 (incentive: monetary incentive, no incentive) between groups design. Results showed that the group who self-set their own goals with no incentive present performed the best overall on the task, and the group with experimenter-assigned goals and no monetary incentive performed the worst (Erez et al., 1990). More recently, Garner et al. (2025) investigated the effects of self-set goals across three experiments. Experiment 1 utilized a psychomotor vigilance task with five time blocks to assess experimenter-set vs. self-set goals (Dinges & Powell, 1985). Findings indicated that those in the self-set group assigned goals that significantly decreased in difficulty over time. Further, there were no statistically significant differences between the two groups for overall RT, time-on-task effects (both displayed longer RTs as the task progressed), or subjective factor ratings (frustrating, boring, difficult, meaningful; Garner et al., 2025). Experiment 2 switched to a novel "Green Means Go" task paradigm (a more intuitive visual task based on the PVT; Dinges & Powell, 1985), added a control condition with no goal, and incorporated pupillary measurements

to assess effort and arousal (Beatty & Lucero-Wagoner, 2000; Hess & Polt, 1964; Kahneman, 1973). Similar to Experiment 1, Garner et al. (2025) found that although both goal conditions performed better than control, they did not differ from each other and suffered the same time-on-task decrement for RT. However, the self-set groups' goals stayed the same over time, and they reported higher self-efficacy. They also exhibited higher overall effort compared to the experimenter-set goal and control group (which did not differ from each other), though all conditions decreased in effort over time. Finally, Experiment 3 had all subjects self-set goals under two between-group conditions: no-points (just instructed to meet their goal) and points (subjects rewarded with points for successfully reaching their goal; more points for more difficult goals). Garner et al. (2025) found that the points group set harder goals compared to the no-points group, but the goals did not change as a function of time. The points group also performed faster overall, but both groups still displayed a vigilance decrement. Additionally, there were no differences between groups on self-reported effort or pupillary phasic responses; they found no main effects of condition or block on effort, nor an interaction effect. Overall, prior goal manipulations have struggled to fully eliminate performance decrements over time during sustained attention tasks, even if performance in general is improved.

Current Study

A key issue with the self-set goal approach is that it runs the risk that motivational factors are influencing the goals rather than vice versa. Here, I proposed that instead of having participants self-set their own goals, giving them experimenter-set HOT goals that are tailored to each individual's skill level would have the following effects: 1) lead to overall faster response times and a mitigated time-on-task RT decline (comparable to group-level HOT goals) vs. a vague control, 2) attentional effort would be higher overall and better maintained than control

(comparable to group-level HOT goals), and most importantly 3) lead to more favorable subjective task experience ratings on motivational factors (e.g., goal-acceptance, goal-commitment, self-efficacy, motivation, goal-difficulty) than both control and group-level HOT goals. Objective behavioral performance outcomes are not necessarily predicted to be enhanced over and above the previously established experimenter-set HOT goals. The primary difference is expected to manifest in the participants' subjective feelings about their task experience.

Under a general resource allocation framework, these predictions follow from the way tailored goals are expected to shape the investment and maintenance of attentional resources. In the framework, the proportion of available resources that an individual commits to a task depends on conative and motivational factors, including goal-acceptance, goal-commitment, and self-efficacy, which determine how strongly the task goal is activated relative to competing goals (Bandura, 1977; Kanfer & Ackerman, 1989; Locke & Latham, 1990; Unsworth, under review). Tailoring the HOT goals to personal ability level is expected to raise initial self-efficacy and goal-acceptance by increasing the personal relevance of the goals in similar ways to self-set goals. Though critically, the experimenter-set aspect prevents subjects from setting unchallenging initial goals or losing motivation and choosing to set easier goals as they go.

Practically speaking, the ability to facilitate a more positive experience could enable broader longevity and willingness to engage in a task again, which could prove useful in workplace interventions aimed at worker retention and satisfaction. Experiment 2 aims to provide further insight into how different HOT goal strategies influence the dynamics of subjective experiences over time versus vague goals. This is an important step in discerning the limits of the HOT goal technique and could provide evidence for future research pathways that look at assessing those limits.

Method

Participants and Procedure

A total of 132 students between the ages of 18 and 35 were recruited from the University of Oregon human subjects pool and were compensated with partial course credit (44 Control vs. 44 HOT goal condition vs. 44 Tailored HOT goal condition). Consistent with prior work, criteria for exclusion was having any of the following: 1) less than 80% overall task accuracy, 2) less than 50% accuracy in any single block, or 3) excessive missing pupil data. One participant in the Tailored goal condition was excluded for having excessive missing pupil data. No other subjects were excluded (Final *N*: 44 Control vs. 44 HOT goal condition vs. 43 Tailored HOT goal condition). The task lasted approximately 40 minutes. Participants provided informed consent and completed a brief demographic survey prior to beginning the task.

Task

Experiment 2 uses the same base 4CRT task from Experiment 1 with a few changes detailed below. Prior to beginning the 3 main task blocks, subjects saw the instructions: "You will now complete some test trials. Please be as accurate AND fast as possible during these test trials." Subjects completed a 22-trial "practice" block. The task then covertly calculated each subject's average response time during the latter 20 trials and rounded up to the nearest millisecond. The first 2 trials and any incorrect trials were excluded.

Goal Instructions

Immediately after the practice block, subjects in the Tailored HOT condition were given the instructions: "The test trials are over. Based on your performance, your goal on this task will be to keep your response times under [INSERT AVERAGE TEST TRIAL RT] milliseconds while keeping your accuracy above 95%. Remember, it is important to be fast, but it is MOST important

to be accurate." Before the second block, the Tailored HOT group saw a "new goal" instruction screen saying: "NEW GOAL: Your goal on this task is to keep your response times under [INSERT AVERAGE TEST TRIAL RT -25 ms] milliseconds while keeping your accuracy above 95%. Remember, it is important to be fast, but it is MOST important to be accurate." The same instructions were given prior to block three with a further 25 ms subtracted. The standard, group-level HOT and Control conditions were not given any information about their performance on the test trials. The group-level HOT condition received the instructions: "The test trials are over. Your goal on this task will be to keep your response times under 450 milliseconds while keeping your accuracy above 95%. Remember, it is important to be fast, but it is MOST important to be accurate." The group-level HOT group saw a "new goal" screen before blocks two and three, with the values 400 ms and 350 ms substituted in respectively. The Control condition received the instructions: "The test trials are over. Your goal on this task is to respond as quickly as possible while keeping your accuracy above 95%. Remember, it is important to be fast, but it is MOST important to be accurate." The Control group was given the same goal for blocks two and three with the words "GOAL REMINDER" instead of "NEW GOAL."

Motivational Measures

Subjects answered a set of questions pre/post-block regarding motivational factors. Pre-block measures assessed self-efficacy, goal-acceptance, goal-commitment, and motivation. Post-block measures assessed goal-difficulty and effort.

The measure for self-efficacy displayed the instructions (with slight wording variation for the Control goal): "Please select the number (via mouse click) that best reflects how confident you are in the statement below, with 10% reflecting the lowest confidence and 100% reflecting the highest confidence in said statement. For example, if asked to indicate your confidence in your

ability to respond under [INSERT GOAL] ms for 1 trial, you would select 100% if you are extremely confident in your ability to do so (i.e., you are positive you will be able to respond at least that fast). If, however, you are certain you will be unable to respond under that time, you would select 10%." Subjects then reported their confidence in each statement: "If completing [INSERT # OF TRIALS] trial(s), I could respond under [INSERT GOAL] ms on [that trial/all of them]." Subjects saw 7 statements where the number of trials had the following values: 1, 10, 20, 30, 40, 50, 60. Responses were averaged to create a self-efficacy strength variable.

Subjects then reported their goal-acceptance by responding to the question: "On a scale of 1-7, do you accept your goal of keeping your response time under [INSERT GOAL] ms while keeping your accuracy above 95%?" The scale ranged from 1 = "Do not accept" to 7 = "Totally accept." Similarly, subjects next reported their goal commitment by responding to: "On a scale of 1-7, how committed are you to the goal of keeping your response time under [INSERT GOAL] ms while keeping your accuracy above 95%?" The scale ranged from 1 = "Not committed at all" to 7 = "Totally committed." On the final pre-block measure, subjects rated their motivation by responding to: "On a scale of 1-7, how motivated are you to achieve the goal of keeping your response time under [INSERT GOAL] ms while keeping your accuracy above 95%?" The scale ranged from 1 = "Not at all motivated" to 7 = "Very motivated."

After each task block, subjects reported how difficult they felt their goal was to achieve: "On a scale of 1-7, how difficult did you find the goal of keeping your response time under [INSERT GOAL] ms while keeping your accuracy above 95%?" The scale ranged from 1 = "Not difficult at all" to 7 = "Very difficult." Subjects then reported their effort level based on the question: "On a scale of 1-7, how much effort do you feel you put in during this block of trials?" The scale ranged from 1 = "No effort at all" to 7 = "Very high effort."

After answering the post-block measures for blocks 1 and 2, subjects were given their goal for the next block and then answered the pre-block measures with the new value substituted in. At the very end of the task, after answering the post-block questions for block 3, subjects then rated their overall goal commitment for all the goals: "Overall, how committed were you to the goals of keeping your response time under [GOAL 1], [GOAL 2], and [GOAL 3] while keeping your accuracy above 95%?" The scale ranged from 1 = "Not committed at all" to 7 = "Totally committed."

Goal Interpretation

To assess how the participants interpreted the goal instructions they responded to one final question asking: "Your accuracy goal on this task was to keep your accuracy above 95%. How did you interpret that goal? Please respond with a key press for the answer that most closely matches:" Response options included: 1) I decided it was okay to have a few incorrect answers in favor of speed, as long as I stayed above 95% accuracy, 2) I decided to focus on accuracy, even if it meant the speed goal wasn't always met, 3) I decided to focus only on speed and disregarded the accuracy goal, 4) I focused on speed and accuracy the same amount, 5) I didn't care about either goal, and 6) other. This question was included as an exploratory measure to get a sense of whether subjects were making any conscious decisions regarding a speed-accuracy trade-off and it is mentioned in the general discussion.

Thought-Probes

Experiment 2 used the same thought-probes as E1 (5 probes per block). There was no self-caught measure included in E2.

Pupil Measurement

Pupil measurement procedures remained the same as E1, except a Tobii T120 eyetracker was used.

Analyses

In order to ensure the three conditions did not significantly differ in their performance on the practice block, the mean RT was compared between groups with a one-way ANOVA. Further analyses mirror those for the behavioral, pupillary, and thought-probe measures used in E1 (with 3 conditions instead of 2). Each motivational measure was also analyzed over time with a 3 (condition) × 3 (time block) ANOVA. The goal interpretation question is addressed in the general discussion and was not formally tested.

Results

Behavioral

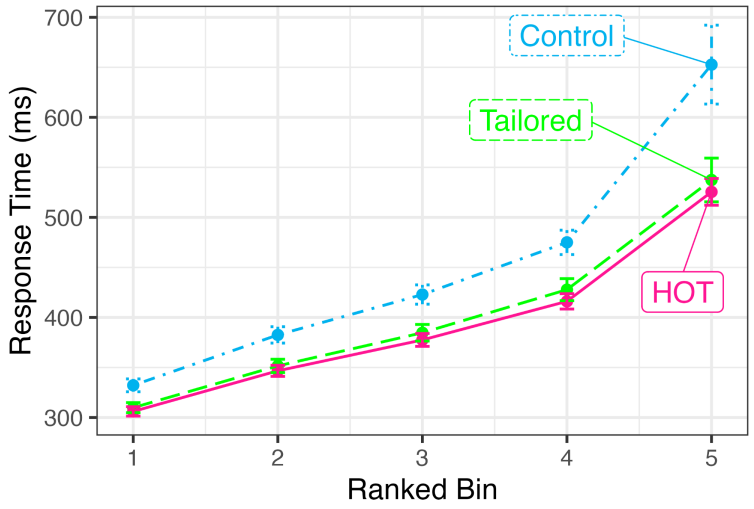
The practice block performance check indicated that all 3 conditions performed similarly in terms of RT before the experimental goal conditions were given, $F(2, 128) = .020$, $p = .98$, $\eta_p^2 = .00$ (Control $M = 459.540$, $SD = 97.719$, HOT $M = 456.610$, $SD = 76.220$, Tailored $M = 455.994$, $SD = 92.206$; note that the group-level HOT goal condition was referred to simply as HOT for this section and all figures).

The RT distribution displayed a main effect of bin as expected due to the nature of the ranking procedure, $F(4, 512) = 248.804$, $p < .001$, $\eta_p^2 = .660$. More importantly, there was a significant main effect of condition, $F(2, 128) = 9.589$, $p < .001$, $\eta_p^2 = .130$, and a significant bin × condition interaction, $F(8, 512) = 4.358$, $p < .001$, $\eta_p^2 = .064$. Both goal conditions showed similar RT distributions while the Control group is notably slower overall. The interaction effect demonstrates that the largest difference in RTs occurred amongst the slowest RTs (Bin 5; see *Fig.*

13), indicating that the Control condition experienced more frequent and/or severe lapses in attention during the task (Bin 1: Control M = 332.139, SD = 42.478, HOT M = 306.057, SD = 31.128, Tailored M = 309.814, SD = 33.055; Bin 5: Control M = 652.699, SD = 261.491, HOT M = 525.481, SD = 88.769, Tailored M = 537.395, SD = 143.279).

Figure 13

Response Time Distribution by Condition for Experiment 2



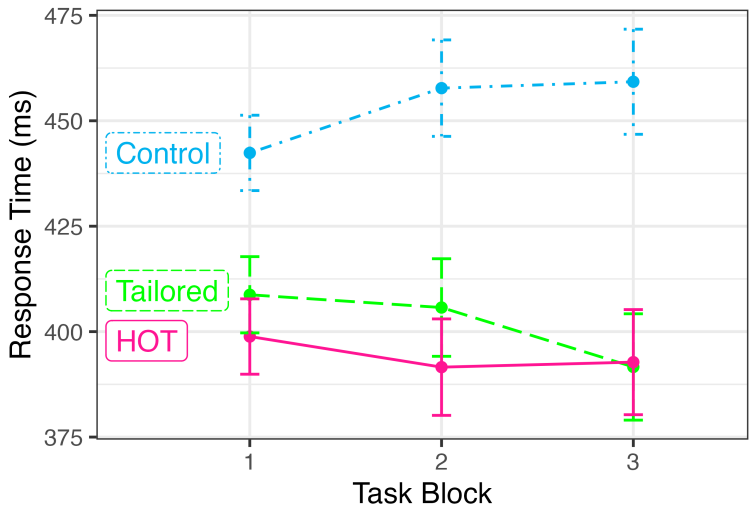
Note. Bars represent one standard error. Response times by condition and ranked bin. Bin = RTs rank-ordered fastest to slowest (1 = fastest, 5 = slowest). Results found a significant main effect of condition and a condition × bin interaction, wherein the Control condition was slower overall compared to the two goal groups and also experienced more attention lapses found in the slowest 20% of the distribution.

RT, RT CoV%, # of lapses, and accuracy were all assessed as a function of time over the three task blocks. The ANOVA for RT found a significant main effect of condition, $F(2, 128) = 9.620$, $p < .001$, $\eta_p^2 = .131$, as well as a condition × block interaction, $F(4, 256) = 3.564$, $p = .008$, $\eta_p^2 = .053$. The main effect of block was not significant, $F(2, 256) = .442$, $p = .643$, $\eta_p^2 = .003$. Pairwise comparison with Bonferroni correction indicated the HOT group's RTs did not significantly change by block (*p-value range* = [.242, .858]). The Control group significantly slowed between blocks one and two (MD = 15.365, SE = 6.172, p = .014, 95% CI [3.144, 27.569]).

The Tailored group's RTs became significantly faster between blocks two and three (*MD* = -14.092, *SE* = 6.696, *p* = .037, 95% CI [-27.341, -.884]). In other words, as seen in *Fig. 14*, those in the Control condition tended to become slower over time, while the group-level HOT condition stayed stable and the Tailored group increased their speed (Block 1: Control *M* = 442.379, *SD* = 69.746, HOT *M* = 398.842, *SD* = 44.944, Tailored *M* = 408.743, *SD* = 60.494; Block 3: Control *M* = 459.234, *SD* = 113.089, HOT *M* = 392.768, *SD* = 58.009, Tailored *M* = 391.626, *SD* = 65.463).

Figure 14

Response Times as a Function of Time-on-Task (Task Block) by Condition for Experiment 2



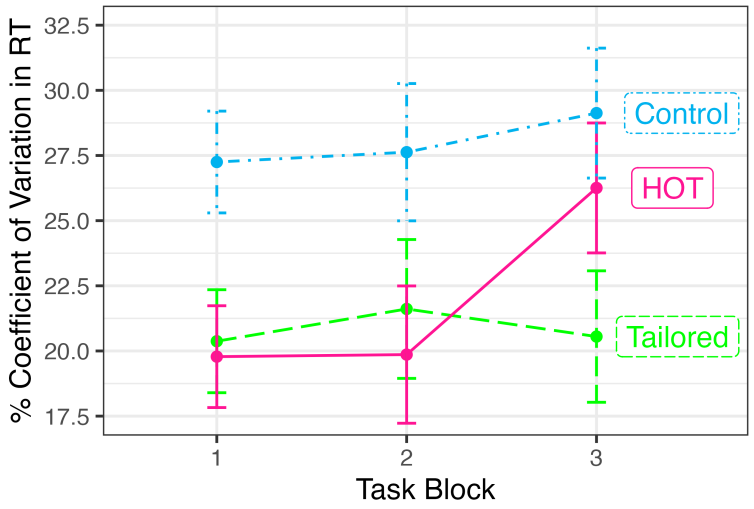
Note. Bars represent one standard error. Response times by condition and task block. Results indicated that the Control condition had slower response times overall and they declined with time-on-task. The HOT condition was stable throughout and the Tailored condition became faster over time.

The ANOVA for RT CoV% found a main effect of condition, $F(2, 128) = 3.757$, $p = .026$, $\eta_p^2 = .055$. The main effect of block was non-significant, $F(2, 256) = 2.589$, $p = .077$, $\eta_p^2 = .020$, as well as the condition × block interaction, $F(4, 256) = 1.605$, $p = .173$, $\eta_p^2 = .024$. Overall, the Control condition exhibited a higher coefficient of variation in RTs compared to both goal conditions (Block 1: Control *M* = 27.25%, *SD* = 20.77%, HOT *M* = 19.78%, *SD* = 6.04%, Tailored

M = 20.37%, *SD* = 5.71%; Block 3: Control *M* = 29.13%, *SD* = 20.64%, HOT *M* = 26.25%, *SD* = 17.55%, Tailored *M* = 20.55%, *SD* = 9.07%; see *Fig. 15*).

Figure 15

Coefficient of Variation in Response Times as a Function of Time-on-Task (Task Block) by Condition for Experiment 2

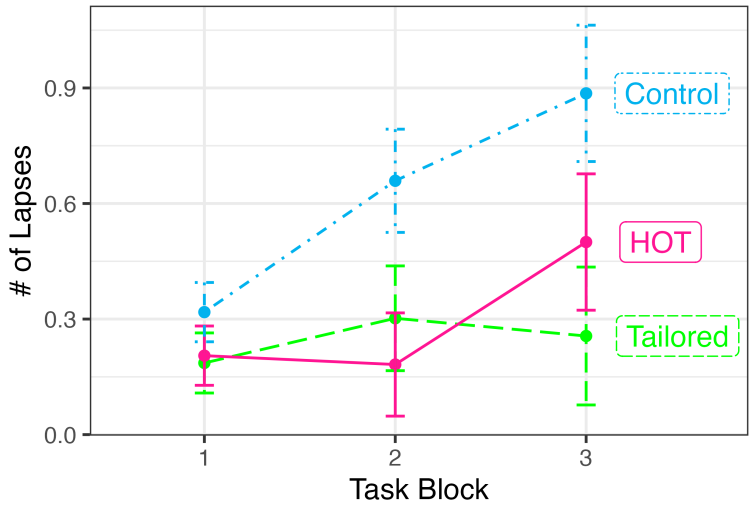


Note. Bars represent one standard error. RT CoV% by condition and task block. Results found a significant main effect of condition in which the Control group exhibited a higher coefficient of variation in RTs compared to both goal groups.

The ANOVA for # of lapses found both a main effect of condition, $F(2, 128) = 4.162$, $p = .018$, $\eta_p^2 = .061$, and block, $F(2, 256) = 5.655$, $p = .004$, $\eta_p^2 = .042$. The condition × block interaction was not significant, $F(4, 256) = 1.708$, $p = .149$, $\eta_p^2 = .026$. The Control condition experienced a higher # of lapses compared to the goal conditions and generally more lapses occurred over time (Block 1: Control *M* = .32, *SD* = .511, HOT *M* = .20, *SD* = .462, Tailored *M* = .19, *SD* = .450; Block 3: Control *M* = .89, *SD* = 1.768, HOT *M* = .50, *SD* = .821, Tailored *M* = .26, *SD* = .539; see *Fig. 16*).

Figure 16

Number of Lapses as a Function of Time-on-Task (Task Block) by Condition for Experiment 2

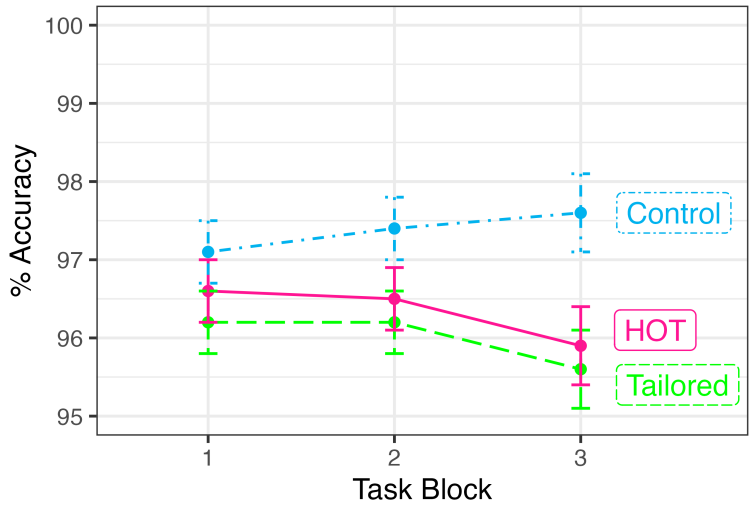


Note. Bars represent one standard error. # of Lapses by condition and task block. Results indicated that the Control group experienced a higher # of Lapses overall, and a significant main effect of block where more lapses tend to occur over time in general.

The ANOVA for accuracy found a main effect of condition, $F(2, 128) = 5.129$, $p = .007$, $\eta_p^2 = .074$. The main effect of block was not significant, $F(2, 256) = .975$, $p = .379$, $\eta_p^2 = .008$. The condition × block interaction was also non-significant, $F(4, 256) = 1.175$, $p = .322$, $\eta_p^2 = .018$. The Control condition maintained higher response accuracy compared to the goal conditions (Control $M = 97.08\%$, $SE = .3\%$, HOT $M = 96.6\%$, $SE = .2\%$, Tailored $M = 96.2\%$, $SE = .3\%$; see *Fig. 17*).

Figure 17

Response Accuracy as a Function of Time-on-Task (Task Block) by Condition for Experiment 2



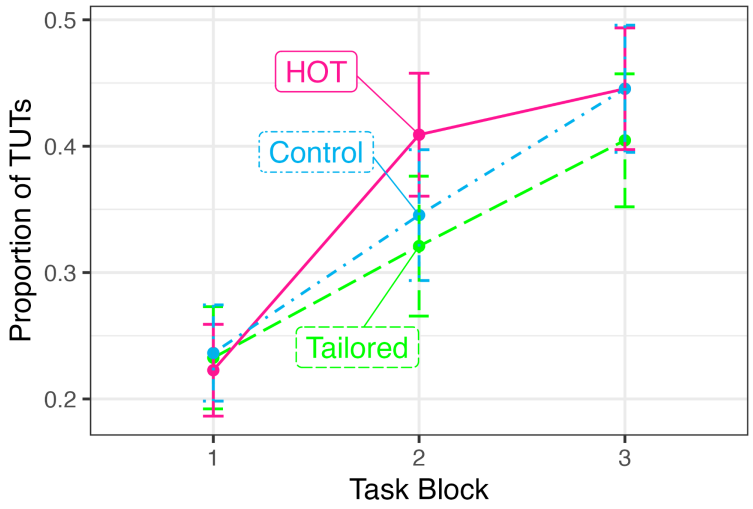
Note. Bars represent one standard error. Percent response accuracy by condition and task block. Results showed a main effect of condition; the Control group maintained higher accuracy than either goal condition.

Mind-Wandering

The ANOVA for proportion of TUTs did not find a main effect of condition, $F(2, 128) = .257$, $p = .774$, $\eta_p^2 = .004$, or a condition × block interaction, $F(4, 256) = .715$, $p = .582$, $\eta_p^2 = .011$. However, there was a significant main effect of block, $F(2, 256) = 30.009$, $p < .001$, $\eta_p^2 = .190$. All conditions displayed a similar proportion of TUTs during the task that rose over the course of time (Block 1: Control $M = .236$, $SD = .253$, HOT $M = .223$, $SD = .241$, Tailored $M = .233$, $SD = .265$; Block 3: Control $M = .446$, $SD = .334$, HOT $M = .446$, $SD = .319$, Tailored $M = .405$, $SD = .345$; see *Fig. 18*).

Figure 18

Proportion of Task-Unrelated Thoughts as a Function of Time-on-Task (Task Block) by Condition for Experiment 2



Note. Bars represent one standard error. Proportion of TUTs by condition and task block. A main effect of block indicated that all conditions tended to experience a similar proportion of TUTs that increased over time.

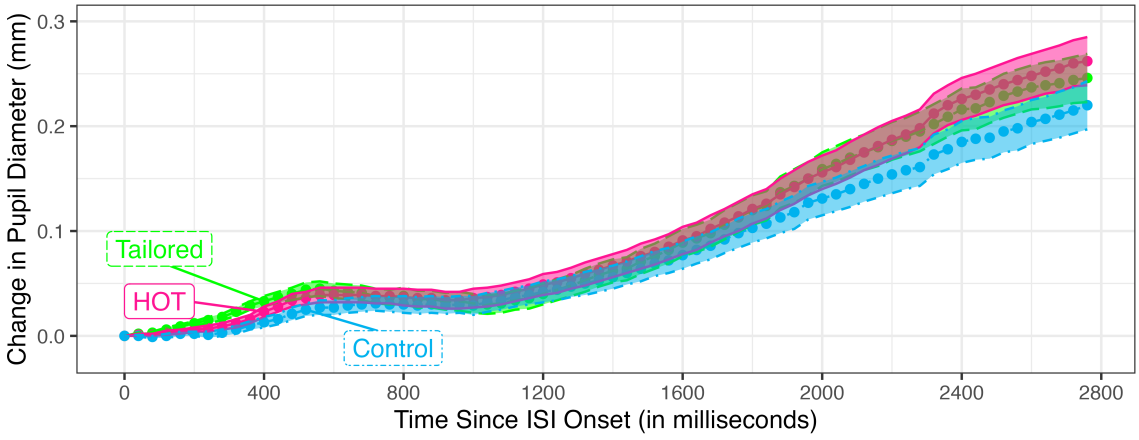
Pupil

The ANOVA for preparatory pupil shows a significant main effect of bin, $F(69, 8832) = 249.070$, $p < .001$, $\eta_p^2 = .661$, indicating that subjects in all conditions are ramping up their attentional effort during the ISI period while waiting for the target to appear (see *Fig. 19a*). The main effect of block, $F(2, 256) = 2.630$, $p = .074$, $\eta_p^2 = .020$, and condition × block interaction, $F(4, 256) = .301$, $p = .877$, $\eta_p^2 = .005$, were non-significant. This suggests that preparatory attentional effort remained relatively stable over the course of the task for all three conditions. Additionally, the main effect of condition was not significant, $F(2, 128) = .921$, $p = .401$, $\eta_p^2 = .014$, indicating that the conditions all displayed a similar amount of preparatory attentional effort (Block 1: Control $M = .091$, $SD = .066$, HOT $M = .106$, $SD = .066$, Tailored $M = .101$, $SD = .066$;

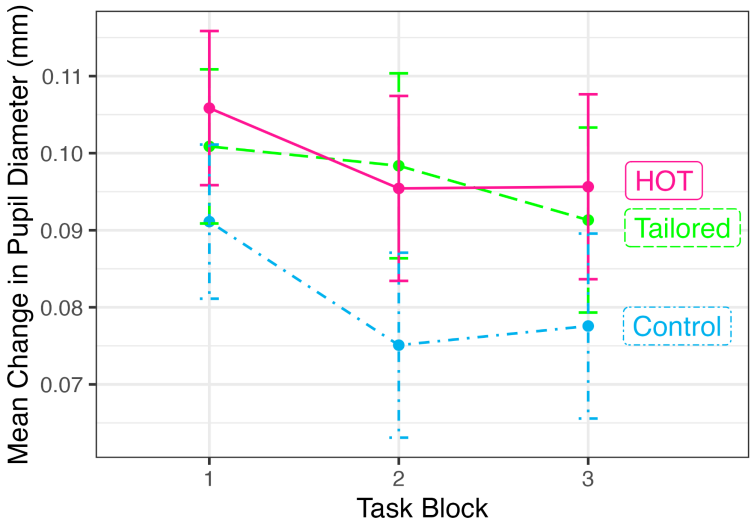
Block 3: Control M = .078, SD = .080, HOT M = .096, SD = .080, Tailored M = .091, SD = .079; see *Fig. 19b*).

Figure 19

Visualizations for Preparatory Pupil Dynamics in Experiment 2



a)



b)

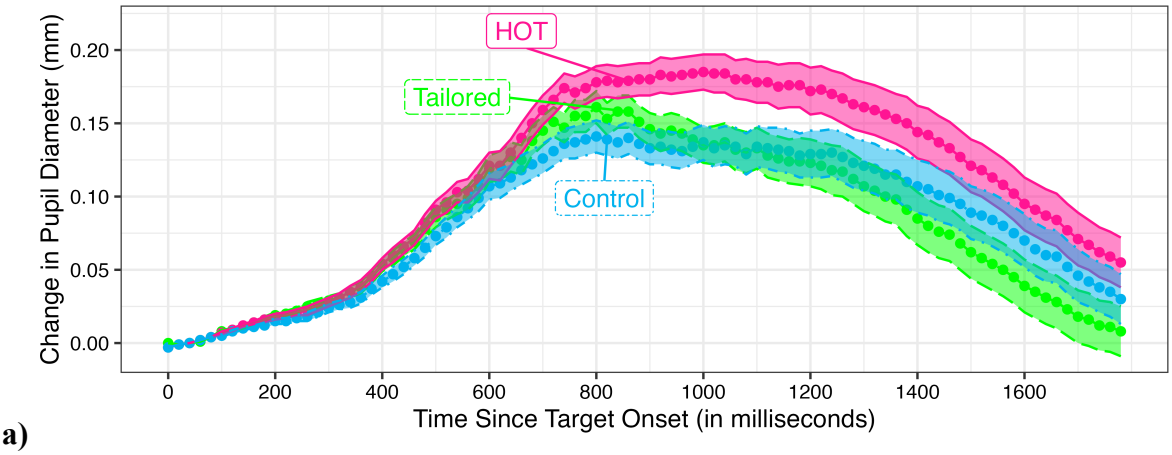
Note. Bars represent one standard error. (**a**) Change in pupil diameter during the ISI period. Results indicated that all conditions exerted a similar amount of preparatory effort. (**b**) Mean change in pupil diameter during the ISI period by task block. Results showed no significant main effect of block or any interactions.

The ANOVA for phasic pupil revealed significant main effects of condition, $F(2, 128)$ = 3.681, p = .028, η_p^2 = .054, block, $F(2, 256)$ = 16.477, p < .001, η_p^2 = .114, and bin, $F(89, 11392)$

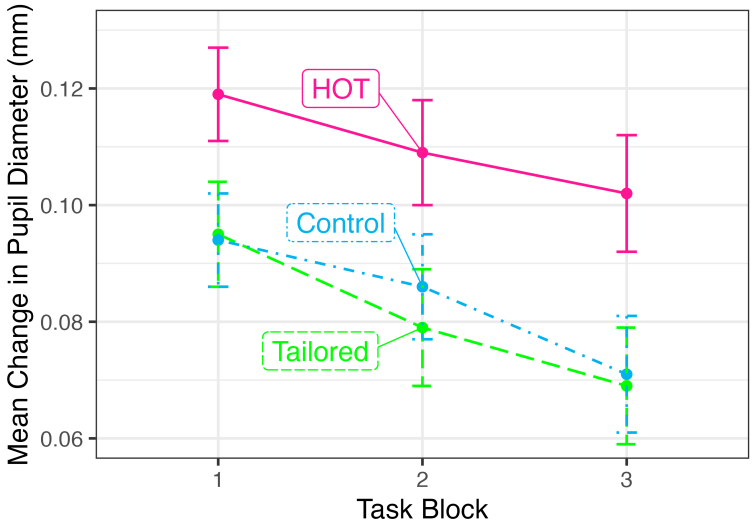
= 100.060, $p < .001$, $\eta_p^2 = .439$, as well as a condition × bin interaction, $F(178, 11392) = 2.153$, $p < .001$, $\eta_p^2 = .033$. As seen in *Fig. 20a*, the group HOT goal condition exhibited markedly larger phasic pupillary responses than both the Tailored goal condition and Control, indicating that the group HOT condition exerted higher attentional effort throughout the task. However, phasic responses in all conditions did diminish over time (Block 1: Control $M = .094$, $SD = .053$, HOT $M = .119$, $SD = .053$, Tailored $M = .095$, $SD = .059$; Block 3: Control $M = .071$, $SD = .066$, HOT $M = .102$, $SD = .066$, Tailored $M = .069$, $SD = .066$; see *Fig. 20b*).

Figure 20

Visualizations for Phasic Pupil Dynamics in Experiment 2



a)



b)

Note. Bars represent one standard error. (**a**) Change in pupil diameter after the target appears. Results indicated that the HOT condition displayed significantly higher phasic pupillary responses compared to both the Tailored and Control groups. (**b**) Mean change in pupil diameter after the target appears by task block. Results indicated a significant main effect of block wherein all groups showed diminished responses as the task went on, though the HOT groups remained higher throughout.

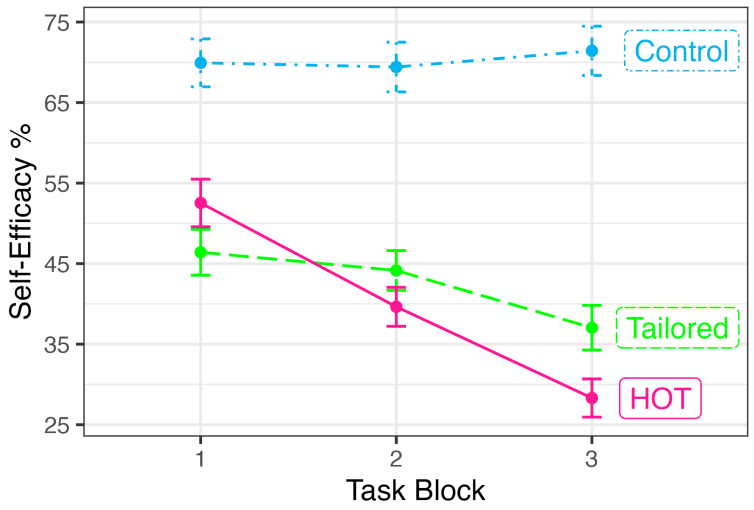
Motivational Measures

The ANOVA for self-efficacy found significant main effects of condition, $F(2, 128) = 49.903$, $p < .001$, $\eta_p^2 = .438$, and block, $F(2, 256) = 26.871$, $p < .001$, $\eta_p^2 = .174$. Additionally, there was a significant condition × block interaction, $F(4, 256) = 13.553$, $p < .001$, $\eta_p^2 = .175$. The

Control condition displayed the highest overall self-efficacy that stayed relatively consistent over the course of the task. The Tailored and group-level HOT goal conditions start with similar self-efficacy scores and a post-hoc pairwise comparison with a Bonferroni adjustment indicates that in block 3 the Tailored goal condition score is significantly higher than the group HOT score (*MD* = 8.73%, *SE* = 0.389, 95% CI [1.03%, 16.43%], p = .027; Block 1: Control *M* = 69.96%, *SD* = 19.74%, HOT *M* = 52.53%, *SD* = 19.60%, Tailored *M* = 46.41%, *SD* = 18.67%; Block 3: Control *M* = 71.43%, *SD* = 20.29%, HOT *M* = 28.31%, *SD* = 15.73%, Tailored *M* = 37.04%, *SD* = 18.14%; see *Fig. 21*).

Figure 21

Self-Efficacy as a Function of Time-on-Task (Task Block) by Condition for Experiment 2



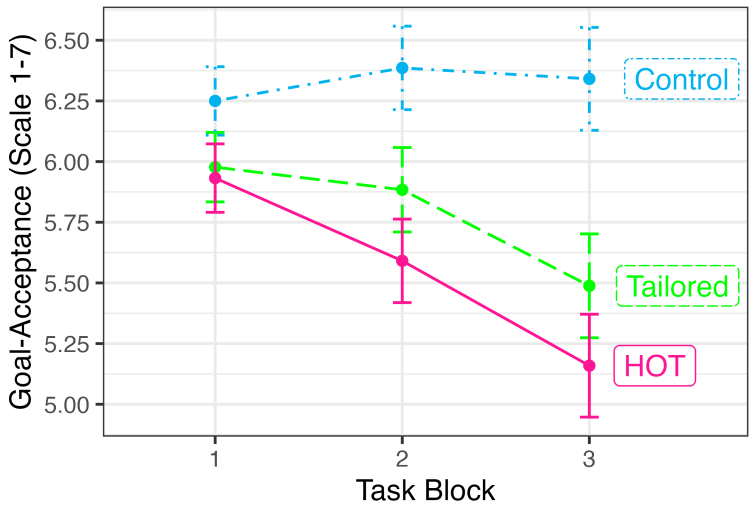
Note. Bars represent one standard error. Percent self-efficacy by condition and task block. Results revealed that the Control group reported significantly higher self-efficacy that did not change over time. Both goal groups declined in self-efficacy as the goal became harder, with an interaction effect in block three where the Tailored condition reported slightly higher self-efficacy than the group-level HOT condition.

The ANOVA for goal-acceptance found significant main effects of condition, $F(2, 128) = 6.942$, $p < .001$, $\eta_p^2 = .098$, and block, $F(2, 256) = 8.876$, $p < .001$, $\eta_p^2 = .065$. Additionally, there was a significant condition × block interaction, $F(4, 256) = 3.579$, $p = .007$, $\eta_p^2 = .053$. The Control

condition displayed the highest overall goal-acceptance that stayed relatively consistent over the course of the task, while both goal conditions started with similarly high goal-acceptance that then diminished over time (Block 1: Control $M = 6.25$, $SD = .892$, HOT $M = 5.932$, $SD = .974$, Tailored $M = 5.977$, $SD = .938$; Block 3: Control $M = 6.341$, $SD = 1.010$, HOT $M = 5.159$, $SD = 1.554$, Tailored $M = 5.488$, $SD = 1.579$; see *Fig. 22*).

Figure 22

Goal-Acceptance as a Function of Time-on-Task (Task Block) by Condition for Experiment 2



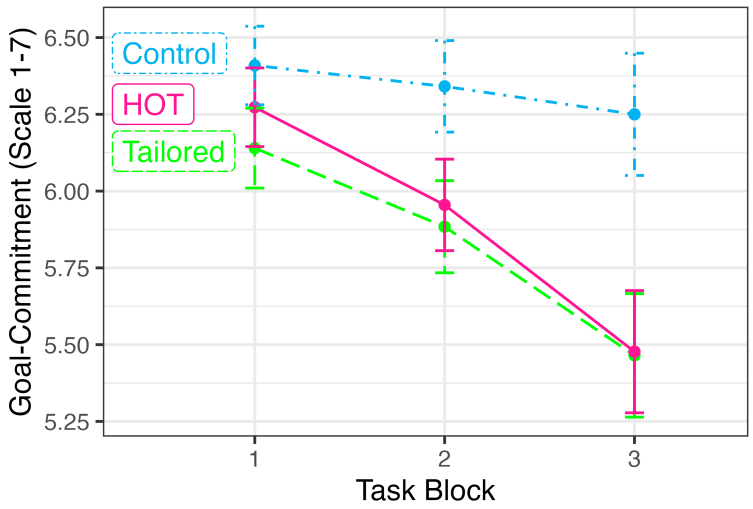
Note. Bars represent one standard error. Goal-acceptance by condition and task block. Results showed Control maintained their goal-acceptance over time, while the two goal conditions declined over time after starting with comparable goal-acceptance reports in the first block.

The ANOVA for goal-commitment found significant main effects of condition, $F(2, 128) = 3.965$, $p = .021$, $\eta_p^2 = .058$, and block, $F(2, 256) = 20.225$, $p < .001$, $\eta_p^2 = .136$. Additionally, there was a significant condition × block interaction, $F(4, 256) = 2.636$, $p = .035$, $\eta_p^2 = .04$. The Control condition displayed the highest goal-commitment that stayed relatively consistent over the course of the task, while both goal conditions started with similarly high goal-commitment that then diminished over time (Block 1: Control $M = 6.409$, $SD = .787$, HOT $M = 6.273$, $SD = .727$,

Tailored $M = 6.140$, $SD = 1.014$; Block 3: Control $M = 6.250$, $SD = 1.184$, HOT $M = 5.477$, $SD = 1.389$, Tailored $M = 5.465$, $SD = 1.369$; see *Fig. 23*).

Figure 23

Goal-Commitment as a Function of Time-on-Task (Task Block) by Condition for Experiment 2



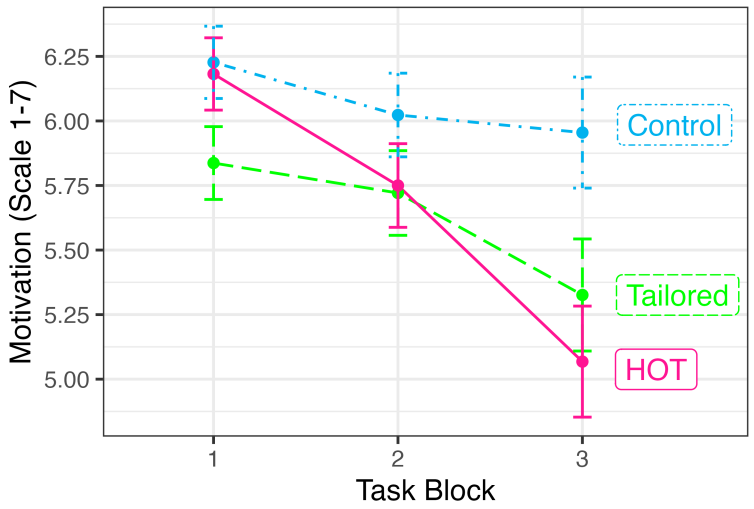
Note. Bars represent one standard error. Goal-commitment by condition and task block. Similar to goal-acceptance, the Control condition reported higher goal-commitment that did not change over time. Both goal groups start with similarly high ratings but significantly decline over time.

The ANOVA for motivation did not find a significant main effect of condition, $F(2, 128) = 2.706$, $p = .071$, $\eta_p^2 = .041$. However, it did display a significant main effect of block, $F(2, 256) = 22.846$, $p < .001$, $\eta_p^2 = .151$, and a significant condition × block interaction, $F(4, 256) = 3.884$, $p = .004$, $\eta_p^2 = .057$. The Control condition reported consistent motivation over the course of the task, while both goal conditions experienced a drop in motivation over time (see *Fig. 24*; Block 1: Control $M = 6.227$, $SD = .774$, HOT $M = 6.182$, $SD = .815$, Tailored $M = 5.837$, $SD = 1.153$; Block 3: Control $M = 5.955$, $SD = 1.275$, HOT $M = 5.068$, $SD = 1.561$, Tailored $M = 5.326$, $SD = 1.426$). Post-hoc pairwise comparisons with a Bonferroni adjustment revealed that the Control group differs from the Tailored goal group overall ($MD = .440$, $SE = 0.210$, 95% CI [.024, .856], $p = .038$). Additionally, in block 3 the Control group scored significantly higher on motivation than

both the Tailored (*MD* = .629, *SE* = 0.306, 95% CI [.024, 1.234], *p* = .042), and the group HOT conditions (*MD* = .886, *SE* = 0.304, 95% CI [.285, 1.488], *p* = .004).

Figure 24

Motivation as a Function of Time-on-Task (Task Block) by Condition for Experiment 2



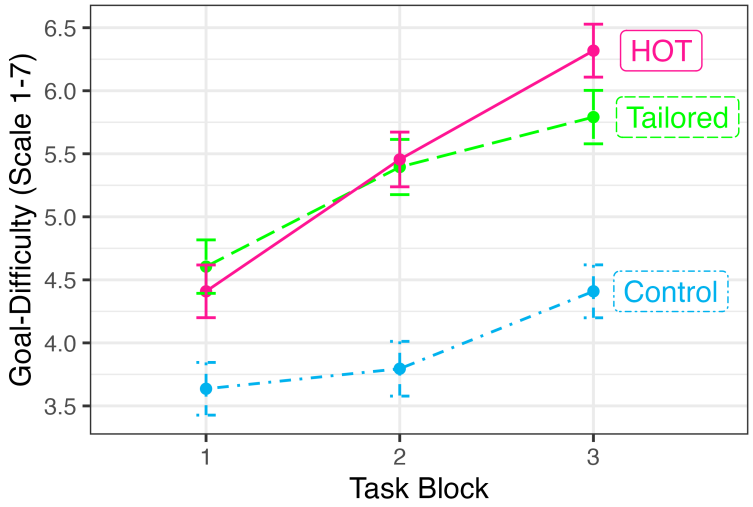
Note. Bars represent one standard error. Motivation by condition and task block. The Control condition reported consistent motivation throughout the task. The Tailored condition reported overall lower motivation that declined over time. The HOT group also significantly declined over time, but only significantly diverged from Control in block three.

The ANOVA for perceived goal-difficulty found significant main effects of condition, $F(2, 128) = 23.475$, $p < .001$, $\eta_p^2 = .268$, and block, $F(2, 256) = 46.637$, $p < .001$, $\eta_p^2 = .267$. There was also a significant condition × block interaction, $F(4, 256) = 3.725$, $p = .006$, $\eta_p^2 = .055$. The Control condition reported their vague goal as being less difficult overall compared to both the Tailored and group HOT goal conditions, but all conditions experienced a rise in goal difficulty over the course of the task (Block 1: Control *M* = 3.636, *SD* = 1.464, HOT *M* = 4.409, *SD* = 1.335, Tailored *M* = 4.605, *SD* = 1.365; Block 3: Control *M* = 4.409, *SD* = 1.743, HOT *M* = 6.318, *SD* = .983, Tailored *M* = 5.791, *SD* = 1.337; see *Fig. 25*). Pairwise comparison with Bonferroni correction indicated only marginal evidence that, in block three, the Tailored group and HOT group

differed in their perception of goal-difficulty (*MD* = .527, *SE* = .298, *p* = .079, 95% CI [-.062, 1.117]).

Figure 25

Goal-Difficulty as a Function of Time-on-Task (Task Block) by Condition for Experiment 2

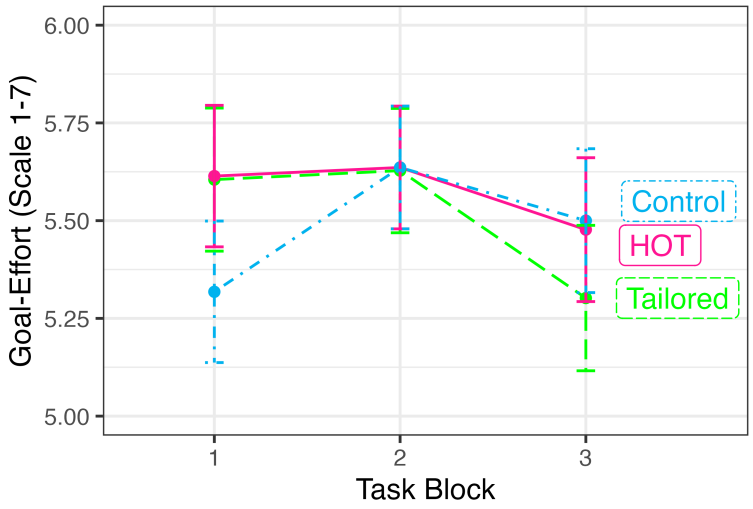


Note. Bars represent one standard error. Perceived goal-difficulty by condition and task block. The Control condition reported that their vague goal felt less difficult overall compared to both the goal conditions but did experience an increase in difficulty over time. Both goal groups reported similarly high goal-difficulty that increased with time-on-task.

The ANOVA for goal-effort (i.e., how effortful it felt to achieve the goal) failed to find significant main effects for condition, $F(2, 128) = .107$, $p = .898$, $\eta_p^2 = .002$, and block, $F(2, 256) = 2.123$, $p = .122$, $\eta_p^2 = .016$, as well as a condition × block interaction, $F(4, 256) = 1.092$, $p = .361$, $\eta_p^2 = .017$. Overall, the three conditions reported working on the goals felt similarly effortful (Block 1: Control $M = 5.318$, $SD = 1.459$, HOT $M = 5.614$, $SD = 1.125$, Tailored $M = 5.605$, $SD = .955$; Block 3: Control $M = 5.500$, $SD = 1.191$, HOT $M = 5.477$, $SD = 1.089$, Tailored $M = 5.302$, $SD = 1.372$; see *Fig. 26*).

Figure 26

Goal-Effort as a Function of Time-on-Task (Task Block) by Condition for Experiment 2



Note. Bars represent one standard error. Perceived goal-effort (i.e., how effortful it felt to achieve the goal) by condition and task block. Results indicated no significant effects.

Discussion

Experiment 2 examined whether tailoring experimenter-set harder-over-time (HOT) goals to each individual's demonstrated ability would preserve the behavioral benefits of group-level HOT goals while producing a more favorable task experience. The behavioral results supported my first hypothesis that those in the Tailored goal group would exhibit similar behavioral performance compared to the group-level HOT goal condition (referred to as the HOT condition) with respect to the Control condition. Both the Tailored and HOT conditions exhibited overall faster response times, less variable response times, and fewer attention lapses compared to the Control group. Both experimental goal conditions also performed faster in each successive task block, while the Control group's slower RTs were consistent over time.

The two goal conditions were not necessarily expected to differ in their behavioral performance metrics, but that the two goal conditions performed so similarly is particularly

unsurprising upon inspection of how the assignment of the Tailored goal played out. The general method of HOT goal-setting in this sustained attention context is extremely novel. This means that there is no established best-practice. The initial group-level HOT goal value for the first block (450 ms) was originally derived from the average performance of prior samples that performed a similar 4-choice reaction time task. Performance on the practice block in the current sample, where mean RTs were extremely close across conditions (~456-460 ms), tracks with that previous task average. The implication of this is that, due to how the Tailored goals were assigned across time, the average block one goal for that condition (~455 ms) was remarkably close to the group-level HOT goal. In other words, for the average participant, the first block for the two goal manipulations was functionally equivalent, differing only in whether the goal was framed as being based on one's own performance. Importantly, the manipulations diverged in rate of difficulty escalation. The group-level HOT goal increases the difficulty by 100 ms over the course of the task (-50 ms per block). This was done so that on average, the 350 ms block three goal was difficult, but still achievable. However, the grouped nature of the standard HOT goals means that for some subjects the average response goal will be too difficult and others too easy. I made the decision to restrict the difficulty range of the Tailored goals (-25 ms per block; -50 ms over the entire task) so that the goals still followed the HOT pattern at equal intervals, but the quickest performers in that condition would not be assigned overly difficult or impossible goals in the second and third blocks. The result is that by the third block, the average Tailored goal ($M \sim 405$ ms, $SD \sim 92$ ms) was substantially more lenient than the group-level HOT goal. This calibration difference is arguably the key to interpreting the remaining results.

My second hypothesis that attentional effort would be higher and better maintained in the Tailored condition relative to the Control received, at best, only partial support. Preparatory

pupillary responses showed no difference across conditions or time, and while the group HOT condition exhibited markedly larger phasic pupillary responses throughout the task, the Tailored condition's responses were indistinguishable from Control. This null phasic result for the Tailored group is interesting in and of itself when integrated with the broader results of Experiment 2. Notably, the Tailored condition achieved the same behavioral performance outcomes as the group HOT condition, while apparently exerting no more attentional effort than the Control condition. One interpretation, concerning the calibration difference in goals noted above, is that on average the Tailored goals stayed comfortably within reach throughout the task. By design, the Tailored condition subjects all had the ability to achieve their first goal (mean practice RT). In contrast, for many individuals in the HOT condition, the initial goal of 450 ms was already more difficult than their average practice RTs and required a relatively larger amount of attentional effort to effectively pursue. Despite this, the challenge and specificity offered by the presence of the group-level HOT goal could have driven continued effort mobilization, even when the goal was too difficult and the extra effort produced no additional performance benefits. This interpretation is consistent with the RT by time block results (see *Fig. 14*), wherein the Tailored condition achieved their average goal in each block, but the HOT condition did not achieve their block three goal. However, the subjective measure of how effortful it felt to work towards the goal fails to corroborate this interpretation, as no significant difference between conditions or over time was detected (*p-value range* = [.122, .898]; see *Fig. 26*).

My third hypothesis, that the Tailored goal group would show more favorable reports regarding subjective task experience compared to both the group-level HOT condition and Control, was largely unsupported, which muddies the above interpretations. The Control condition reported the highest self-efficacy, goal-acceptance, goal-commitment, and motivation, and stayed stable in

those reports over time. Both goal conditions began with comparably high ratings for goal-acceptance, goal-commitment, and motivation, but noticeably declined with time-on-task. The goal conditions' self-efficacy ratings similarly declined but also started off significantly lower compared to Control. However, it is important to interpret the seeming advantage of the Control group on these measures with caution. As discussed in the introduction of this chapter, the vagueness of the "respond as quickly as possible" goal provides no anchor against which participants can evaluate their performance. When there is no concrete way to fail, the acceptance, commitment, and self-efficacy ratings are likely inflated relative to conditions in which the goal presents a solid criterion. Nonetheless, with the current multiple-report method, Experiment 2 answered the question left open in Experiment 1 and prior work (Strayer et al., 2024; Strayer & Unsworth, 2026): the relatively low retrospective goal-commitment scores previously observed in HOT goal groups are not demonstrative of low commitment from the start. The current results showed that both experimental goal groups accepted and committed to their block one goals comparably to Control. It was only after the goals escalated in difficulty that acceptance, commitment, and motivation, along with the self-efficacy score that was already lower from the beginning, deteriorated. This pattern is consistent with the idea that diminishing self-efficacy, when faced with increasingly difficult goals, pulls goal-commitment down with it (Phillips & Gully, 1997).

The one significant point of divergence between the two goal conditions was indeed associated with self-efficacy. By the third block, the Tailored condition reported significantly higher self-efficacy than the group HOT condition (M = 37.04%, SD = 18.14% vs. M = 28.31%, SD = 15.73% respectively) mirroring the marginal difference in perceived goal-difficulty in the same block (Tailored: M = 5.791, SD = 1.337 vs. HOT: M = 6.318, SD = .983). Tailoring thus did

confer a measurable subjective benefit, but it only emerged once the goal-difficulty meaningfully diverged between the two experimental conditions. It also did not extend to acceptance, commitment, or general motivation. In terms of the general resource allocation framework, keeping the goals attainable protected the self-efficacy that helps maintain resource allocation and bolster outward performance, but this localized protection was not sufficient to counteract broader deterioration of the other conative factors as difficulty rose. Collectively, these results highlight how the success of goal-setting interventions hinges on nuanced calibration. More broadly, Experiment 2 demonstrated that individually tailored HOT goals reproduced the behavioral benefits of group-level HOT goals, and potentially offered partial protection to self-efficacy as difficulty rose, but they did not resolve the broader erosion of goal-acceptance, commitment, and motivation that accompanied the same escalating difficulty.

In a wider sense, Experiments 1 and 2 share a common theme: HOT goal manipulations improved outward behavioral performance, likely in part due to regularly re-upping goal salience during the task. However, they both do so while participants are continuously engaged with some aspect of the task. Further, some time-on-task effects persisted across conditions, irrespective of how the goals were framed or calibrated (e.g., rising TUTs, diminishing pupillary responses, declining motivation). This raises the possibility that maintaining goal salience over a long stretch can only go so far, and that periodic breaks away from the task may offer a complementary strategy for maintaining sustained attention performance in the long run. Consequently, Experiment 3 shifted away from manipulating the motivational factor of task goals, to instead manipulate a contextual factor: the temporal structure of task engagement itself.

CHAPTER IV

EXPERIMENT 3: DIFFERENTIAL SEGMENTATION OF EQUAL BREAK TIME AND ITS IMPACTS ON THE VIGILANCE DECREMENT AND ATTENTION LAPSES

Incorporating break periods during sustained attention tasks is a popular strategy for restoring performance and attenuating time-on-task effects (see Schumann et al., 2022). An abundance of evidence exists that task performance tends to decline as a function of time, possibly due to mental fatigue (overload) or under-stimulation (underload) during simple, repetitive tasks (Warm et al., 2008; Pattyn et al., 2008). While different in many ways, these theories are both receptive to the notion that temporarily disengaging from a task (i.e., taking breaks) can be beneficial for restoring attentional control and motivation. Initial vigilance research emphasized the requirement of continuous watchkeeping demands in order to accurately capture vigilance decrement measurements, and considered breaks to be a confound of sorts that should be minimized (See et al., 1995). However, subsequent work suggested that brief rest intervals can be an effective manipulation for improved overall performance (See et al., 1995). For example, as previously discussed in the Meta-Awareness section, Ariga and Lleras (2011) found that short, rare breaks (in the form of task-switching) during a vigilance paradigm mitigated time-on-task effects and argued that the breaks served to reactivate goal representations which enhanced attentional monitoring post-break. Likewise, Ralph et al. (2017) found evidence that both rest breaks (no activity) and task-switching breaks were associated with better task performance and reduced time-on-task effects compared to performing the task straight through. Both of these findings coincide with vigilance theories that claim time-on-task effects are due in part to a growing loss of goal salience and suggest that occasionally disengaging from the task at hand can

be beneficial in the long-run. Experiment 3 explored whether the differential allocation of an equal amount of break time impacted attention lapses and vigilant attention dynamics.

Vigilant Attention

Before turning to the ways in which breaks can be categorized, it is worth distinguishing two terms that are often used interchangeably in this literature. Sustained attention broadly encompasses our ability to maintain engagement with a task over an extended amount of time and across a variety of task demands (Robertson & O'Connell, 2010; Fortenbaugh et al., 2017; Esterman & Rothlein, 2019). Vigilant attention falls under the umbrella of sustained attention but focuses more narrowly on the ability to stay ready to catch rare, unpredictable, and often faint signals across prolonged periods of monotonous monitoring. In other words, vigilant attention can be considered a subtype of sustained attention (vs. a separate ability) that is constrained by the conditions these mental operations have to hold up under (Langner & Eickhoff, 2013). This is relevant for comparison across my experiments. The 4-choice reaction time task used in Experiments 1 and 2 requires subjects to make decisions concerning response selection (i.e., they have 4 choices), which places it under the broader sustained attention umbrella, while the psychomotor vigilance task used here in Experiment 3 removes those decisions and leaves the readiness to respond to a target component (Dinges & Powell, 1985; Unsworth & Robison, 2016).

Break Classifications

Breaks can be categorized based on type, onset-timing, and duration (Schumann et al., 2022). Break types can be passive or active. Passive rest breaks may include activities like shutting your eyes or stretching, and generally facilitate recovery of arousal (Steinborn & Huestegge, 2016; Helton & Russell, 2015). Whereas active breaks comprise activities like switching to an alternative task and serve to re-engage attentional control systems and combat

boredom (Ralph et al., 2017). Thomson, Smilek, & Besner (2015) determined that brief, interspersed perceptual variation during a vigilance task helped combat time-on-task effects, suggesting that even slight alterations in task modes can help prevent underload-related performance declines. Another line of research indicates that breaks containing mindfulness-based or goal reorientation exercises can improve meta-awareness and reduce unintentional mind-wandering during a task (Mrazek et al., 2012; Mrazek et al., 2013). As for timing of the breaks, findings indicate that the most effective implementation strategy is to take preemptive breaks (i.e., before performance declines significantly) that head off attention lapses; reactive breaks in response to performance lapses tend to facilitate less attentional restoration (Ariga & Lleras, 2011; Ralph et al., 2017). These findings regarding the efficacy of preemptive breaks coincide with literature concerning cognitive fatigue, which indicates recovery processes are more productive if initiated early on (i.e., prior to severe motivational disengagement or cognitive fatigue; Hockey, 2013; Fortenbaugh et al., 2017). Finally, break duration is also a key element to consider. Oftentimes, breaks that are brief (seconds to minutes) and frequent are associated with better outcomes than longer, infrequent breaks. One neurocognitive account for these findings is that these frequent, short breaks facilitate recalibration of the locus coeruleus-norepinephrine system while not allowing for a total shift towards resting-state mode (Aston-Jones & Cohen, 2005; Unsworth & Robison, 2018). This account is backed up by pupillometric findings showing that breaks as short as a few seconds can refresh baseline pupil diameter and enhance system responsiveness to upcoming task targets (Van den Brink et al., 2016). Altogether, prior research indicates that break periods work via mechanisms like cognitive restoration, task goal reactivation, motivation restoration, and the promotion of meta-awareness. These mechanisms share a large amount of overlap with those supporting attention control and goal processes in general sustained

attention (Fortenbaugh et al., 2017). Therefore, investigating different break implementation strategies is a practical direction when looking at ways to help support general sustained attention and reduce the frequency/severity of attention lapses.

Current Study

Despite the large amount of prior literature regarding break periods, there remains a lack of experimental findings that incorporate pupillometry and thought-probes in order to discern how breaks affect the dynamics of attentional effort, behavioral attention lapses, and mind-wandering. In fact, to my knowledge, no study has investigated how simple, differential allocation of passive break time impacts attentional effort (via pupillometry), behavioral attention lapses, and mind-wandering reports in the context of vigilant attention. The psychomotor vigilance task lends itself well to this question since it has a long-established history in vigilance research (PVT; Dinges & Powell, 1985). Since breaks are thought to work more on arousal and goal salience aspects of sustained attention, rather than decision-making processes, using a task that isolates readiness to respond may result in a clearer test for the simple manipulation. To address the research gap noted above, Experiment 3 utilized the PVT with three between-group conditions: 1) One 3-Minute break (1 3-Min) at the halfway mark, 2) Three 1-Minute breaks (3 1-Min) that divided the task into quarters, and 3) Control (no timed breaks). Theoretically, three shorter passive breaks should lead to more stable effort allocation because the goal is being reactivated (made more salient) each time the task starts back up again.

Method

Participants and Procedure

A total of 152 students between the ages of 18 and 35 were recruited from the University of Oregon human subjects pool and were compensated with partial course credit (Control = 50, 3

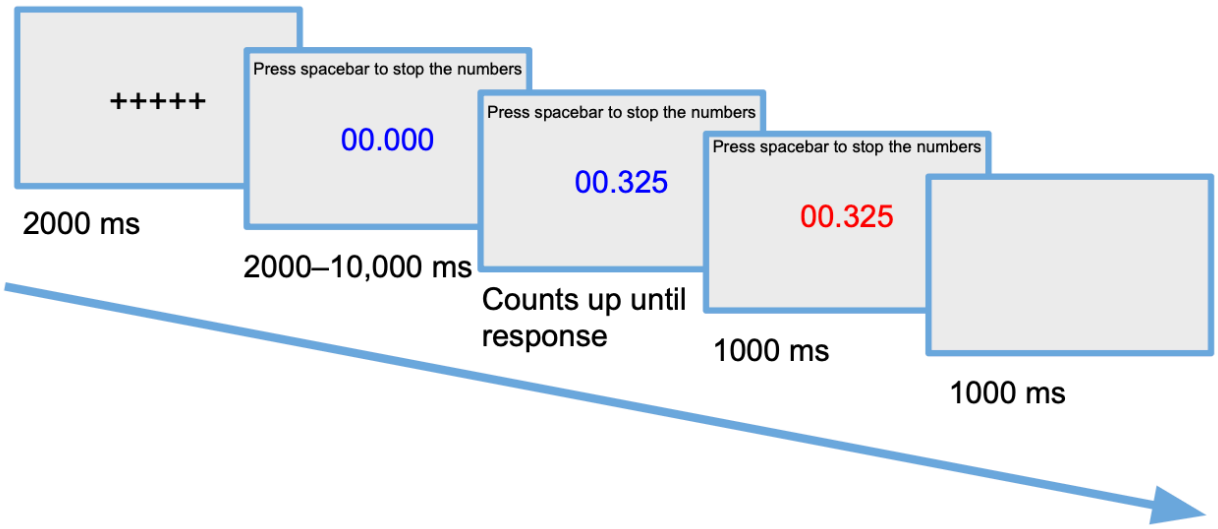
1-Min = 51, 1 3-Min = 51). Several participants were excluded in each condition due to excessive missing pupil data, leaving final $N = 130$ (Control = 43, 3 1-Min = 45, 1 3-Min = 42). The task lasted approximately 17 minutes for the Control condition and approximately 20 minutes for the experimental conditions. Participants provided informed consent and completed a brief demographic survey prior to beginning the task.

Task

Participants completed a version of the psychomotor vigilance task (Dinges & Powell, 1985; Unsworth & Robison, 2016). Each trial started with a 2000 ms fixation composed of 5 plus signs (+++++). Then, a row of blue zeroes appeared in the middle of the screen (00.000). Soon after the zeroes appeared (random time intervals between 2 s–10 s in 500 ms intervals), the numbers started to count up like a stopwatch. The participants were instructed to hit the spacebar once as fast as possible when they saw the numbers start to count. After the subject pressed the spacebar, the numbers stopped counting, turned red, and remained on-screen for 1s as feedback. The next trial began after a 1 s blank screen (see *Fig. 27* for visual).

Figure 27

Task Paradigm Visual of a Single Trial on the Psychomotor Vigilance Task in Experiment 3



All 3 conditions performed 72 trials. The Control condition received them in the typical 3-block manner: ⅓ of the trials (24) → a screen indicated the first block was over and to press the spacebar to continue → another ⅓ of the trials → a screen indicated the second block was over and to press the spacebar to continue → the final ⅓ of trials was presented. The Control condition did not have any time requirements in the between-block screens, they were allowed to press the spacebar whenever they felt ready.[1] The Control condition took approximately 17 minutes to finish the task. The subjects in the 1 3-Min condition were presented the trials over 2 blocks with a mandatory timed break in between: ½ of the trials (36) → a screen indicated that the participant would be taking a 3-minute break from the task and the screen would automatically move on when the time was done → the second ½ of trials were presented. Finally, the subjects in the 3 1-Min condition were presented the trials over 4 blocks with mandatory timed breaks in-between each

[1] The Control condition took ~17 minutes to finish and both break conditions took ~20 minutes, indicating that those in the self-paced Control condition did not take extended breaks comparable to either goal condition.

block: ¼ of the trials (18) → a screen indicated that the participant would be taking a 1-minute break from the task and the screen would automatically move on when the time was done → another ¼ of the trials → another 1-minute break screen → another ¼ of the trials → another 1-minute break screen → final ¼ of the trials. Both experimental conditions took approximately 20 minutes to finish the task.

Thought-Probes

Experiment 3 used the same thought-probes as E2 (5 probes per block[2]; no self-caught measure).

Goal-Commitment

After completing the task, subjects reported their overall goal-commitment based on the question: "On a scale of 1-7, how committed were you to the goal of responding as quickly as possible?"

Pupil Measurement

Pupil measurement procedure remained the same as E2.

Analyses

The planned analyses for E3 generally coincided with those in the previous experiments for RT, RT CoV%, TUTs, and overall goal-commitment. The most notable difference is that, due to a programming error, thought-probes were unequally distributed between the conditions. To account for this, I used a generalized linear mixed model (GLMM) with a beta-binomial distribution to examine the effects of condition (3) × time block (3) on the proportion of TUTs reports, with a random intercept for subject and a dispersion parameter to account for

[2] Due to a programming error, blocks were defined based on when breaks occur (3 1-Min = 4 blocks, 1 3-Min = 2 blocks, and Control = 3 blocks) which led to an unequal number of thought-probes to be administered between groups. Please refer to the E3 Analyses section to see how this was statistically corrected.

overdispersion. Additionally, accuracy was not assessed since the PVT relies on signal detection and contains only one option (just pressing the spacebar instead of four options).

The two primary pupil measures were still preparatory and phasic responses. However, on the PVT the preparatory period (i.e., the ISI prior to target onset) begins when the "00.000" appears and phasic responses (i.e., after target onset) start when the row of zeroes begins to count up like a stopwatch. Since the random ISI period during the PVT ranged from 2,000 – 10,000 ms (in 500 ms intervals), the preparatory data was split into 50 bins of 200 ms each. Only the first 48 bins were included in the analyses in order to maintain the majority of subjects. The preparatory data was then analyzed with a 3 (condition: Control vs. 3 1-Min breaks vs. 1 3-Min break) × 48 (time bin) mixed ANOVA. The phasic data was split into 55 bins of 20 ms each and assessed with a 3 (condition: Control vs. 3 1-Min breaks vs. 1 3-Min break) × 55 (time bin) mixed ANOVA. Both pupil measures were also examined as a function of time using 3 (condition: Control vs. 3 1-Min breaks vs. 1 3-Min break) × 3 (time block) mixed ANOVAs.

Results

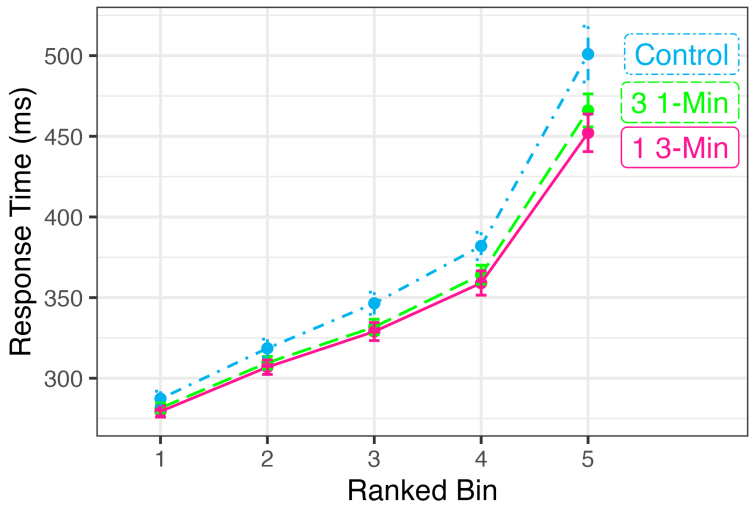
Behavioral

The ANOVA for RT distribution revealed main effects of both condition, $F(2, 127) = 3.089$, $p = .049$, $\eta_p^2 = .046$, and bin, $F(4, 508) = 666.099$, $p < .001$, $\eta_p^2 = .840$. The bin × condition interaction was also significant, $F(8, 508) = 2.806$, $p = .005$, $\eta_p^2 = .042$. Pairwise comparisons with Bonferroni correction indicated that RTs were significantly slower in the Control condition than the 1 3-Min break condition ($MD = 21.775$, $SE = 9.163$, $p = .019$, 95% CI [3.644, 39.906]), while the comparison of the Control and 3 1-Min breaks was not quite significant ($MD = 16.430$, $SE = 9.007$, $p = .070$, 95% CI [-1.392, 34.253]; Bin 1: Control $M = 287.284$, $SD = 30.331$, 3 1-Min $M = 281.542$, $SD = 20.952$, 1 3-Min $M = 279.376$, $SD = 22.652$; Bin 5: Control $M = 500.964$,

SD = 113.531, 3 1-Min *M* = 466.069, *SD* = 68.495, 1 3-Min *M* = 452.138, *SD* = 75.429). No significant difference was found between the two break conditions (*MD* = 5.344, *SE* = 9.061, *p* = .556, 95% CI [-12.586, 23.275]). Taken together, this evidence suggests that subjects in both break conditions experienced fewer lapses in attention than the Control group, though the difference is greatest for the 1 3-Min condition (see *Fig. 28*).

Figure 28

Response Time Distribution by Condition for Experiment 3



Note. Bars represent one standard error. Response times by condition and ranked bin. Bin = RTs rank-ordered fastest to slowest (1 = fastest, 5 = slowest). Results indicated no significant difference between the two break conditions, but Control did differ significantly from the 1 3-Min condition. Overall, the results suggest that Control experienced more attention lapses than the break conditions, but the difference is larger with the 1 3-Min group.

RT, RT CoV%, and # of Lapses were all assessed as a function of time over three equal time blocks. The ANOVA for RT showed a significant main effect of block, $F(2, 254) = 76.950$, $p < .001$, $\eta_p^2 = .377$, and a condition × block interaction, $F(4, 254) = 2.441$, $p = .047$, $\eta_p^2 = .037$. The main effect of condition was not quite significant, $F(2, 127) = 3.040$, $p = .051$, $\eta_p^2 = .046$.

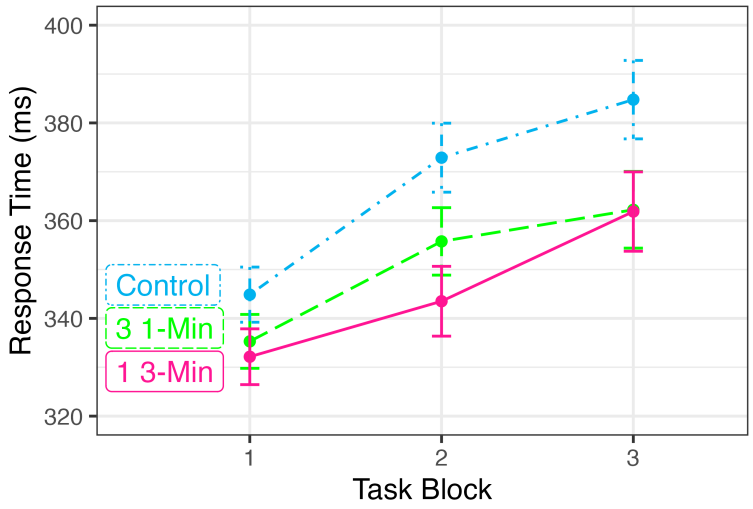
Pairwise comparisons with Bonferroni correction indicated that there were no significant differences between conditions in block 1 (*p-value range* = [.116, .693]). By block 2 there was a

significant difference between Control and the 1 3-Min break condition (*MD* = 29.376, *SE* = 10.043, *p* = .004, 95% CI [9.503, 49.248]), but not quite between the Control and 3 1-Min breaks group (*MD* = 17.131, *SE* = 9.872, *p* = .085, 95% CI [-2.403, 36.665]). In block 3, the Control group's RTs differed significantly from both the 1 3-Min condition (*MD* = 22.900, *SE* = 11.420, *p* = .047, 95% CI [.302, 45.498]), and the 3 1-Min condition (*MD* = 22.535, *SE* = 11.226, *p* = .047, 95% CI [.321, 44.748]).

As can be seen in *Fig. 29*, the Control and 1 3-Min break conditions both became slower in each time block (*p-value range* = [<.001, .006]). The 3 1-Min breaks group experienced a reduction in speed between blocks 1 and 2 (*MD* = 20.458, *SE* = 3.926, *p* < .001, 95% CI [12.689, 28.228]), but not blocks 2 and 3 (*MD* = 6.472, *SE* = 4.426, *p* = .146, 95% CI [-2.285, 15.230]). The combined results indicate that all conditions experienced a vigilance decrement over the course of the task, but the decrement in the Control condition was steeper than both break conditions (Block 1: Control *M* = 344.858, *SD* = 42.799, 3 1-Min *M* = 335.296, *SD* = 30.711, 1 3-Min *M* = 332.154, *SD* = 36.740; Block 3: Control *M* = 384.762, *SD* = 62.350, 3 1-Min *M* = 362.227, *SD* = 43.237, 1 3-Min *M* = 361.862, *SD* = 50.937).

Figure 29

Response Times as a Function of Time-on-Task (Task Block) by Condition for Experiment 3



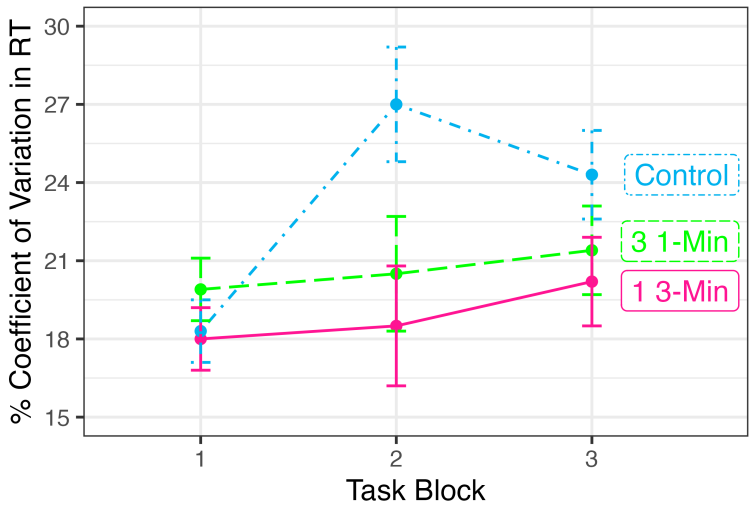
Note. Bars represent one standard error. Response times by condition and task block. Results indicated that the Control condition experienced a steeper vigilance decrement than either break condition.

The ANOVA for RT CoV% revealed a significant main effect of block, $F(2, 254) = 5.347$, $p = .005$, $\eta_p^2 = .040$, and a condition × block interaction, $F(4, 254) = 2.846$, $p = .025$, $\eta_p^2 = .043$. The main effect of condition was not quite significant, $F(2, 127) = 2.558$, $p = .081$, $\eta_p^2 = .039$. Pairwise comparisons with Bonferroni correction for the interaction effect indicated that there were no significant differences between conditions in block 1 (*p-value range* = [.259, .892]). A significant difference was found in block 2 between the Control group and both the 3 1-Min breaks condition (*MD* = 6.5%, *SE* = 3.1%, $p = .041$, 95% CI [.30%, 12.7%]) and the 1 3-Min break condition (*MD* = 8.5%, *SE* = 3.2%, $p = .009$, 95% CI [2.2%, 14.8%]). Finally, in block 3 the conditions converge again with no significant difference (*p-value range* = [.090, .599]). Relatedly, comparisons for the main effect of block found that both the 3 1-Min breaks condition (*p-value range* = [.375, .797]) and 1 3-Min break condition (*p-value range* = [.222, .831]) did not show a significant change over time. The Control group differed significantly when comparing block 1

to block 2 (*MD* = -8.7%, *SE* = 2.3%, $p < .001$, 95% CI [-13%, -4.2%]) and block 3 (*MD* = -6.1%, *SE* = 1.7%, $p < .001$, 95% CI [-9.5%, -2.7%]). Blocks 2 and 3 were not significantly different from each other in the Control condition ($p = .176$). This indicates that the main effect of block is primarily driven by the large block 2 shift in the Control condition (Block 2: Control *M* = 27.0%, *SD* = 2.2%, 3 1-Min *M* = 20.5%, *SD* = 2.2%, 1 3-Min *M* = 18.5%, *SD* = 2.3%; see *Fig. 30*).

Figure 30

Coefficient of Variation in Response Times as a Function of Time-on-Task (Task Block) by Condition for Experiment 3



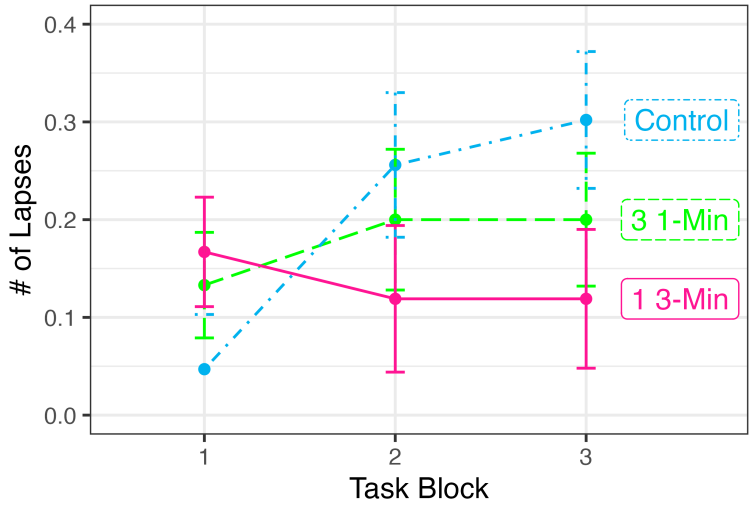
Note. Bars represent one standard error. RT CoV% by condition and task block. Results indicate a significant main effect of block and a condition × block interaction. However, the main effect of block seems to be driven by a large spike in block two for the Control group. Both break conditions maintained their level of variability over time.

The ANOVA for # of Lapses found no significant main effect of condition, $F(2, 127) = .646$, $p = .526$, $\eta_p^2 = .010$, or block, $F(2, 254) = 1.768$, $p = .173$, $\eta_p^2 = .014$. The condition × block interaction was also non-significant, $F(4, 254) = 1.638$, $p = .165$, $\eta_p^2 = .025$. These findings indicate that, according to the # of Lapses measure, all three conditions experienced a similar level of attention lapses over the course of the task (Block 1: Control *M* = .05, *SD* = .213, 3 1-Min *M* =

.13, *SD* = .405, 1 3-Min *M* = .17, *SD* = .437; Block 3: Control *M* = .30, *SD* = .558, 3 1-Min *M* = .20, *SD* = .457, 1 3-Min *M* = .12, *SD* = .328; see *Fig. 31*).

Figure 31

Number of Lapses as a Function of Time-on-Task (Task Block) by Condition for Experiment 3



Note. Bars represent one standard error. # of Lapses by condition and task block. Results found no significant effects.

Task-Unrelated Thoughts

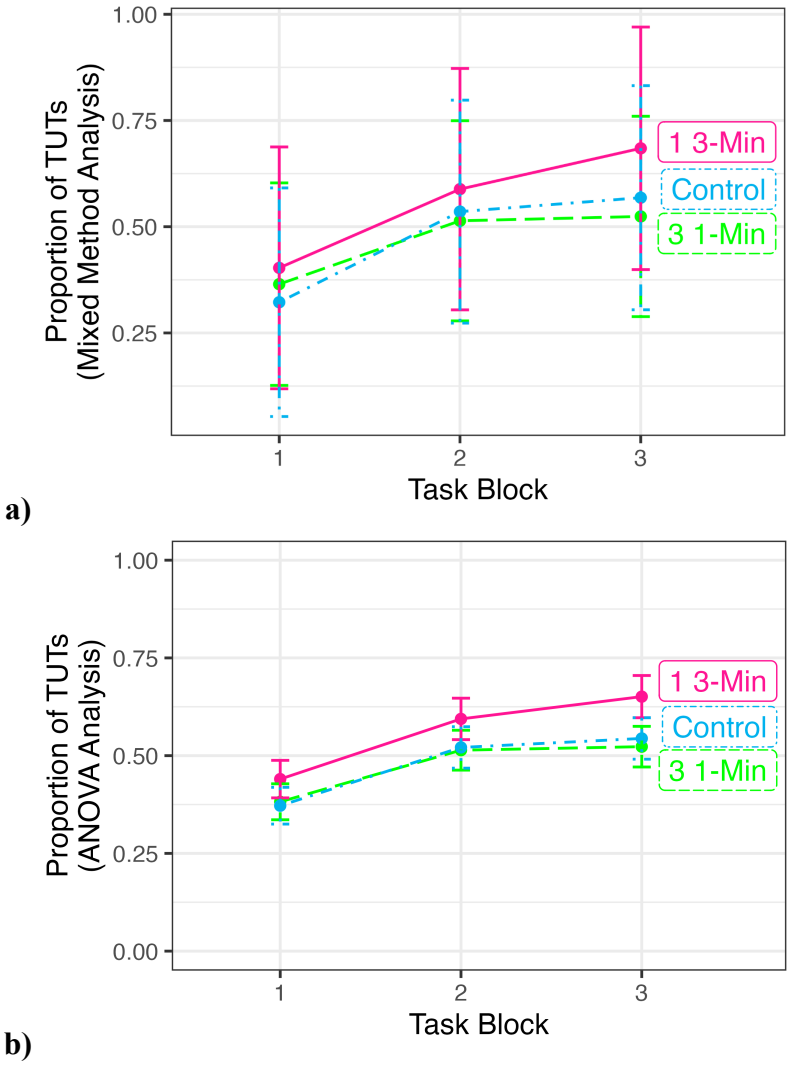
The thought-probes were assessed using a generalized linear mixed model with a beta-binomial distribution to examine the effects of condition (3) and time block (3) on the proportion of TUT reports, with a random intercept for subject and a dispersion parameter to account for overdispersion (see *Fig. 32*a). The GLMM results for the TUT analyses match the results found in the assumptions-violated ANOVA (see the Analyses subsection of Method for details; *Fig. 32b*). Type III Wald chi-square tests revealed a significant main effect of block, $\chi^2(2) = 10.96$, $p = .004$, but no significant main effect of condition, $\chi^2(2) = 0.81$, $p = .667$, and no significant condition × block interaction, $\chi^2(4) = 2.56$, $p = .634$. The model accounted for a substantial proportion of variance in TUT reports overall (conditional $R^2 = .957$), the large majority of which was

attributable to stable between-subject differences (marginal $R^2 = .119$), indicating that individual variability in TUT propensity was far more influential than either condition or time block.

Estimated marginal proportions (averaged across condition) showed that TUT reports increased from .363 at Block 1 (95% CI [.296, .435]) to .546 at Block 2 (95% CI [.472, .618]) and .594 at Block 3 (95% CI [.521, .664]). Tukey-adjusted pairwise comparisons confirmed that TUT proportions were significantly higher in Block 2 vs. Block 1 (OR = 0.47, $SE = 0.07$, $z = -4.81$, $p < .001$) and in Block 3 vs. Block 1 (OR = 0.39, $SE = 0.06$, $z = -6.03$, $p < .001$), but did not differ significantly between Block 2 and Block 3 (OR = 0.82, $SE = 0.13$, $z = -1.29$, $p = .402$). In other words, subjects reported a steep rise in TUTs from the first to second block, then remained relatively consistent in TUT reports from the second to third block.

Figure 32

Proportion of Task-Unrelated Thoughts as a Function of Time-on-Task (Task Block) by Condition for Experiment 3



Note. Bars represent one standard error. (**a**) Proportion of TUTs by condition and task block for the GLMM analysis. Results showed a significant main effect of block where all conditions experience a higher proportion of TUTs as time goes on. (**b**) Proportion of TUTs by condition and task block from the assumptions-violated ANOVA for comparison. Results did not differ from the GLMM analysis.

Goal-Commitment

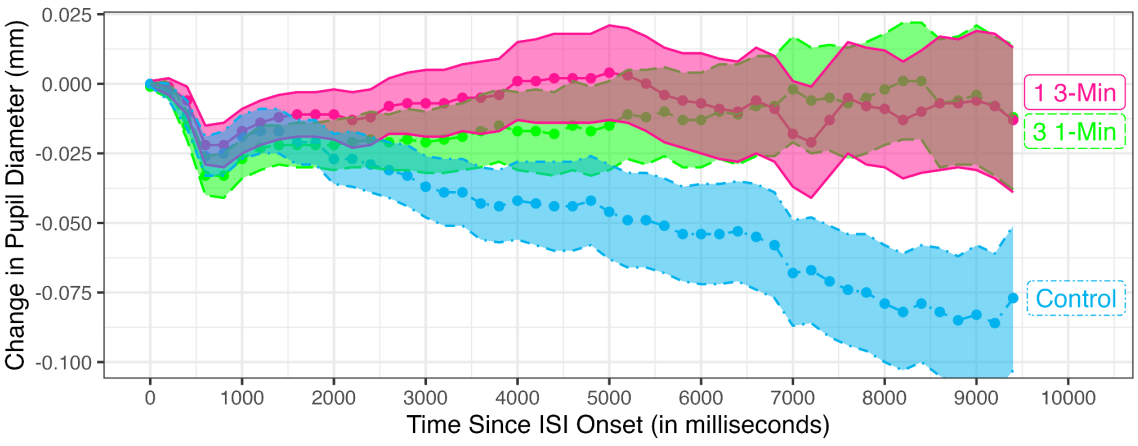
Goal-commitment scores showed no significant difference between conditions, $F(2, 127) = 2.051$, $p = .133$ (Control $M = 5.791$, $SD = 1.301$; 3 1-Min $M = 5.289$, $SD = 1.180$; 1 3-Min $M = 5.571$, $SD = .991$).

Pupil

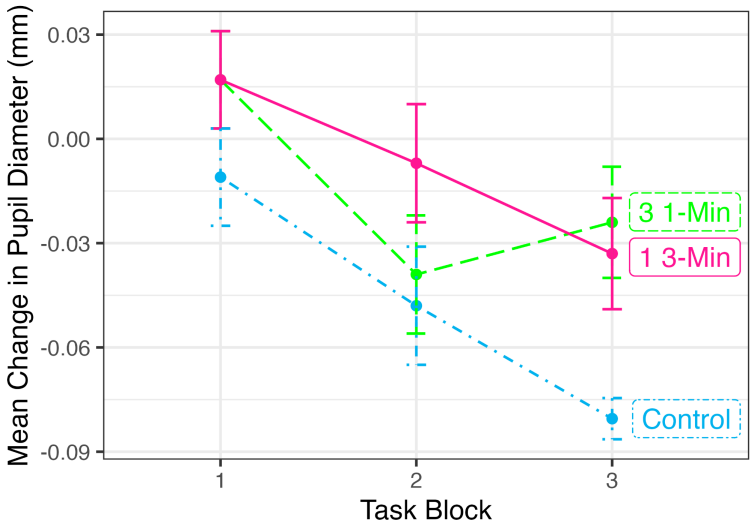
The ANOVA for preparatory pupil showed no main effect of condition, $F(2, 127) = 2.392$, $p = .096$, $\eta_p^2 = .036$, or condition × block interaction, $F(4, 254) = 1.494$, $p = .204$, $\eta_p^2 = .023$. Importantly, the main effect of time bin was significant, $F(47, 5969) = 1.697$, $p = .002$, $\eta_p^2 = .013$, as well as the condition × bin interaction, $F(94, 5969) = 2.358$, $p < .001$, $\eta_p^2 = .036$. As seen in *Fig. 33a*, all 3 conditions experience an initial dip in pupil size (likely due to a small luminance shift from the fixation screen), but both break conditions tend to rise back up over time while the Control condition further declines over the ISI period. This suggests that the break conditions were allocating more attentional effort toward the task while waiting for the target. Additionally, the main effect of block was significant, $F(2, 254) = 18.862$, $p < .001$, $\eta_p^2 = .129$, such that the preparatory pupil responses of all 3 conditions tended to decline over the course of the task (Block 1: Control $M = -.011$, $SD = .092$, 3 1-Min $M = .017$, $SD = .094$, 1 3-Min $M = .017$, $SD = .091$; Block 3: Control $M = -.078$, $SD = .105$, 3 1-Min $M = -.024$, $SD = .107$, 1 3-Min $M = -.033$, $SD = .104$; see *Fig. 33b*).

Figure 33

Visualizations for Preparatory Pupil Dynamics in Experiment 3



a)



b)

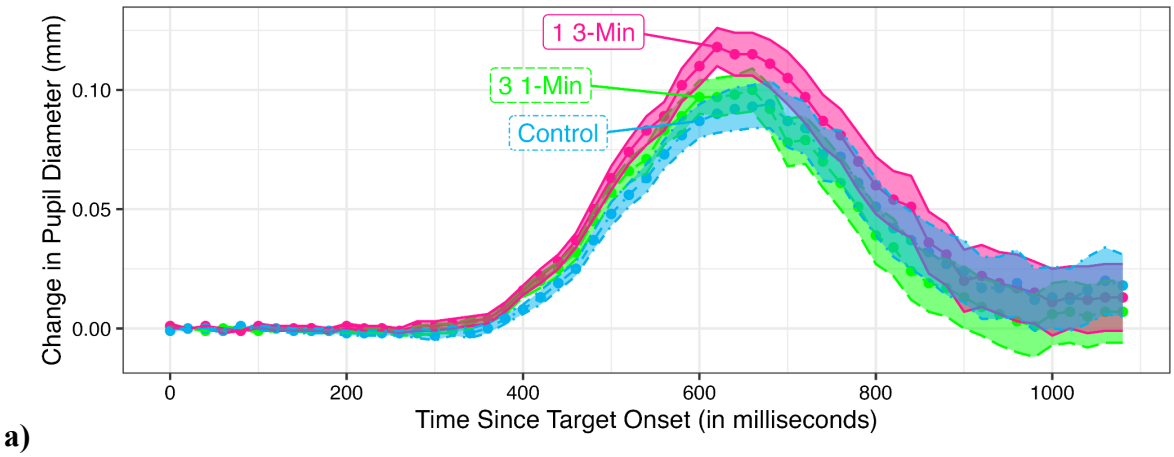
Note. Bars represent one standard error. (**a**) Change in pupil diameter during the ISI (preparatory) period by condition. Results indicated the Control condition exerted less preparatory attentional effort throughout the task compared to both break conditions. (**b**) Change in pupil diameter during the ISI period by condition and task block. Results showed preparatory attentional effort generally declines in all conditions over time.

The ANOVA for phasic pupil response indicated no main effect of condition, $F(2, 127) = .692$, $p = .503$, $\eta_p^2 = .011$, and no interaction effects of condition × block, $F(4, 254) = .965$, $p = .427$, $\eta_p^2 = .015$, or condition × bin, $F(108, 6858) = .779$, $p = .956$, $\eta_p^2 = .012$. As expected, there was a significant main effect of bin, $F(54, 6858) = 95.136$, $p < .001$, $\eta_p^2 = .428$, marking a noticeable phasic response to the target (see *Fig. 34a)*. The main effect of block was also

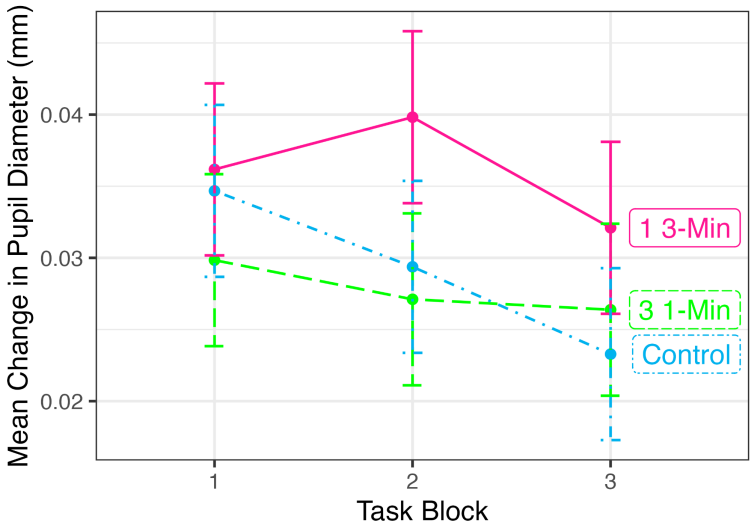
significant, $F(2, 254) = 3.518$, $p = .031$, $\eta_p^2 = .027$. As can be seen in *Fig. 34b*, the average phasic pupil response diminished over time for all conditions (Block 1: Control $M = .035$, $SD = .039$, 3 1-Min $M = .030$, $SD = .040$, 1 3-Min $M = .036$, $SD = .039$; Block 3: Control $M = .023$, $SD = .039$, 3 1-Min $M = .026$, $SD = .040$, 1 3-Min $M = .032$, $SD = .039$).

Figure 34

Visualizations for Phasic Pupil Dynamics in Experiment 3



a)



b)

Note. Bars represent one standard error. (**a**) Change in pupil diameter after target appears (i.e., after the zeroes begin to count) by condition. Results indicated a main effect of bin, generally showing that all conditions displayed phasic pupillary responses to target. (**b**) Change in pupil diameter after target appears (i.e., after the zeroes begin to count) by condition and task block. Results showed phasic orienting responses to target generally decline over time.

Discussion

Experiment 3 examined how differentially segmenting an equal amount of passive break time affects the vigilance decrement, behavioral attention lapses, attentional effort, and mind-wandering during a psychomotor vigilance task. Participants completed the same total number of trials in one of three conditions: a single three-minute break at the task midpoint (1 3-Min), three one-minute breaks dividing the task into quarters (3 1-Min), or a Control condition that advanced through three task blocks without a mandated break duration. I had hypothesized that distributing the break time across three shorter, more frequent intervals, would produce more stable performance and a shallower vigilance decrement than a single longer break or no timed break, on the premise that each time the task is restarted the task goal is reactivated which may help mitigate time-on-task effects.

The behavioral results provide partial support for the benefit of breaks in general, but not for the specific prediction that more frequent segmentation is superior. The response time distribution showed that both break conditions responded faster overall than Control, with the largest difference occurring among the slowest 20% of RTs (Bin 5; key attention lapse measure). This pattern mirrors the Bin 5 effects observed in Experiments 1 and 2 and is consistent with the interpretation that breaks reduce the frequency and/or severity of attention lapses. Critically, however, the two break conditions did not differ from one another, and the clearest separation from Control occurred in the 1 3-Min (longer break) break condition, counter to my prediction. The analysis of RT over time is also consistent with a general break effect. All three conditions exhibited a vigilance decrement, but the Control group experienced the steepest decline, and the 3 1-Min condition was the only group whose slowing did not continue significantly into the final

block. Thus, breaks attenuated but did not eliminate the time-on-task cost, and the manner of segmentation appeared to matter less than the mere presence of a mandated break in general.

The remaining behavioral measures provide some further detail that helps support the general effect of breaks. For example, both break groups displayed similar RT CoV% with respect to each other and over time. The Control condition started off with similar RT CoV% before experiencing a sharp increase in block two, and in block 3 was no longer significantly different than the break conditions. This mid-task benefit is consistent with the idea that breaks help maintain performance stability. While the results showed that this benefit washes out in the third block, it is likely a byproduct of the Control condition also responding significantly slower than the break groups by the end of the task. In other words, the Control group's RTs in block three compared to block two are more tightly clustered, but the cluster is composed of notably slower RTs. The # of Lapses measure revealed no significant effect of condition, block, or their interaction. This dissociation from the RT distribution results highlights the previously discussed insensitivity of the # of Lapses measure. It also indicates that rather than interpreting the benefit as a reduction in discrete lapses, the break effect is better characterized as a modest compression of the slow tail of the distribution.

Looking at the preparatory pupil responses as an index of anticipatory attentional effort, there was a significant condition × time bin interaction. All three conditions exhibited an initial dip in pupil size early in the preparatory period, but both break conditions bounced back and rose across time, whereas Control largely declined. This suggests that the participants who were given mandatory breaks sustained more anticipatory effort while waiting for the target, which is consistent with the idea that breaks help preserve goal-directed engagement. However, the preparatory pupil responses still declined with time-on-task for all conditions. Phasic responses

also declined over time and were not significantly different across conditions. These results indicate that breaks supported the preparatory mobilization of effort in the moment-to-moment ISI without mitigating broader time-on-task decline in either the anticipatory or reactive pupillary responses. The collective pupil results can be attributed to the arousal channel of a general resource allocation framework and are consistent with neurocognitive accounts that brief rest breaks can help recalibrate the LC-NE system, though the effect shown was only an attenuation and not an elimination of time-on-task effects (Aston-Jones & Cohen, 2005).

Under a general resource allocation framework, the absence of any meaningful difference between the two break schedules is informative regarding the mechanism of the break effect and speaks against my primary hypothesis. If the benefit of breaks had been driven primarily by goal reactivation, then the number of restarts (as opposed to total rest time) should have been the operative variable. The 3 1-Min condition with three reactivation events should have outperformed the 1 3-Min condition with a single reactivation. Instead, the break conditions were largely interchangeable behaviorally. This pattern leans more towards arousal-based replenishment of the total resource pool that is more regulated by the complete sum of rest, as opposed to toward the motivational goal-salience route that Experiments 1 and 2 relied on.

The outcomes that were untouched by break effects help further define the boundaries of Experiment 3's manipulation. Task-unrelated thoughts showed a sharp rise from the first to second block then largely stabilized, but this effect was shared across all three conditions. Additionally, a substantial portion of the variance in TUT reports was better attributed to stable between-subject differences instead of condition or time. Moreover, phasic responses to the target diminished with TOT, goal-commitment was unchanged between-groups, and the # of Lapses measure showed no significant effects at all. These results work together under the general resource allocation

framework to suggest that passive breaks helped partially replenish the available resource pool (mitigating the vigilance decrement in RT, stabilizing RT CoV%, and supporting preparatory effort), but they did not prevent resources from being reallocated to TUTs as TOT grew. That is to say, restoring the general size of the resource pool is demonstrably different from influencing how those resources are allocated between the task, TUTs, and self-regulatory processes. The increase in TUTs over time reflects the allocation aspect of the framework shifting a larger proportion of resources off-task even as the availability aspect is restored.

Overall, Experiment 3 demonstrates that inserting equal passive break time into a vigilance task attenuates the vigilance decrement, stabilizes response variability, and sustains preparatory effort relative to working straight through, all of which indicate some level of reduction in the frequency and/or severity of attention lapses. However, it seems to matter little how that fixed amount of time is segmented.

CHAPTER V
GENERAL DISCUSSION

The overarching aim of this dissertation was to advance our understanding of why and under what circumstances attention lapses occur, how they relate to performance, and ways to reduce the frequency and/or severity of their occurrence. I approached this aim from three complementary angles across three experiments, each targeting a different class of factor implicated in sustained attention: a cognitive factor (meta-awareness), a motivational factor (individually tailored goals vs. group-level and vague goals), and a contextual factor (the temporal segmentation of break time). Experiment 1 asked whether a cognitive-motivational intervention with previously established behavioral benefits (specific goals that become harder-over-time/HOT) operates via enhanced meta-awareness of task-unrelated thoughts. Experiment 2 asked where the limits of that intervention lie by tailoring the HOT goals to individual ability and tracking motivational factors across task rather than as retrospective scores, as is often shown in the literature. Experiment 3 shifted from manipulating the task goal itself to manipulating the temporal structure of engagement and tested whether differentially segmenting a fixed amount of break time better preserves vigilant attention. Throughout, I interpreted the results within a general resource allocation framework (Kahneman, 1973; Kanfer & Ackerman, 1989; Thomson et al., 2015; Unsworth, under review), in which a limited and arousal-constrained pool of attentional resources is distributed between a primary task, off-task thoughts, and self-regulatory processes, and wherein optimum performance depends on activating and maintaining the current task goal above competing personal and somatic goals.

In Experiment 1, I replicated key behavioral and pupil outcomes previously associated with a novel harder-over-time (HOT) goal-setting method (Strayer et al., 2024; Strayer & Unsworth, 2026). When compared to a group that received a vague goal to “do your best,” those in the HOT

condition responded faster overall, showed a significant reduction of attention lapses in the tail of the RT distribution, managed to eliminate the typical time-on-task effect of slowing and actually responded faster over time, and mobilized more preparatory attentional effort shown via pupil. Critically, my core hypothesis was unsupported. Experiment 1 did not find any significant effect of the goal-setting manipulation on meta-awareness of task-unrelated thoughts, whether operationalized as the self-caught to probe-caught ratio (Chu et al., 2023; Meier, 2019) or modeled at the level of individual thought events. Within the framework, this places the goal effect squarely on the allocation and goal-activation components, with no significant evidence for the self-regulating/monitoring component being influenced.

Experiment 2 similarly reproduced behavioral benefits with both the previously used group-level HOT goal method and a novel HOT goal method tailored to individual ability, but again, my primary hypothesis was unsupported. The novel temporal measurement of motivational aspects implicated in goal-setting theory showed that both goal groups started with acceptance, commitment, and motivation as high as Control and eroded as goal difficulty escalated. Within a general attention allocation framework, these conative factors are key determinants that regulate how much of the available resource pool is committed to the task. This means their deterioration under rising difficulty marks a progressive weakening of the motivational drive that sustains attentional allocation over time (Bandura, 1977; Kanfer & Ackerman, 1989; Unsworth, under review). The tailoring manipulation itself turned out to be behaviorally interchangeable with the group-level HOT goal. Both goal conditions were faster, less variable, and lapsed less than Control, but did not differ from each other. The one small difference shown in the Tailored condition was that self-efficacy was significantly higher in the final task block compared to the group-level HOT condition, which mirrors the marginal divergence in perceived goal difficulty on

block three. No significant differences emerged in the subjective report of how effortful achieving the goal felt. However, the pupil data indicate that the group-level HOT condition exhibited markedly larger phasic pupillary responses, whereas the Tailored condition matched the group-level HOT behavioral gains while seemingly exerting no more effort than the Control condition. Under the cost-benefit logic in the framework, this may be because the leniently calibrated Tailored goals could be met while sparing capacity, while the group-level HOT goal continued to drive effort mobilization past the point of diminishing returns (Kurzban et al., 2013; Shenhav et al., 2017; Unsworth, under review). Finally, on the surface, the Control group reported more favorable subjective scores on all motivational items, but since this condition lacked a criterion to distinguish success from failure on the task, those self-reports are likely inflated relative to the specific goal conditions. Experiment 2 thus places the goal effect on the allocation and goal-activation components again. Additionally, it reveals that how a goal is calibrated could determine the resource cost at which a given level of performance is purchased, and that subjective motivational reports and actual resource allocation do not necessarily move in tandem.

Experiment 3 turned from focusing on the task goal toward the temporal structure of the task engagement by segmenting a fixed amount of passive break time into either one long (1 3-Min) or three short (3 1-Min) chunks vs. a Control condition that performed the task as per usual without any mandated breaks. Both break conditions exhibited fewer attention lapses in the slow tail of the RT distribution. They also both showed a shallower vigilance decrement, with the 3 1-Min group the only condition whose slowing did not carry significantly into the final block. The preparatory pupil data complemented the behavioral data and showed that both break conditions sustained attentional effort better during the waiting interval while Control declined. Critically, however, my hypothesis driven by a goal-reactivation account was not supported. Both break

schedules were largely interchangeable, with total rest time, not number of restarts, appearing to be the operative variable. This points instead to the arousal aspect of the framework, wherein passive rest replenishes the arousal-limited pool of resources (Aston-Jones & Cohen, 2005; Unsworth & Robison, 2018; Unsworth, under review). As in the earlier experiments, several outcomes proved resistant to manipulation. One is that TUTs rose with time-on-task and appeared more reliant on stable between-subject differences. Another is that phasic responses declined over time regardless of condition. Finally, the discrete # of Lapses variable showed no significant effects. Experiment 3 therefore isolates a distinct route to the same general behavioral endpoint: whereas goals modulate how the pool is allocated, breaks modulate how large the pool is, and neither on their own can halt the drift of attention towards task-unrelated thoughts over time.

Findings Across Experiments

One prominent divergence between the E1 and E2 results is that, in E1, the HOT group became faster across blocks while the Control remained stable. In E2, the goal groups stayed stable while the Control became slower over time. The base task and manipulation were essentially identical. The clearest procedural difference was that E2 added motivational questionnaires between blocks. Under the general resource allocation framework, the time spent task-switching to answer the questionnaires may have functioned as brief self-regulatory interruptions that reactivated the task goal (Ariga & Lleras, 2011). This is a clear parallel to the logic involved with Experiment 3. It highlights that the exact shape of the goal effect on response time as a function of TOT is sensitive to procedural/temporal context, even where the direction of the between-condition benefit is stable.

The data also show a pattern worth addressing that runs counter to the general direction of the goal effects. In Experiment 2, response accuracy showed a main effect of condition, with the

Control group maintaining higher accuracy (M = 97.08%) than either the group-level HOT (M = 96.6%) or Tailored HOT (M = 96.2%) conditions, with no main effect of block or interaction effect. Experiment 1 showed the same ordering as a non-significant trend (condition p = .099; condition × block p = .065), and there the Control group's accuracy drifted upward across blocks (95.9% to 97.3%) while the HOT group's remained flat (95.8% to 95.7%). In other words, if we take the marginal evidence into consideration, the conditions that responded faster, lapsed less in the slow tail of the RT distribution, and mobilized more attentional effort were also slightly less accurate (i.e., a speed-accuracy trade-off). The magnitude of this trade affects interpretation. The accuracy difference between Control and the goal conditions in E2 was under a single percentage point, and every condition achieved the shared goal of 95% accuracy throughout the task. Therefore, the trade-off was present to a small degree, but within-bounds of the overall task goals. One interpretation is that the goal groups converted an accuracy surplus into speed while continuing to satisfy the accuracy constraint.

The contrarian interpretation is that HOT goals did not reduce attention lapses at all but simply relocated participants along the speed-accuracy function, and that the Bin 5 reduction I have used as an index of attention lapses is an artifact of that shift. This is a valid concern to address, but a few features of the data argue against the idea of a pure speed-accuracy trade-off. First, a uniform criterion shift should compress the entire RT distribution proportionally, whereas the condition × bin interactions in both experiments localized the effect disproportionately in the slowest 20% of responses. Second, the accuracy cost did not deepen as goals escalated. If participants were trading away accuracy for speed, the cost should have grown as the goal moved beyond reach (as in E2 where mean RT in block 3 = 392.768, well behind the goal of 350 ms). Instead, accuracy showed no effect of block or interaction in both E1 and E2. Third, Experiment

3 produced the same Bin 5 compression in a task without any accuracy component to trade against. Finally, the exploratory measure in E2 that assessed whether the manipulations led to conscious speed-accuracy decisions, showed no visible divide. This means if a trade-off is occurring, it may be subtle and unconscious rather than completely altering how participants decided to engage with the task. Collectively, these reasons suggest that even if there is a slight speed-accuracy trade-off, it does not account for the entire goal effect on attention lapses.

Another notable pattern, and perhaps the most important, that emerged across all three experiments is that each manipulation moved the behavioral expression of lapsing (slow tail of the RT distribution), yet none moved the proportion of task-unrelated thoughts, which rose with time-on-task at essentially the same rate regardless of condition. On the surface, a behavioral lapse and a self-reported TUT seem to index the same underlying event, but a growing amount of research has found similar dissociations (Strayer et al., 2024; Kucyi et al., 2016; Robison et al., 2021; Steinborn et al., 2017; Unsworth et al., 2022). The current study, taken in context with previous research, emphasizes the proposition that although behavioral lapses and TUTs may correlate they are distinct concepts that overlap to different degrees depending on circumstances (Welhaf & Kane, 2024). There are several non-mutually exclusive accounts that may shed light on this discrepancy. One account is that the two measures capture different components of the general attention allocation framework. A behavioral lapse in the RT tail reflects the allocation of resources toward the task in the moment of responding. A probe-caught TUT reflects the content of conscious experience, or the subjective destination of attention when it is off-task. The manipulations in this study all act on either the amount of available resources committed to task processing or on the arousal that scales the available pool. They do not have any obvious connection to acting on where wandering attention goes when it drifts. From this perspective, the

interventions successfully increased the resources reaching the task (tightening the behavioral tail), without changing the rate at which attention shifted toward internally generated thought. Restoring or reallocating capacity is not the same as suppressing the competing stream of personal concerns that dominate off-task experiences. A second explanation is that the measures differ significantly in temporal grain. The RT distribution is built from far more data points and is sensitive to a handful of very slow responses. A manipulation that prevents even a small number of deep attentional disengagements will notably compress the tail. In contrast, the TUT measure is a coarse snapshot taken at five probes per block, each probe collapsing a relatively long stretch of experience into a single binary report. A manipulation could meaningfully reduce the depth or duration of off-task episodes, without changing the coarse probability that a probe happens to land during an off-task moment. In other words, the behavioral measure may detect a change in severity of lapses that the thought-probe, blind to severity, cannot capture. With these accounts in mind, the framework predicts that lapses and mind-wandering should dissociate whenever a manipulation targets the quantity of resources reaching the task, without targeting the destination of attention when it strays. This kind of manipulation is what was used in all three experiments. This suggests that the consistent findings across the three experiments may not be a failure of the manipulations per se, but rather a hint at the potential underlying architecture.

Limitations

Several limitations should be noted for proper interpretation of the results. The most relevant across all three experiments is that the observed effect sizes were smaller than anticipated. Several theoretically central tests (e.g., the meta-awareness analyses in E1) hovered near conventional significance thresholds. This means that, although I processed the null results and provided alternative theoretical explanations, these modestly powered studies were not well-

equipped to fully interpret the outcomes for potentially small effects. Generally, the null outcomes should be treated as an absence of detectable effects rather than positive evidence of no effect.

A related constraint is the analytic treatment of the motivational data in Experiment 2. Sampling goal acceptance, commitment, self-efficacy, motivation, perceived difficulty, and perceived effortfulness at multiple timepoints was a marked improvement over the single retrospective ratings typical of prior work and helped resolve some lingering questions from prior work (including E1). However, these measures were analyzed largely as isolated outcomes. The framework itself proposes a mediational structure, in which arousal and conative factors govern resource allocation, which in turn drives performance. Testing this structure would require a formal mediation model and a sample sized to support it. Experiment 2 is best understood as a steppingstone toward that analysis rather than a true test of that mediational chain.

The measurement of meta-awareness is a further limitation (and future direction). The construct is inherently difficult to operationalize and the literature relevant to the method in E1 is relatively young and inconsistent in its definitions (see Chu et al., 2023). It is possible the null meta-awareness findings reflect limitations of the instrument as much as an absence of effect. The present method does not appear to be a fine-tuned fit for questions in the realm of sustained attention and requires deep psychometric work moving forward.

One design feature also warrants correction in any future replication attempts. The thought-probes in Experiment 3 were unequally distributed across conditions owing to a programming error. Although the beta-binomial model statistically accommodated the imbalance, it remains a flaw that should be adjusted for initial data collection instead of accounted for after the fact.

Future Directions

The most straightforward next step is to address some of the limitations noted above. Notably, Experiment 2 warrants an adequately powered replication built around a formal mediation model. This would allow the framework's central claim (i.e., that conative and arousal factors drive allocation, which drives performance) to be tested as a structured pathway rather than inferred from a set of parallel outcomes.

Another priority is to probe the limits of the HOT goal technique that Experiment 2 began to map. The Tailored and group-level HOT goals were largely interchangeable behaviorally and diverged only when their difficulty levels became significantly different. A design that parametrically varies the rate and ceiling of difficulty escalation, while tracking pupillary effort throughout, could locate the point at which a goal shifts from productively challenging to counterproductively costly (or even counterproductively too easy). This could help clarify whether the self-efficacy advantage glimpsed in the Tailored condition is a real, exploitable phenomenon, or an artifact of the particular calibration used here.

Third, the persistence of time-on-task effects across experiments points to future studies with combined-channel designs. Since it appears goals may be acting more on the allocation aspect of the framework, and breaks on the availability of resources, intentionally pairing the two together could assess any additive effects. This would also help address the speculation on why the RT TOT decrements differ so much between E1 and E2, even though they use the same base task.

Fourth, the recurring finding that mind-wandering (or TUTs) was largely untouched by the manipulations, and likely governed more by stable individual differences, argues for an explicit individual-differences approach. Linking measures of attentional capacity, motivation, and everyday attention lapses to the dynamics observed here would clarify for whom these

interventions work best and determine whether/how the propensity to mind-wander acts as a moderator of intervention efficacy (McVay et al., 2009; Unsworth & McMillan, 2017).

Finally, the attentional competition modeled in these experiments was largely internal, pitting the task goal against endogenous off-task thought. Extending the paradigm to conditions of salient external distraction would test whether the same allocation principles govern lapses driven by environmental attentional capture. This question has clear relevance to applied settings in which sustained attention actually fails by adding an element not typically captured in lab settings.

Practical Implications

The findings across all three experiments provide support for applications in multiple practical settings that require sustaining focus, including: transportation, radar monitoring, industrial quality control monitoring, education, and even general daily living tasks (Galera et al., 2012; Smallwood, Fishman, & Schooler, 2007; Unsworth & McMillan, 2017; Lindquist & McLean, 2011; Mackworth, 1948; Yanko & Spalek, 2014; McVay, Kane, & Kwapil, 2009; Williamson et al., 2011). First, the behavioral efficacy of HOT goals, replicated across E1 and E2, reinforces that goal-setting is a low-cost, easily implemented intervention for sustaining performance that still holds untapped potential for fine-tuning (Locke & Latham, 2002, 2019; Strayer et al., 2024; Robison et al., 2021; Garner et al., 2025). Second, the modest efficiency bump observed when tailoring HOT goals implies that calibrating goal-difficulty to individual ability may secure the same performance benefits at a lower effort cost (Kanfer & Ackerman, 1989; Kurzban et al., 2013). This could prove useful in contexts where workers must sustain attention across long shifts and where unnecessary effort expenditure risks accelerating fatigue (Hockey, 2013; Warm et al., 2008; Inzlicht et al., 2018). Third, Experiment 3 indicates that when a fixed

amount of rest time is assigned, how it is segmented seemingly matters less than that the breaks are taken proactively as is found in the literature (Ariga & Lleras, 2011; Ralph et al., 2017; Schumann et al., 2022). This finding could help facilitate conversations geared towards raising worker autonomy and allowing them to choose how to split their break time.

Conclusion

Across three experiments spanning cognitive, motivational, and contextual manipulations, this dissertation shows that the behavioral expression of attention lapses (namely in the slow, error-prone tail that accumulates with time-on-task in the response time distribution) can be influenced via multiple routes. Interpreted through the general resource allocation framework, each manipulation engaged a different component of the same system, and each could enhance the amount of available attentional resources being allocated toward the task, thus buffering against observable behavioral degradation. However, subjective/experiential and physiological components associated with time-on-task proved considerably more resistant. Harder-over-time goals improved performance and enhanced effort without measurably altering meta-awareness. Tailoring HOT goals to be more in line with individual abilities reproduced the behavioral benefit and provided some localized preservation of self-efficacy without stopping the broader decline of other motivational measures in the face of rising difficulty. Moreover, mandated passive breaks mitigated the vigilance decrement and supported preparatory attentional effort, regardless of how the breaks were split up, but failed to protect against increases in mind-wandering over time. Collectively, the findings support the notion that attention lapses are a heterogeneous consequence of how a finite, arousal-constrained pool of resources is made available and allocated over time. Thus, the effort to find ways to support sustained attention and reduce lapses is less about finding just one, super-effective intervention (if only life were that easy) and more about understanding

which factor of the resource allocation equation a given manipulation addresses in order to determine practical combinations thereof that can handle a wider range of nuanced situations.

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