Evaluating the Relationship Between Media Multitasking and Sustained Attention

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Abstract

Sustained attention is a crucial cognitive ability for individuals to achieve social and occupational success. As our relationship with technology rapidly changes with the pace of innovation, the implications of this adoption on sustained attention remain unclear. I explored the relationship between media multitasking and sustained attention in the present work. Specifically, Study One explored the relationship between task-based sustained attentional performance and a tendency to media multitask with inputs that are theorized to be demanding and cause interference during processing (maladaptive) relative to a tendency to media multitask with inputs theorized to be either less demanding or not cause interference during processing (adaptive). There was a significant relationship between a greater tendency to habitually multitask with media inputs theorized to cause cognitive or perceptual interference and poorer sustained attentional performance across cognitive dimensions. Study Two explored whether situational media multitasking was associated with subsequent task-based sustained attentional performance and whether situational resource utilization influenced this relationship. Situational media multitasking had no significant influence on subsequent sustained attention relative to single media use. However, a significant relationship existed between greater perceived mental effort during situational media multitasking and poorer subsequent sustained attention. These results collectively motivate the need to further characterize the role of cognitive and perceptual resource utilization during media multitasking and its influence on sustained attention.

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Introduction

Sustained attention is the ability to focus on a task for a period of time. Sustained attention is a fundamental cognitive ability needed to effectively accomplish activities in daily life, such as work and school activities (Steinmayr et al., 2010), drive safely (Yanko & Spalek, 2013), and communicate effectively in social settings (Murphy et al., 2007). Sustained attention is considered a "cognitive gatekeeper" to other crucial cognitive abilities such as executive functioning, memory, and learning (Fortenbaugh et al., 2017). Sustained attention has even been found to be a critical factor in better understanding individual differences in psychiatric disorders such as post-traumatic stress disorder, mood disorders, and substance abuse (Esterman et al., 2019).

Researchers have developed tasks to assess sustained attention in a laboratory setting. Early measures of sustained attention were vigilance tasks that spanned minutes to hours with infrequent target presentation. This paradigm was utilized to better understand errors made by radar monitors in WWII, in which operators would encounter high-stakes rare events (Mackworth, 1948). While this approach may carry benefits of ecological validity to specific occupations, it comes with several caveats when quantifying sustained attention. The infrequent target presentation in this type of task limits the number of trials that include important behavioral data (e.g., accuracy and reaction time). Further, a vigilance task with an infrequent target presentation often induces a low cognitive load relative to continuous performance tasks (CPTs) with a high target presentation, which may limit the task's ability to characterize individual differences in performance (Robertson et al., 1997). Two novel CPT paradigms were

developed to address limitations with previous vigilance tasks: the Connors Continuous Performance task (CCPT) and the sustained attention to response task (SART).

During the CCPT, participants are instructed to respond when any letter (target) is presented on screen when the letter is anything but an "X" (non-target) with a 9:1 target-to-distractor ratio. The CCPT is divided into 18 blocks of 20 trials, in which each trial presents at varying intervals of 1, 2, and 4 seconds (Conners, 2000). Similarly, during the SART, participants are instructed to respond any time a number other than three is presented on the screen, with each digit between 1-9 carrying an equal probability for presentation, resulting in 11% of no-go trials and 89% of go trials (Robertson et al., 1997). Digits are presented with abrupt onset and offsets for 250 ms with a 900 ms mask in between trials. These modified CPTs are more difficult than previous iterations, notably by requiring the participant to withhold their prepotent motor response when infrequent no-go trials were presented (Conners, 2000; Robertson et al., 1997).

Studies utilizing the CCPT and SART have been instrumental in refining theories of sustained attention (Martínez-Pérez et al., 2023). However, researchers have proposed that these tasks have limitations. Specifically, abrupt onset and offsets in stimuli presentation included in the CCPT and SART may act as alerting cues, readily capturing bottom-up attention (Esterman et al., 2013; Fortenbaugh et al., 2017). This may lead to less reliance on top-down mechanisms vital for attentional maintenance, leading to less sensitivity in capturing individual differences in performance decrements as a function of time on task. It is also possible that the small breaks in between stimuli presentation allow the participant time to reorient their attention, reducing the overall sensitivity to detect individual differences in performance (Esterman et al., 2013;

Fortenbaugh et al., 2017). Finally, researchers have argued that speed-accuracy trade-offs, the strategic choice to prioritize either a quick or accurate response, heavily influence performance on the SART (J. S. Dang et al., 2018).

To address these potential shortcomings, Esterman et al. (2013) developed a gradual-onset continuous performance task (gradCPT) that removes abrupt onset and offsets when presenting each stimulus in favor of stimuli gradually fading into one another. The gradCPT maintains the 9 to 1 ratio of go/ no trials utilized in the SART but replaces the stimuli of digits in favor of greyscale cities and mountains. Several variations of the gradCPT have been utilized in previous literature, with versions lasting as short as 4 minutes (Fortenbaugh et al., 2015) to as long as 10 minutes (Madore et al., 2020; Rioja et al., 2023). During the original 8-minute version of the task, participants view a series of gray-scale scene images that gradually transition from one to the next using linear pixel-by-pixel interpolation (Esterman et al., 2013). The primary measure of the gradCPT is discrimination ability (*d*'), an accuracy measure of a participant's ability to distinguish targets from distractors (Esterman et al., 2013). Secondary measures include the coefficient of variation in reaction time (CV), commission errors (i.e., failures of inhibitory control when incorrectly responding to a mountain), and omission errors (i.e., failing to respond to a city scene) (Esterman et al., 2013).

The gradCPT has contributed considerably to how researchers measure sustained attention by utilizing normalized trial-to-trial variability in reaction time to create a variance time course (VTC). This VTC is sensitive to moment-to-moment fluctuations in sustained attention during the gradCPT. Using the VTC, researchers can characterize performance variability while the participant completes the task (Esterman et al., 2013). This approach has led to several

neuroimaging studies that demonstrate unique patterns of brain activity when participants are performing optimally compared to sub-optimally, defined by a median split in the VTC with stable performance considered "in-the-zone" and unstable performance considered "out-of-the-zone" (Esterman et al., 2013; Yamashita et al., 2021).

Models of Sustained Attention

Several theories explain individual differences in an individual's ability to sustain attention. Under the resource depletion model, an individual has a finite number of resources for sustained attention (Parasuraman et al., 1987). As a person performs a sustained attention task, their performance wanes as a function of time on task as their finite resources are consumed (i.e., vigilance decrements). Building on this research, additional theories account for fluctuations in sustained attention during tasks (i.e., while performance declines as a function of time of task, the decline is inconsistent). There are brief periods during sustained attention in which participants perform better later in a task and worse earlier. Further, previous work suggests that sustained attention can be influenced by situational motivation (Esterman et al., 2014), mind-wandering (Thomson et al., 2015), and boredom (Hunter & Eastwood, 2018).

To account for the role of subjective effort and task engagement in sustained attention, Kurzban et al. (2013) proposed the opportunity-cost model. The opportunity-cost model suggests that attentional resources are utilized for a given task, and the deployment of these attentional resources is influenced by intrinsic and extrinsic motivations rather than time on the task itself (Kurzban et al., 2013). The opportunity-cost model proposes that one deploys resources for sustaining attention based on the mental representation of costs and benefits associated with task performance, and subjective effort during task performance is the felt output of cost/benefit

computations (Kurzban et al., 2013). Greater subjective effort expended represents a shift in the preferred utilization of attentional resources. Instead of expending attentional resources on the primary task, resources shift towards the next best use of these resources. This reorganization of attentional resources results in a decline in acute performance on the primary task (Kurzban et al., 2013).

While the opportunity-cost model focuses on the role of subjective effort in the deployment of attentional resources, the resource-control model proposes that humans have a bias when allocating attentional resources to mind-wandering (Thomson et al., 2015). Specifically, the resource-control model argues that attention decrements increase as a function of time on task because of competition for attentional resources between task-relevant thoughts and mind-wandering. Specifically, attentional failures occur as more and more attentional resources are allocated towards mind-wandering beyond what is free and available. This misallocation of attentional resources to mind-wandering occurs because of failures of executive control, leading to resources needed for task performance consumed by mind-wandering (Thomson et al., 2015). The opportunity-cost model and resource-control theory have been instrumental in incorporating recent research that demonstrates several factors influencing sustained attention (Esterman & Rothlein, 2019; Kurzban et al., 2013; Thomson et al., 2015).

Media Multitasking and Attentional Outcomes

Models of sustained attention hypothesize a complex mix of motivation, effort, as well as cognitive and perceptual demands influence situational sustained attentional performance (Esterman & Rothlein, 2019; Kurzban et al., 2013; Thomson et al., 2015). Further, a body of research has established that individual differences in sustained attention are influenced by habits

in one's daily routine, like exercise (Hajar et al., 2019), diet (Shiraseb et al., 2016), and the practice of mindfulness (Gorman & Green, 2016). Another important habit that appears to influence one's sustained attention is media consumption (Rioja et al., 2023). American young adults spend about 6.5 hours daily consuming media, more than any other activity (Voorveld & Van Der Goot, 2013). When young adults consume media, they spend about a fourth of that time consuming media through multiple sources concurrently; this behavior is called media multitasking, MM (Moses, 2010; Voorveld & Van Der Goot, 2013). MM involves tasks such as browsing the internet while working, scrolling social media while watching a movie, or texting while talking. While multitasking is not a novel phenomenon, the fast proliferation of technology for media consumption in the past two decades has led to constant access to media, and increased opportunities to multitask throughout the day. Since MM is becoming increasingly ubiquitous in daily life, researchers have started to investigate whether this rapid shift in media behavior is associated with sustained attention.

Evidence across neuroimaging, cognitive assessment, and self-reported attention surveys paint a nuanced relationship between MM and sustained attention. For example, researchers have demonstrated that individuals who report a greater tendency to media multitask exhibit smaller gray matter density in the anterior cingulate cortex (Loh & Kanai, 2014) and weakened resting-state activity in the attentional networks (Zhang et al., 2024). This suggests individuals who report a greater tendency to media multitask exhibit less efficient and effective neural architecture for attentional processing compared to those who report a lower tendency to media multitask. Yet, a recent study utilizing electroencephalogram found that heavy media multitaskers exhibit neural patterns associated with increased attentional readiness and greater attention control during a response discrimination task (Zhang et al., 2025).

When examining the relationship between the tendency to media multitask and sustained attention in a meta-analysis of self-report and performance-based measures, Parry & Le Roux (2021) found a small, pooled effect size linking greater habitual MM to more self-reported attentional errors, ADHD symptoms, and mind-wandering across 26 studies. However, Parry & Le Roux (2021) found no relationship between the tendency to media multitask and performance-based measures of sustained attention, albeit across a sample of only four studies. This left the authors of the meta-analysis to declare that ten years after the first study on MM and cognition (Ophir et al., 2009), researchers are still far from fully understanding the relationship between MM and attention (Parry & Le Roux, 2021).

In another recent meta-analysis across 33 studies assessing the relationship between MM and attention, researchers found a greater tendency to habitually MM was significantly associated with poorer attention (Chen et al., 2025). Importantly, researchers found the only significant moderating variable across studies was measurement type (e.g., self-report questionnaires compared to objective performance-based assessments). Specifically, researchers found a medium effect size when assessing the relationship between a greater tendency to habitual MM and poorer self-reported attention, and a small effect size when assessing the relationship between a greater tendency to habitually MM and poorer performance on objective performance-based measures of attention (Chen et al., 2025).

Several studies have explored the relationship between MM and sustained attention utilizing a sensitive measure of performance, the gradCPT. First, Jun et al. (2019) conducted three smaller-scale experiments in which participants completed variations of the gradCPT that varied in target-to-distractor ratio, and they found no statistically significant relationship between MM and sustained attention using *A'*, the non-parametric equivalent to *d'*. Another study found

no difference in *d'* among heavy and light media multitasking junior high school students (Z. Li et al., 2024). In contrast, Madore et al. (2020) and Rioja et al. (2023) both found a greater tendency to media multitask was negatively associated with *d'* on the gradCPT. Rioja et al. (2023) was particularly compelling, replicating this finding across three online samples. These studies demonstrate greater support for a relationship between a greater tendency to media multitask and poorer sustained attention, with some ambiguity remaining.

Potential Mechanisms Linking Media Multitasking and Sustained Attention

While there is no consensus comprehensive theoretical framework outlining the relationship between MM and sustained attention, Baumgartner et al. (2017) proposed three possible overlapping mechanisms of action by which MM may negatively influence attention. First, it's possible that frequent MM over time leads to greater perceptual sensitivity to irrelevant information, leading to more fragmented and less sustained attention (Ophir et al., 2009). This scattered attention hypothesis proposes that exposure to concurrent media inputs over time is associated with changes in attentional processing, biasing a user's style of information processing toward "breadth-biased" processing of both relevant and irrelevant information across multiple inputs in one's environment (Ophir et al., 2009; Parry & Le Roux, 2021; Ralph et al., 2014). This "breadth-biased" processing may make it more difficult for an individual to intentionally attend and process a single information stream or stimuli due to unintentionally attending to irrelevant information thus consuming shared attentional resources (Salvucci & Taatgen, 2008).

Second, frequent MM may lead to a deterioration of mechanisms that allow for successful attentional control (Baumgartner, 2022; Baumgartner et al., 2017). Specifically, this deficit producing hypothesis argues that relying on external media stimulation to guide attention may impair one's internal ability to sustain attention (Ralph et al., 2014). Engaging with multiple

media streams concurrently may outsource control of attention to exogenous factors in one's environment, leading to the degradation of endogenous goal-oriented attentional control mechanisms (Ralph et al., 2014). The deficit-producing hypothesis is the natural complement to the scattered attention hypothesis, in which both argue that MM over time leads to a fundamental bias in attention, a shift away from top-down, goal-oriented attentional processes (Ralph et al., 2014) and a shift towards bottom-up, sensory-driven attentional processes (Ophir et al., 2009).

Third, it's possible that MM over time leads to a perceptual habituation to high level of arousals (Baumgartner et al., 2017; Beyens et al., 2018; Yeykelis et al., 2014; Zamanzadeh & Rice, 2021). Weighing the trade-offs between sustaining attention to a primary task and exploring alternative options is a natural consequence of the current media landscape and is not considered maladaptive according to the exploitation-exploration model of MM (Wiradhany et al., 2021). However, habituation to high levels of arousal may bias these evaluations, negatively influencing one's ability and motivation to attend to a single task in daily life that carries low arousal (Baumgartner et al., 2017; Yeykelis et al., 2014; Zamanzadeh & Rice, 2021). This may be particularly problematic for sustained attention, as individuals habituated to high levels of arousal may lack intrinsic motivation to sustain attention to a singular task for prolonged periods of time (Kurzban et al., 2013; Schutten et al., 2017). Instead of focusing on a consequential task, an individual who frequently media multitasks may be prone to mind-wander or shift their attention to task-unrelated distractions to meet situational cognitive and emotional gratification at the expense of longer term goal attainment (Baumgartner & Wiradhany, 2022; Kurzban et al., 2013; Wang et al., 2015).

Capturing the Relationship Between Media Multitasking and Sustained Attention

While all three mechanisms are plausible in linking MM to sustained attention, none of these mechanisms account for the specific characteristics and experiences within different MM pairs. Specifically, all studies that explore performance-based sustained attention and MM utilize variations of the Media Use Questionnaire, MUQ (Chen et al., 2025; Jun et al., 2019; Madore et al., 2020; Parry & Le Roux, 2021; Rioja et al., 2023). The original MUQ assesses media consumption and pairs across 12 different media inputs: printed media television, computer-based video, video games, music, non-music audio (such as podcasts), phone calls, instant messaging, text messaging, email, web surfing, and other computer-based activities (Ophir et al., 2009). More recent modified versions of the MUQ also include items related to media use during face-to-face conversions, social media use, non-music audio, and video chatting (Ralph et al., 2015). While completing the MUQ, participants provide both the total number of hours per week spent on the primary media and the frequency in which they concurrently use other media types along with the primary media during a typical media-consumption hour assessed on a four-point Likert scale with options that included "Never", "A little of the time", "Some of the time", and “Most of the time” (coded as 0, 0.33, 0.67, and 1). From responses on the MUQ, researchers create the media multitasking index (MMI) that represents the level of MM a participant engages in during a typical media-consumption hour (Ophir et al., 2009). The MMI is traditionally calculated as the weighted sum of all MM pairings, summarized in Figure 1 below.

Figure 1

Formula To Calculate Media Multitasking Index

$$\sum_{i=1}^{n_{pairs}} = \frac{m_i \times h_i}{h_{total}}$$

Note. n_{pairs} = the total number of media inputs assessed; m_i = the frequency of which a participant reports multitasking between two media inputs, h_i = the amount of time in hours a participant reports using the primary media stream per week, h_{total} = the total amount of time in hours a participant spends on all media.

The MMI is an aggregate measure that has received substantial criticism (Parry & Fisher, 2024). Researchers criticize the MMI for poor measurement validity, ignoring MM involving non-media activities, quality issues due to participant fatigue, and theoretical inconsistencies (Parry & Fisher, 2024). Regarding the theoretical inconsistencies, researchers reason that the MMI fails to capture MM in a manner consistent with theories that argue MM influences attention and cognitive abilities more broadly. The MMI is intended to measure the tendency for an individual to media multitask during a typical media hour, not overall MM. In practice, this means an individual who constantly engages with media but spends a small percentage of that time media multitasking may have a lower MMI score relative to individual who almost never engages with media, but engages with multiple devices during that time (Parry & Fisher, 2024). In addition, habitual MM is theorized to influence attention over time through mechanisms of conditioning and neuroplasticity in a dose-response relationship (i.e., greater habitual MM is associated with poorer attention) (Parry & Fisher, 2024). The MMI functionally does not capture this.

Another major limitation of the MMI is its inability to account for MM with specific pairs to have differential relationships with outcome measures (Parry & Fisher, 2024; Parry & Le Roux, 2021). Researchers have argued that MM is not a unidimensional behavior; it is instead a rich assortment of unique behaviors with unique antecedents (Zhou & Deng, 2023), motivations (Kononova & Chiang, 2015) and associations with cognition (Parry & Le Roux, 2021). Different

MM pairs vary considerably in demands and utilization of cognitive and perceptual resources (Baumgartner & Wiradhany, 2022). Watching television and scrolling social media requires different resource utilization relative to listening to music and writing a manuscript. Not only do specific media inputs carry unique situational demands, the interaction of two media inputs likely influence resource utilization in complex ways not captured by the MMI (Baumgartner & Wiradhany, 2022). Specifically, the MMI does not capture whether two media inputs require similar processing demands, which may cause interference and a vastly different information processing experience relative to engaging with two dissimilar media inputs (Baumgartner & Wiradhany, 2022). It's likely that failing to capture *how* individuals MM contributes to measurement error and may contribute to the mixed results in the literature.

The Role of Cognitive Dimensions in Capturing Cognitive and Perceptual Resource Utilization During Media Multitasking

Considering the limitations of using a singular value to represent a variety of unique behaviors, researchers have started to explore novel methods to quantify how individuals media multitask beyond the MMI (Baumgartner & Wiradhany, 2022; Wang et al., 2015; Zamanzadeh & Rice, 2021). Specifically, researchers have created MM measures that differentiate behaviors based on the utilization of cognitive and perceptual resources unique to specific MM pairs (Baumgartner & Wiradhany, 2022; Wang et al., 2015). Specifically, researchers argue that the degree to which MM influences or is influenced by attention does not vary in magnitude as a function of MM tendencies or even MM duration more broadly (Zamanzadeh & Rice, 2021). Instead, the relationship between MM and attention may vary as (1) a function of how cognitive and perceptual resources are utilized and deployed during MM, and (2) the frequency of MM in which cognitive and perceptual resources are utilized in an inefficient manner (Zamanzadeh &

Rice, 2021). This work is largely informed by theories of limited cognitive and perceptual resources pools for information processing (Kahneman, 1973; Lang, 2000; Salvucci & Taatgen, 2008; Wickens, 2002, 2020). Inefficiency and interference during MM are expected when media inputs carry a high demand and require utilization of shared cognitive and perceptual resources (Baumgartner & Wiradhany, 2022; Wang et al., 2015). Conversely, efficient MM may be accomplished if media inputs utilize dissimilar and diverse cognitive and perceptual resources (Baumgartner & Wiradhany, 2022; Wang et al., 2015).

Researchers have proposed that the frequency in which certain MM pairs are chosen can be predicted by this framework (Baumgartner & Wiradhany, 2022; Wang et al., 2015). Specifically, researchers argue that MM pairs in daily life are chosen in an adaptive way to conserve limited resources and avoid interference (Baumgartner & Wiradhany, 2022; Wang et al., 2015). Wang and colleagues (2015) proposed that MM behaviors vary across several cognitive dimensions based on the specific characteristics of the media pairs consumed. Using a large sample of survey-based data and a smaller sample utilizing experience sampling, Wang et al. (2015) found that participants were less likely to combine media types if both media types engaged a specific sensory modality across auditory, visual, or motor domains. Participants were also less likely to engage in MM pairs in which both media inputs were transient (i.e., the pace of the information flow was constant and continuous). Examples of more transient media inputs include gaming, watching videos, talking on the telephone, and listening to music or non-music audio. Conversely, participants were more likely to MM when at least one media source was static (i.e., the individual dictates the pace of information). Examples of more static media sources include reading books, using social media, instant messaging, and browsing the internet (Wang et al., 2015).

Participants were also less likely to combine MM pairs in which both media types required a behavioral response compared to pairs that required one or no behavioral response (Wang et al., 2015). Examples of media sources that likely require a behavioral response include talking on the telephone, messaging, using social media, gaming, and browsing the web. Examples of media sources that do not likely require a behavioral response are passive media sources, such as reading, watching videos, listening to music, or listening to non-music audio.

Baumgartner and Wiradhany (2022) argued the study conducted by Wang et al. (2015) was limited by a narrow characterization of MM for each dimension. For example, only four media inputs (web browsing, chatting, online video, and email) were considered in testing the effects of control over information flow and behavioral response requirements. Limiting the analysis to only a few MM inputs adds uncertainty. Specifically, it's unclear whether cognitive effort varies across shared characteristics within cognitive dimensions, as argued by Wang et al. (2015), or whether differences are unique to the specific MM pairs. To investigate this further, Baumgartner and Wiradhany (2022) reanalyzed 15 existing datasets that utilized the MUQ. This allowed them to test hypotheses with 36 to 144 unique media pairs based on the specific version of the MUQ used. Each author individually qualitatively coded media activities across each cognitive dimension, with additional input from two additional independent raters (Table 1).

Table 1

Overview of Coding For Individual Media Activities In Datasets (Baumgartner & Wiradhany, 2022)

	Dimensions and coding value						
Media	Likelihood visual modality (1 = high; 0 = low)	Likelihood auditory modality (1 = high; 0 = low)	Likelihood motor modality (1 = high; 0 = low)	Likelihood control over task switching (1 = high; 0 = low)	Level of information flow (1 = rather transient; 0 = rather static)	Likelihood requiring behavior response (1 = high; 0 = low)	Likelihood providing instant gratification (1 = high; 0 = low)
Reading	1	0	0	1	0	0	0
TV	1	1	0	1	1	0	1
Online video	1	1	0	1	1	0	1
Music	0	1	0	1	1	0	1
Nonmusic	0	1	0	1	1	0	0
Gaming	1	1	1	0	1	1	0
Phone calling	0	1	1	0	1	1	1
Instant messaging	1	0	1	1	0	1	1
SMS	1	0	1	1	0	1	1
E-mail	1	0	1	1	0	1	0
Browsing	1	0	1	1	0	1	1
Other computer activities	1	0	1	1	0	1	0
Social media	1	0	1	1	0	1	1

Across this sample, authors replicated the findings from Wang et al. (2015) that participants were less likely to combine MM inputs with shared sensory processing, communicated information transiently. Findings in the behavioral response dimension were mixed, in which participants were most likely to MM with pairs in which one behavioral response was required, but least likely to MM with pairs in which neither input required a behavioral response. Beyond these initial findings, they also demonstrated that media pairs in which switching between tasks was difficult for both media inputs (e.g., video games and phone conversations) were less likely to be selected for MM than pairs in which task switching was more accessible for one or both media inputs (Baumgartner & Wiradhany, 2022). Together, these studies demonstrated that the qualitative characteristics of media inputs predicted how likely participants would engage with specific MM pairs. Generally, individuals were less likely to combine media inputs with high demand and greater potential for interference (maladaptive MM) compared to media inputs with lower demand and less potential for interference, adaptive MM (Baumgartner & Wiradhany, 2022; Wang et al., 2015).

Are Specific Media Multitasking Pairs Associated with Attentional Outcomes?

Previous work has suggested that the cognitive and perceptual resource utilization during MM predicts which MM pairs individual are likely to choose (Baumgartner & Wiradhany, 2022; Wang et al., 2015). Yet, no study to date has explored whether the relationship between MM and sustained attention varies as a function of cognitive and perceptual resource utilization during MM. In fact, only one study has explored whether the relationship between MM and attention differs based on *how* an individual media multitasks (J. T. Fisher et al., 2023). Fisher et al. (2023) utilized a data-driven, network approach to explore whether specific MM pairings exhibited a significant link to self-reported ADHD symptom severity and attentional errors in daily life. They found that relative degree centrality (i.e., the importance of individual media inputs to the overall media input network after accounting for the size of the network) for music and mobile apps was positively associated with greater ADHD symptom severity. Interestingly, the relative degree of centrality for the non-music audio and print nodes was negatively associated with ADHD symptoms (J. T. Fisher et al., 2023). They speculated that easily accessible media inputs like listening to music may be utilized in those with more significant ADHD symptoms to alleviate under-stimulation (J. T. Fisher et al., 2023). Conversely, constant switching between tasks (as in the case of using mobile phone apps with other media) may acclimate users over time to overstimulation, potentially leading to greater severity of attention problems over time (J. T. Fisher et al., 2023). This study demonstrated relationships between unique media pairings and self-reported attention that would not be present when utilizing the composite MMI score. This finding suggests that certain MM pairs exhibit differential relationships with self-reported attentional difficulties depending on the unique characteristics of

the media inputs. Yet, it is unclear whether findings in J.T. Fisher et al. (2023) would extend to task-based measures of sustained attention.

How Does Situational Media Multitasking Influence Sustained Attention?

Despite 15 years of studies exploring the relationship between self-report habitual MM and attentional processing, very little work has been done to characterize situational MM and sustained attention (Parry & Le Roux, 2021). Habitual MM is often characterized using the MUQ, in which participants report media use and MM frequency during an average week (Ophir et al., 2009). Due to the retrospective nature of the MUQ, researchers are unable to assess temporal patterns between MM and sustained attention; the possibility that sustained attention fluctuates as a function of when and how individuals MM (Parry & Le Roux, 2021).

To date, no study has explored the potential acute carry-over effects of MM on subsequent sustained attentional performance. Although not focused on sustained attention, one study explored whether MM subsequently influences information processing during a controlled laboratory study in which MM was experimentally manipulated. More specifically, Kazakova et al. (2015) assessed whether situational MM subsequently influenced perceptual and conceptual processing styles relative to sequential media use. In study one, participants in the MM condition viewed a video simultaneously while scrolling through a website. In contrast, those in the sequential media condition first viewed a video and afterward scrolled a website. All participants subsequently completed a perceptual processing task. Kazakova et al. (2015) found that participants in the MM condition differed in their perceptual processing style relative to participants in the sequential media condition. Specifically, participants in the MM condition demonstrated a greater tendency for local processing relative to global processing compared to participants in the sequential media condition (Kazakova et al., 2015). This suggests that

situational MM leads a greater tendency to concentrate on individual elements during information processing, at the expense of processing the bigger picture.

In study two, Kazakova et al. (2015) aimed to explore whether situational MM influences subsequent conceptual processing style, specifically whether participants construe behaviors as concrete or abstract. For example, pushing a doorbell can be construed concretely as moving a finger or abstractly as seeing if someone is home. To account for visual switching, Kazakova et al. (2015) added a third condition in which participants media multitasked with two videos shown on each display. This meant that participants in the visual switching condition would switch between two identical video streams that contained two videos playing on each side of the screen, rather than separating each video across screen. This was done so participants in the visual switching conditions would still switch between screens, but the content of each screen would not differ conceptually. Following the media manipulation, participants completed a conceptual processing questionnaire in which they construed behaviors as abstract or concrete. Results indicated that participants in the MM condition construed behaviors more concretely than participants in the other two conditions (Kazakova et al., 2015). This suggests the narrowing of perceptual processing demonstrated in study one extends to narrowing of conceptual processing in study two, in which participants exhibited a bias to construe behaviors based on concrete details rather than the more abstract, high-level purpose of the behavior (Kazakova et al., 2015). Together, these studies suggest that situational MM may narrow an individual's perceptual and conceptual focus, which could impact sustained attention. This may enhance or degrade sustained attention based on the degree of narrowing. Too much narrowing may hinder an individual's ability to adapt to situational demands during sustained attention, while too little

narrowing may hinder one's ability to discriminate targets from distractors based on image characteristics (Brau et al., 2022; Rothlein et al., 2018).

While the implications of Kazakova et al. (2015) on situational MM and sustained attention remain unclear, there is substantial evidence that fluctuations in attentional ability and tendencies are influenced by multitasking and task switching habits (Leroy, 2009; Mark et al., 2015, 2016). Specifically, Leroy (2009) found that switching between unfinished tasks can lead to attentional residue, a carry-over effect in which cognitive resources are being dedicated to a previous unfinished task despite the intention to focus on a different task. Leroy (2009) tested this theory through a series of experiments in which participants were told they would complete two unrelated tasks. Task A was a word completion task in which participants guessed words based on clues. Task B was described as a resume assessment task in which participants would read resumes and subsequently evaluate their suitability for specific job descriptions (Leroy, 2009). In study one, researchers used a lexical decision-making task following a word completion task to quantify attentional residue. Specifically, researchers focused on the activation of task goals and content during the lexical decision-making task through certain key words presented in Task A. Activation of content was assessed using reaction time to words associated with five clues in Task A, identified in pre-testing as clues that stayed on participants' minds when Task A remained unfinished (Leroy, 2009). Researchers found that attentional residue was present when participants finished Task A under no perceived time pressure and when participants did not finish Task A regardless of time pressure (Leroy, 2009). In study two, researchers explore the influence of attentional residue on recall performance (Leroy, 2009). Similar to study one, Leroy (2009) found that attentional residue negatively influenced performance when participants did not finish that task or were under no perceived time pressure.

Together these studies demonstrated that attentional residue can negatively influence subsequent task performance, especially under conditions in which individuals perceive no time pressure during Task A or did not finish Task A (Leroy, 2009).

Similar to the effects of attentional residue, Snider et al. (2023) explored whether distractions while driving exhibited residual effects on performance once the distraction was ended. To accomplish this, Snider et al. (2023) had participants complete a divided attention task and car following task across two 30-minute simulated driving sessions. The first driving session included intermittent hands-free distraction through a phone call, while the second driving session included intermittent texting on a smartphone as a distraction (Snider et al., 2023). Researchers found individuals exhibited riskier simulated driving performance and were less able to correctly identify peripheral cues well after distractions were concluded (Snider et al., 2023). This study demonstrated that situational multitasking with technology can cause a "distraction hangover", in which the act of multitasking diminishes performance well after the distraction has ended (Snider et al., 2023).

While Leroy (2009) and Snider et al. (2013) demonstrated attentional residue and distraction hangover effects in experimental settings, Mark and colleagues (2015) explored the malleability of attentional states in an occupational setting. Specifically, researchers set out to characterize how attentional states during work influence an individual's vulnerability to distraction and subsequent productivity using heart rate sensors, computer activity logging, and questionnaires (Mark et al., 2015). Mark and colleagues (2015) found workers were drawn to different media inputs following bouts of work based on whether the work was engaging but not challenging (rote) or engaging and challenging (focused). Following rote work, participants were more likely to engage with social media or in-person conversations, while focused work was

often followed by email (Mark et al., 2015). These tendencies had important implications for productivity, as participants reported feeling less productive the more they engaged in conversations and email (Mark et al., 2015). Lower perceived productivity was also associated with more frequent screen switching (Mark et al., 2015).

Together, these studies suggest that how an individual deploys their attention for a given task may influence an individual's ability or motivation to sustain their attention to a subsequent task. Yet, no study to date has tested whether situational MM influences subsequent sustained attention.

Summary of Purpose

There are currently several unaddressed questions in literature linking MM and sustained attention. First, it's unclear if *how* an individual media multitasks predicts sustained attentional performance, rather than the tendency of an individual to MM reported in previous work using the MMI (Chen et al., 2025). More specifically, it's unclear if utilization of cognitive and perceptual resources during MM is associated with sustained attention. Based on the heterogeneous nature of media inputs included in self-report habitual MM questionnaires, it's possible that MM pairs that utilize cognitive and perceptual resources inefficiently (maladaptive MM) may be responsible for the negative relationship between MM and sustained attention in previous work. Conversely MM with pairs that utilize diverse and dissimilar resources in an efficient manner (adaptive MM) may have no relationship with sustained attention.

Second, it's unclear whether situational MM influences one's ability to sustain attention immediately after a period of MM. If the relationship between MM and sustained attention is influenced by resource utilization during MM, sustained attention may be influenced by acute

carry-over effects immediately after MM (Brand et al., 2022; Zamanzadeh & Rice, 2021). Situational MM may diminish attentional ability due to shared cognitive resources being utilized to process the previous task (Leroy, 2009). It's also possible that situational MM negatively affects subsequent sustained attention by influencing intrinsic motivation in the moment to sustain attention to a task by increasing the value of task-unrelated distractions (Kurzban et al., 2013). By allocating shared resources to off-task activities during sustained attention like mind-wandering, resources available for attentional processing may be further limited (Kurzban et al., 2013). Yet, no study has assessed whether situational MM influences subsequent sustained attention, or the potential for resource utilization during MM to play a role in this relationship.

Third, it's unclear whether subjective mental effort exerted during MM predicts sustained attention. Kurzban and colleagues (2013) argue that perceived mental effort represents the felt output of mental computations regarding the opportunity of engaging in a current activity or shifting one's attention to something else. If situational MM does subsequently influence one's intrinsic motivation to sustain attention to a task, perceived mental effort exerted during MM may be a strong predictor of subsequent performance. Specifically, higher perceived mental effort exerted during MM may diminish an individual's ability or willingness to subsequently sustain attention to a single task if acute carry-over effects are present. This may also offer individuals insight on the acute effects of MM on their own ability to sustain attention without being able to objectively quantify the efficiency of resource utilization during MM. In other words, an individual may be able to get an idea of the specific acute effects of MM on their personal ability to subsequently sustain attention by considering how they feel during MM.

In the following sections, I propose studies to further our understanding of the role of resource utilization during MM in its relationship with sustained attention (Study One) and the

potential influence of situational MM on subsequent sustained attention in an experimental paradigm (Study Two). In Study One, I utilized analytic and qualitative techniques inspired by previous work to create categories of maladaptive and adaptive MM pairs theorized to differ across cognitive dimensions of (1) sensory processing, (2) information flow, and (3) behavioral response. In Study Two, I designed a novel experimental paradigm in which participants were randomly assigned to either MM or engage with a single media input. Participants were then asked to rate their perceived mental effort exerted during media use, complete a task-based measure of sustained attention, and complete questionnaires about MM habits and perceptions of mental effort during MM. These studies stand to better characterize the mechanisms that underly the relationship between MM and sustained attention.

Study One: The Relationship Between Habitual Media Multitasking and Sustained Attention

Sustained attention, the ability to maintain focus on a task for a period, is a crucial ability in daily life that is critical for individuals to succeed in occupational and classroom settings (Steinmayr et al., 2010). Previous work has identified several factors that influence an individual's ability to sustain attention successfully, such as mental health (Esterman et al., 2019), time of day (Riley et al., 2017), and metabolic health (Wooten et al., 2019). Recent evidence also suggests that how an individual interacts with media may also be an essential predictor of sustained attention (Castelo et al., 2025; Rioja et al., 2023). Specifically, researchers propose greater media multitasking (MM); engaging in two media inputs simultaneously may be associated with poorer sustained attention, but the literature is mixed (Chen et al., 2025; Parry & Le Roux, 2021; Rioja et al., 2023).

As previously stated, a meta-analysis from 2021 found no significant relationship between MM and performance-based measures of sustained attention (Parry & Le Roux, 2021), while a more recent meta-analysis from 2025 found a weak but significant relationship between a greater tendency to media multitask and poorer sustained attention (Chen et al., 2025). One major difference between the meta-analyses was Chen et al. (2025) included studies that utilized a well validated measure of sustained attention, the gradCPT (Fortenbaugh et al., 2018; Jun et al., 2019), whereas Parry & Le Roux (2021) did not. The gradCPT utilizes gradually fading images to remove abrupt onset and offsets, addressing issues with speed-accuracy trade-offs in other tasks (Esterman et al., 2013). These characteristics of the gradCPT and a wealth of validation studies suggest that the gradCPT may be more sensitive to capturing individual differences in

sustained attention relative to other continuous performance tasks (Castelo et al., 2025; Esterman et al., 2013, 2014; Fortenbaugh et al., 2015, 2017, 2018).

Four studies have explored whether there is a cross-sectional relationship between a tendency to media multitask and gradCPT performance, with mixed results. Jun et al. (2019) conducted three experiments in which participants completed variations of the gradCPT along with self-report measures of media multitasking, mindful attentional awareness, and attentional errors in daily life. Their gradCPT variations manipulated target frequency within the task utilizing the original 9:1 target-to-distractor ratio in study one, a 1:1 ratio in study two, and a 1:9 ratio in study three. The outcome measure of interest for sustained attention across all studies was *A'*, a non-parametric equivalent to the standard measure of discrimination ability (*d'*). Across all variations of the gradCPT in their study, there was no significant relationship between sustained attention performance and the MMI (Jun et al., 2019).

Li et al. (2024) conducted a study to explore whether MM was associated with performance on the gradCPT among junior high school students. To accomplish this, researchers used the extreme group approach in which a group of 354 students completed the MUQ, but only 48 students participated in the study. Specifically, 24 students who exhibited the lowest MMI scores were retained and classified as light media multitaskers while 24 students who exhibited the highest MMI scores were retained and classified as heavy media multitaskers (Z. Li et al., 2024). Researchers found no difference in performance on the gradCPT across groups of heavy and light media multitaskers (Z. Li et al., 2024).

Next, Madore et al. (2020) explored the relationship between self-reported MM and performance on the gradCPT in eighty young adults. In this study, they utilized a variety of

multimodal methods, including the MMI, gradCPT, electroencephalography, pupillometry, memory tasks, and several self-report measures of attention, impulsivity, and memory in daily life (Madore et al., 2020). They found that a greater tendency to media multitask was associated with worse sustained attention. Specifically, participants who reported a greater tendency to media multitask exhibited a higher commission error rate and higher reaction time variability on the gradCPT. Further, they found that performance on the gradCPT mediated the relationship between heavy MM and memory performance (Madore et al., 2020). This suggests that MM is not only associated with sustained attention but that sustained attention may be an essential factor in the relationship between MM and other cognitive domains, such as memory (Madore et al., 2020).

Finally, the largest (n = 924) study to explore the relationship between MM and sustained attention utilized online samples across MTurk, Prolific, and university students (Rioja et al., 2023). In addition to using the MMI to characterize MM, these researchers created a novel frequency-based MUQ (F-MMI) which they used to measure the duration of MM rather than the number of media types used simultaneously in a typical media hour. The authors hypothesized that the F-MMI might address several limitations of the traditional MMI, specifically by measuring overall MM and removing outdated and irrelevant distinctions between certain media (e.g., online videos and TV) (Rioja et al., 2023). They found a greater tendency to media multitask was associated with poorer sustained attention. Specifically, higher MMI scores were associated with lower *d'* on the gradCPT with a medium effect size, while higher F-MMI scores were associated with lower *d'* with a small effect size. Similar findings were demonstrated when assessing differences in d' across light and heavy media multitaskers as defined by the MMI and the F-MMI.

Interestingly, after considering variability from different samples and the F-MMI, they found that the MMI explained an additional 6% of unexplained variance. After doing a series of analyses accounting for differences across samples and exploring the sensitivity of individual components of the MMI, they concluded that the way individuals use media, precisely how many media inputs individuals use simultaneously, was more predictive of sustained attention than how often someone engages in MM (Rioja et al., 2023). In other words, *how* individuals engaged in MM was more predictive of lapses in sustained attention than the total time spent MM.

The Role of Resource Utilization in the Relationship Between Media Multitasking and Sustained Attention

Researchers have proposed that several possible mechanisms of action in which MM may influence and be influenced by sustained attention. Specifically, researchers have proposed that habituation to high arousal levels (Baumgartner et al., 2017; Beyens et al., 2018; Yeykelis et al., 2014; Zamanzadeh & Rice, 2021), an inability to filter irrelevant information from relevant information (Ophir et al., 2009), and a degradation of top-down attentional control mechanisms (Baumgartner et al., 2017; Ralph et al., 2014) are plausible cognitive mechanisms linking MM and sustained attention. While these mechanisms are plausible, the evaluation of these mechanisms are thoroughly lacking due to methodological approaches in the field. Specifically, the majority of behavioral findings that support a relationship between MM and sustained attention utilize a composite measure of MM that ignores the inherent heterogeneity of MM as a behavior, the media multitasking index (MMI) (Parry & Le Roux, 2021). This approach treats dissimilar activities like listening to music and texting the same as watching online videos while playing video games in the context of MM. Further, this approach ignores the potentially meaningful influence of cognitive and perceptual resource utilization that varies across the

countless ways an individual can media multitask. Similar to predicting the likelihood of MM with specific pairs, resource utilization likely plays a key role in whether habitual MM is associated with sustained attention, and the relative strength of the relationship (Baumgartner & Wiradhany, 2022; Wang et al., 2015).

In order to better characterize the role of cognitive and perceptual resource utilization during MM, and the implications for its relationship with sustained attention, I relied on a qualitative media input coding structure demonstrated in previous work (Baumgartner & Wiradhany, 2022). Specifically, I relied on Baumgartner & Wiradhany's (2022) work that qualitatively coded MM pairs based on its likely cognitive and perceptual resource utilization across cognitive dimensions of sensory processing, information flow, and behavioral response. These cognitive dimensions are informed by the theories that propose that MM utilizes distinct cognitive and perceptual resource pools based on the specific characteristics and demands of media inputs (Basil, 1994; Salvucci & Taatgen, 2008; Wickens, 2002). When two media inputs both require similar utilization of resources, such as both requiring a motor response, this MM pair leads to interference and inefficient utilization of resources (Salvucci & Taatgen, 2008). Conversely, if media inputs require dissimilar and diverse resources, such as one input requiring only auditory resources and the second input requiring only motor and visual resources, then these pairs can be combined more efficiently and avoid interference.

Based on this, Baumgartner & Wiradhany (2022) proposed that cognitive and perceptual resource utilization during MM can vary as a function of (1) the likelihood of both media inputs engaging the same sensory modality (visual, auditory, motor), (2) the likelihood of both media inputs requiring a behavioral response, and (3) the likelihood of both media inputs transmitting information transiently (i.e., in a manner where the user cannot decide the pace of the

information flow) (Baumgartner & Wiradhany, 2022; Wang et al., 2015). Using this modified framework, I tested whether resource utilization during habitual MM was associated with sustained attention. To explore this, I characterized adaptive forms of MM that utilize cognitive and perceptual resources efficiently using an existing dataset from Rioja et al. (2023). I also characterized maladaptive forms of MM that utilized these resources inefficiently and potentially led to interference. I broadly hypothesized that a tendency to adaptively MM would not be associated with sustained attention, while a greater tendency to maladaptively MM would be associated with poorer sustained attention across the (1) sensory processing, (2) information flow, and (3) behavioral response dimensions.

Hypotheses

Hypothesis 1a. Sensory interference during MM is an important influence on the efficiency of cognitive and perceptual resource utilization (Baumgartner & Wiradhany, 2022; Hwang & Jeong, 2018). Specifically, researchers propose that multitasking costs increase and participants are less likely to MM when two media inputs occupy and compete for the same sensory resources across auditory, visual, and motor modalities (Baumgartner & Wiradhany, 2022; Hwang & Jeong, 2018). In line with these theories, I hypothesized that competition for shared sensory resources during MM would lead to interference and inefficiency. I predicted that a greater tendency to media multitask with two media inputs competing for the same sensory resources would be negatively associated with a measure of overall accuracy on the gradCPT, discrimination ability (*d'*). I further predicted that the tendency to media multitask with two media inputs that do not share a sensory response (adaptive MM) would not be associated with *d*' when included in the same model with MM inputs that share sensory resources.

Hypothesis 1b. Information flow is a critical determinant in learning efficacy (Biard et al., 2018; L. Li et al., 2022). When information is presented transiently (i.e., the learner does not control the pace of the information flow) or if information is presented too quickly, the demands on working memory may exceed capacity during learning (Biard et al., 2018; L. Li et al., 2022). I hypothesized that a greater tendency to media multitask with media inputs that both transmit information transiently, would require greater shared cognitive and perceptual resource utilization. I predicted that a greater tendency to media multitask with two transient media inputs would be negatively associated with *d'*. I further predicted that the tendency to media multitask with at least one static media input would not be associated with *d'* when included in the same model as MM with two transient inputs.

Hypothesis 1c. Media activities with behavioral responses required are theorized to be more cognitively demanding than passive media inputs (Baumgartner & Wiradhany, 2022; Hwang & Jeong, 2018). While one can readily ignore a passive media input when cognitive demand is too high, this is not the case with a media input that requires a behavioral response (Hwang & Jeong, 2018). I hypothesized that a greater tendency to media multitask with inputs that both require a behavioral response would utilize shared cognitive and perceptual resources, resulting in inefficiency and interference (Baumgartner & Wiradhany, 2022; Hwang & Jeong, 2018). I predicted that a greater tendency to media multitask with media inputs that both require a behavioral response would be negatively associated with *d'*. I further predicted that a greater tendency to media multitask with at least one media input that does not require a behavioral response would not be associated with *d'* when included in the same model as MM with two inputs requiring a behavioral response.

Methods

Participants

Rioja et al. (2023) conducted an online study using three data collection platforms: (1) Amazon Mechanical Turk (www.mturk.com), Prolific (Prolific sample, www.prolific.co), and (3) remote testing within the student pool of the University of Amsterdam. Studies were approved by the University of Amsterdam ethics board. The entire study lasted an estimated 25-30 minutes, and participants were compensated as follows: (1) $3.25 for MTurk, £3.80 for Prolific, and course credit for the student sample. Within the MTurk sample, 409 participants were initially recruited based on the following qualifications: (1) Human Intelligence Task Approval Rate greater than or equal to 99, (2) Number of HITs Approved greater than 1000, (3) an age range 18-35 years old. Within the Prolific sample, 302 participants were initially recruited based on the following qualifications: (1) Approval Rate greater than or equal to 95 and (2) an age range between 18 and 35 years old. Within the student sample, 299 undergraduate psychology or communication science students between 18-30 years old were initially enrolled.

Measures

Adapted Media Use Questionnaire (A-MUQ). This study utilized the version of the MUQ used in Madore et al. (2020), which was based on the original MUQ utilized in Ophir et al. (2009), but with several changes to modernize and truncate the survey. Specifically, the number of media inputs was reduced from twelve to nine to include (1) reading, (2) watching videos, TV, and movies, (3) listening to music, radio audiobooks, and podcasts, (4) playing video games, (5) browsing the internet, (6) texting, using social media, or instant messaging, (7) talking on the phone or video chatting, (8) other computer activities; (9) performing work or studying (Rioja et al., 2023). Wording about specific media was also modified. Redundant items were removed (i.e., after probing about media *i* and *j*, the questions about media *j* and *i* were removed.

Participants provided both the total number of hours per week spent on the primary media and the frequency in which they concurrently use other media types along with the primary media during a typical media-consumption hour assessed on a four-point Likert scale with options that included "Never", "A little of the time", "Some of the time", and “Most of the time” (coded as 0, 0.33, 0.67, and 1).

Gradual Onset Continuous Performance Task (gradCPT). The gradCPT is a go/no-go continuous performance task designed to measure sustained attentional control (Esterman et al, 2013). During the 10-minute version of the task utilized by Rioja et al. (2023), participants viewed a series of gray-scale scene images that gradually transition from one to the next sequentially at a rate of one picture every 1.2 seconds (with a 0.6 second shared between picture n fading out and picture n + 1 fading in) using linear pixel-by-pixel interpolation. The gradCPT required participants to respond via button press to frequently occurring city images (90%) and withhold responses to rare mountain images (10%). In addition to the gradual and overlapping nature of the task, the rapid tempo encouraged a consistent reaction time. The primary measure of sustained attention ability on the gradCPT is discrimination ability (*d'*), a measure that applies signal detection analyses to quantify the ability to discriminate between targets/non-targets independent of response strategy (Esterman et al., 2013, 2019; Fortenbaugh et al., 2015).

Demographics and Additional Measures. Participants provided demographic responses for age and gender. Several additional measures were collected in Rioja et al. (2023) but are not used in the current study. These measures include a novel frequency-based Media Multitasking Use Questionnaire (F-MUQ), demographics such as educational attainment and sex, as well as self-report measures of attentional problems, motor impulsiveness, and sensation seeking (see Rioja et al. (2023) for more details).

Procedure in Rioja et al. (2023). After reading a short description of the study, participants were redirected to Qualtrics, where they were asked to provide informed consent. Task and survey order was as follows: (1) demographic questions; (2) A-MUQ or F-MUQ based on randomized assignment; (3) GradCPT; (4) three self-report questionnaires and one of A-MUQ or F-MUQ based on which version was completed in step 2. Data for Rioja et al. (2023) was processed, analyzed, and visualized in R (v3.6.1; R Core Team, 2019). A detailed list of all R packages used in the original study can be found in Rioja et al. (2023).

Statistical Methods

Development of Maladaptive and Adaptive Media Multitasking Measures. The relationship between MM and sustained attention may vary across three cognitive dimensions: (1) sensory processing, (2) information flow, and (3) behavioral response. To measure MM across these cognitive dimensions, I used a modified version of the MMI equation utilized in Fisher et al. (2023) to create weighted MM frequency measures for individual MM pairs, as outlined in Figure 2 below.

Figure 2

The Equation For Calculating Weighted Frequency Measures Of Individual Media Multitasking Pairs (J. T. Fisher et al., 2023)

$$MM_{ij} = \frac{(m_{ij} \times h_i) + (m_{ij} \times h_j)}{h_{total}}$$

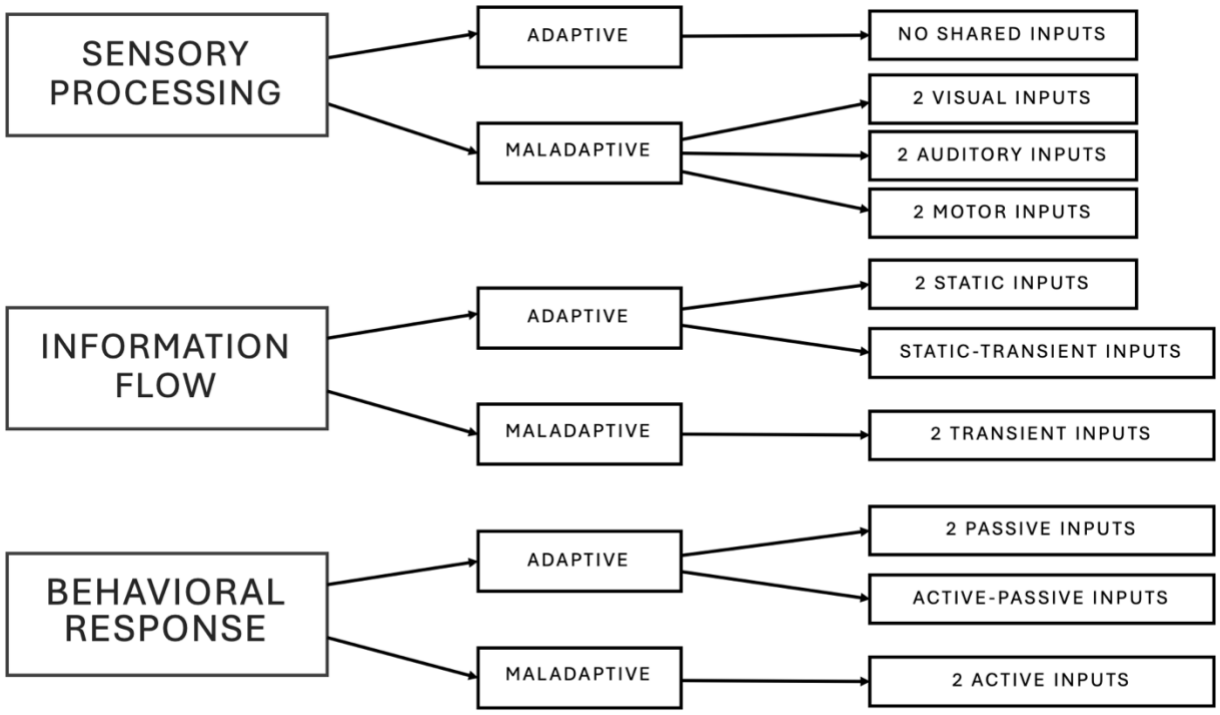
Note. MM_{ij} = weighted frequency of two specific media inputs; m_{ij} = the frequency that a participant reports multitasking between the media task i and media task j; h_i= the total number of hours a participant reports using media task i during a typical week; h_j= the total number of hours a participant reports to use media task j during a typical week; h_{total} = the total number of hours a participant reports to use media in a given week across all media inputs. In this example,

I used an adapted version of the MUQ in which redundant MM pairs have been removed (e.g., after reporting the frequency of MM for video and music, participants do not have to report the frequency of MM for music and video).

After calculating weighted frequency measures for each MM pair within the MUQ, I computed the means of all weighted frequencies across specific cognitive dimensions based on an abbreviated categorization from Baumgartner and Wiradhany (2022). MM pairs were classified as maladaptive if both media inputs were likely to interfere with each other and carry a high cognitive or perceptual demand during MM. Specifically, MM measures were classified as maladaptive if they both (1) required shared sensory processing (e.g., visual, auditory, or motor), (2) transmitted information transiently, or (3) required a behavioral response. MM pairs were classified as adaptive if either media input did not (1) require shared sensory processing (e.g., visual, auditory, or motor), (2) transmit information transiently, or (3) require a behavioral response (Figure 3).

Figure 3

Proposed Adaptive and Maladaptive Media Multitasking Classifications Across Cognitive Dimensions



For example, to calculate the maladaptive MM measure for sensory processing (Figure 4), I first calculated individual weighted frequency measures of each MM pair, where this would occur based on coding in Table 1 (Baumgartner & Wiradhany, 2022). After calculating a MM measure that only included weighted frequency measures of MM that do not share sensory processing in Figure 4, I then used the sample approach to create MM measures that represent MM pairs that do not share sensory processing in a specific modality across visual, auditory, or motor senses. Due to telephone and videochatting being combined as one measure in Rioja et al. (2023)'s A-MUQ, I did not include the MM pair of telephone/video when combined with print

media for the dimension of sensory processing, as this was the only MM pair where the uncertainty of engaging the visual modality was meaningful for the sensory processing classification of adaptive vs. maladaptive.

Figure 4

The Equation for Calculating the Adaptive Media Multitasking Measure for Sensory Processing

$$MM_{S-adaptive} = \Sigma(MM_{S\text{-}adaptive\ pairs}) / n$$

$$MM_{S-adaptive} = \Sigma(MM_{read\text{-}music}, MM_{work\text{-}music}, MM_{web\text{-}music}, MM_{text\text{-}music}, MM_{other\text{-}music}) / 5$$

Note. $\sum$ = Sum notation, $MM_{s\text{-}adaptive}$ = media multitasking with inputs that do not share sensory processing, n = number of media pairs that qualify as adaptive for the sensory processing dimension

Data Exclusions. For the two online samples, an open-ended question was asked immediately after gradCPT completion, "What were the instructions for the task?". This question filtered out probable bots, which identified 29 for MTurk and none for Prolific. In addition, participants across the three samples were excluded if (1) they were outside the age range of 18-35 years old (3 for MTurk, 0 for Prolific and student samples), (2) displayed the same participant ID (26 for MTurk, 0 for Prolific and student samples), (3) did not reach the last trial of the gradCPT (6 for MTurk, 3 for Prolific, 2 for Student), or (4) reported inconsistent answers across the A-MUQ and F-MUQ (3 for MTurk, 0 for prolific, 1 for Student).

In addition to the exclusion criteria described in Rioja et al. (2023), I further excluded data for individuals who demonstrated task non-compliance, (i.e., participants who took greater than 12-minutes to complete the 10-minute task, or participants who were greater than -2 standard

deviations below the mean for the outcome measure of *d'*). An individual taking 12 minutes to complete the task indicates they likely failed to respond for a significant amount of time, which causes the task to pause in the version used in Rioja et al. (2023). In most variations of the gradCPT, individuals who fail to respond for 10 seconds or greater are excluded from analysis (Fortenbaugh et al., 2017). These additional exclusion criteria were included to minimize differences between the version of the gradCPT used in Rioja et al. (2023) and previous work that utilized a more stringent exclusion criterion (Fortenbaugh et al., 2015). This resulted in a total sample of n = 885, excluding n = 13 for non-responsiveness and an additional n = 26 for 2 SDs below the mean from the original n = 924 participants.

Data Analysis. To assess whether cognitive, motor, and perceptual resource utilization during MM plays a role in the relationship between MM and sustained attention, I conducted sequential regressions for the dimensions of sensory processing, information flow, and behavioral response (utilizing Bonferroni multiple comparisons correction to adjust the p-value for significance from $p < .05$ to $p < 0.0167$). The dependent variable in Study One was the primary accuracy-based measure of performance on the gradCPT, discrimination ability (*d'*).

Sequential linear regressions in Study One included three steps. The first step included demographic predictors previously found to be influential in MM and *d'*, specifically age and gender (Kononova & Chiang, 2015; Voorveld & Van Der Goot, 2013). In step two, I added the weighted MM measure for the specific MM pairs theorized to be adaptive as the independent variable. In step 3, I added in the weighted MM measure for the specific MM pairs theorized to be maladaptive.

Comparing steps one and two informed whether adaptive MM predicts sustained attention after accounting for demographic characteristics. Comparing steps two and three informed

whether maladaptive MM predicts sustained attention and, if so, to what degree after accounting for adaptive MM and demographic characteristics. I hypothesized that in final step of the model, greater maladaptive MM would be negatively associated with *d'* but adaptive MM would not be related to *d*' for all three cognitive dimensions.

Data was assessed for normality using visual inspection of distribution and QQ plots. Multicollinearity was assessed by reporting the variance inflation factor between adaptive and maladaptive MM variables for each regression model. All regression models reported R^2, F-statistics, and p-values across steps one, two, and three. Changes in R^2, F-statistics, and p-values were reported for comparisons across models one and two and models two and three to assess the relative change in variance accounted for *d'* across each step for each model. Regression coefficients, standard error for regression coefficients, standardized regression coefficients, and p-values were reported for all independent variables across models.

Results

Data Screening

Preliminary analyses were completed to assess the distribution of the continuous outcome variables and identify outliers. First, I assessed descriptive statistics for the outcome variable discrimination ability (*d'*). Next, I tested if the data were sampled from a normal distribution by examining histograms, Q-Q plots, and skewness and kurtosis values (Field et al., 2012) Histograms and Q-Q plots revealed that the dependent variable *d'* followed a normal distribution. Further, predictors for adaptive MM measures across shared sensory (S-adaptive MM), information flow (IF-adaptive MM), and behavioral response (BR-adaptive MM) dimensions exhibited a relatively normal distribution with a moderate right skew. Maladaptive sensory MM

(S-maladaptive MM) and maladaptive behavioral response MM (BR-maladaptive) also exhibited a relatively normal distribution with a moderate right skew, while maladaptive information flow MM (IF-maladaptive MM) exhibited a significant right skew.

Bivariate relationships between the predictors and *d'* were explored through an ocular assessment of the scatter plots along with statistical assessments using Pearson correlations for predictors with a normal distribution and Spearman correlations for predictors with a significantly skewed distribution. Scatterplots and correlations revealed no significant relationship between *d'* and adaptive sensory MM (S-adaptive MM) ($r(883) = .001$, $p = .969$). Scatterplots and correlations revealed significant negative relationships between *d'* and the following: S-maladaptive MM ($r(883) = -.202$, $p < .001$), IF-adaptive MM ($r(883) = -.169$, $p < .001$), IF-maladaptive MM ($rho(883) = -.113$, $p < .001$), BR-adaptive MM ($r(883) = -.153$, $p < .001$), and BR-maladaptive MM ($r(883) = -.169$, $p < .001$). Based on data screening, as well as evaluation of univariate and bivariate relationships between the predictors and outcomes, no participants were excluded in the subsequent analyses.

Sequential Multiple Linear Regression Models

Shared Sensory Processing Dimension. Shared sensory processing regression results are summarized in Table 2 and visualized in Figure 5. For this regression model predicting *d',* I entered age and gender into the first step of the model. In this step, age ($\beta = 0.044$, $p = .198$) and gender (male relative to female, $\beta = 0.124$, $p = .071$, non-binary relative to female, $\beta = 0.435$, $p = .121$), did not account for a significant amount of variance in *d'* ($R^2 = 0.009$, $F(3, 881) = 2.543$, $p = .055$). S-adaptive MM was added in the second step of the model. In this step, S-adaptive MM ($\beta = 0.013$, $p = .701$) did not account for a statistically significant amount of variance in *d'* ($R^2 = 0.009$, $F(4, 880) = 1.943$, $p = .101$) and explained 0.0% of the unique variance in *d'* after

accounting for age and gender ($F(1, 880) = 0.148$, $p = .701$). S-maladaptive MM was added in the third step of the model. In this step, S-maladaptive MM ($\beta = -0.217$, $p < .001$) accounted for a statistically significant amount of variance in *d'* ($R^2 = 0.053$, $F(5, 879) = 9.839$, $p < .001$) and explained 4.4% of the unique variance in *d'* after accounting for age, gender and S-adaptive MM ($F(1, 879) = 41.073$, $p < .001$).

Table 2

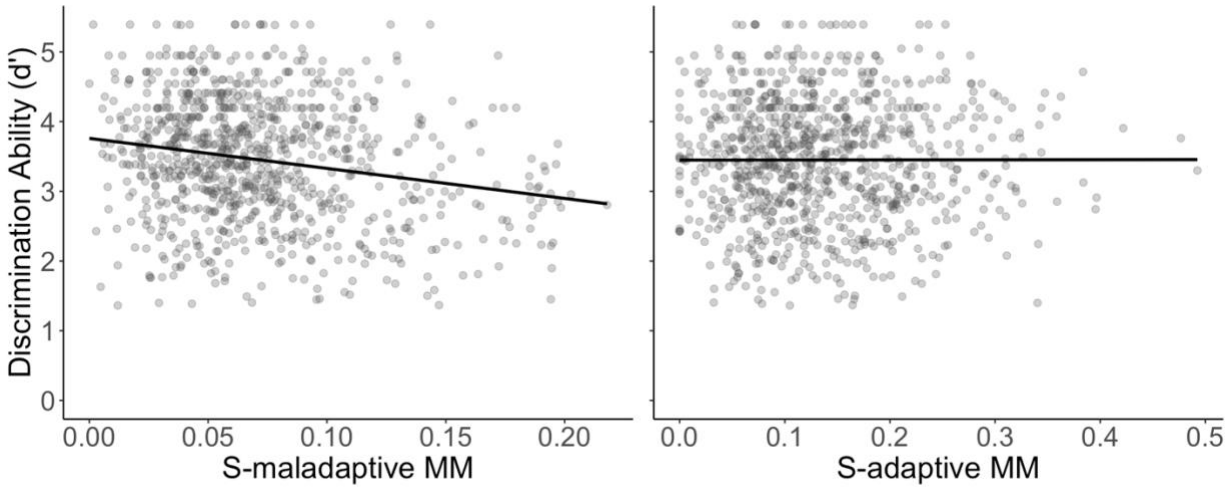
Regression Summary Table for the Sensory Modality

	Model 1			Model 2			Model 3		
Variable	*B*	*SE(B)*	β	*B*	*SE(B)*	β	*B*	*SE(B)*	β
Age	0.010	0.008	0.044	0.011	0.008	0.046	0.013	0.008	0.054
Gender (Male)	0.108	0.060	0.124	0.109	0.060	0.125	0.125	0.059	0.143
Gender (Non-binary)	0.379	0.244	0.435	0.382	0.245	0.438	0.256	0.240	0.294
S-adaptive MM				0.143	0.372	0.013	0.698	0.374	0.064
S-maladaptive MM							-4.629	0.722	-0.217**
R^2		0.009			0.009			0.053	
F for change in R^2					0.148			41.073**	

Note. *p < .0167, **p < .001. B = effect size, SE(B) = standard error for effect size, β = standardized effect size, S-adaptive MM = media multitasking pairs that do not share sensory processing, S-maladaptive MM = media multitasking pairs that share sensory processing. Gender was coded as 0 = Female, 1 = Male, 2 = Other, with female as the reference group.

Figure 5

Maladaptive vs. Adaptive Sensory Media Multitasking and Discrimination Ability (d')



Note. S-adaptive MM = the tendency to media multitask with pairs that do not share sensory processing, S-maladaptive MM = the tendency to media multitask with pairs that share sensory processing.

Information Flow Dimension. Information flow regression results are summarized in Table 3 and visualized in Figure 6. For this regression model predicting *d',* I entered age and gender into the first step of the model. In this step, age (β = 0.044, p = .198) and gender (male relative to female, β = 0.124, p = .071, non-binary relative to female, β = 0.435, p = .121), did not account for a significant amount of variance in *d'* (R^2 = 0.009, $F(3, 881) = 2.543$, p = .055). IF-adaptive MM was added in the second step of the model. In this step, IF-adaptive MM (β = -0.162, p < .001) accounted for a statistically significant amount of variance in *d'* (R^2 = 0.034, $F(4, 880) = 7.841$, p < .001) and explained 2.6% of the unique variance in *d'* after accounting for age and gender ($F(1, 880) = 23.538$, p < .001). IF-maladaptive MM was added in the third step of the model. In this step, IF-maladaptive MM (β = -0.112, p = .002) accounted for a statistically significant amount of variance in *d'* (R^2 = 0.045, $F(5, 879) = 8.236$, p < .001) and explained

1.0% of the unique variance in *d'* after accounting for age, gender and IF-adaptive MM ($F(1, 879) = 9.516$, $p = .002$).

Table 3

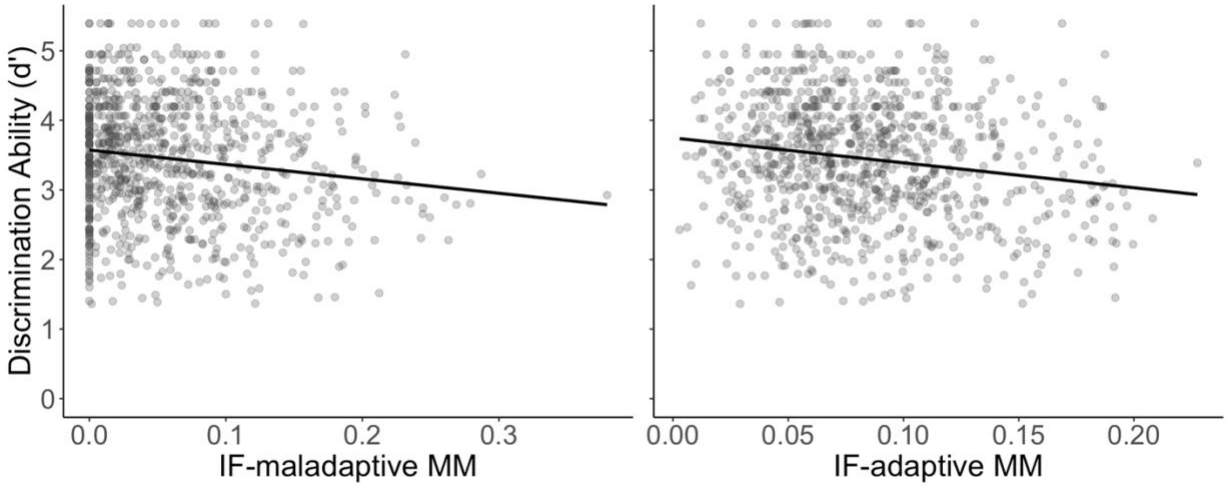
Regression Summary Table for the Information Flow Dimension

	Model 1			Model 2			Model 3		
Variable	*B*	*SE(B)*	β	*B*	*SE(B)*	β	*B*	*SE(B)*	β
Age	0.010	0.008	0.044	0.009	0.008	0.037	0.009	0.008	0.038
Gender (Male)	0.108	0.060	0.124	0.098	0.060	0.112	0.141	0.061	0.162
Gender (Non-binary)	0.379	0.244	0.435	0.268	0.242	0.308	0.286	0.241	0.328
IF-adaptive MM				-3.435	0.708	-0.162**	-2.540	0.762	-0.120**
IF-maladaptive MM							-1.671	0.542	-0.112*
R^2		0.009			0.034			0.045	
F for change in R^2					23.538**			9.516*	

Note. *p < .0167, **p < .001. B = effect size, SE(B) = standard error for effect size, β = standardized effect size, IF-adaptive MM = the tendency to media multitask with that contain at least one static media input, IF-maladaptive MM = the tendency to media multitask with two transient media inputs. Gender was coded as 0 = Female, 1 = Male, 2 = Other, with female as the reference group.

Figure 6

Maladaptive vs. Adaptive Information Flow Media Multitasking and Discrimination Ability (d')



Note. IF-adaptive MM = the tendency to media multitask with that contain at least one static media input, IF-maladaptive MM = the tendency to media multitask with two transient media inputs.

Behavioral Response Requirement Dimension. Behavioral response regression results are summarized in Table 4 and visualized in Figure 7. For this regression model predicting *d',* I entered age and gender into the first step of the model. In this step, age (β = 0.044, p = .198) and gender (male relative to female, β = 0.124, p = .071, non-binary relative to female, β = 0.435, p = .121), did not account for a significant amount of variance in *d'* (R^2 = 0.009, F(3, 881) = 2.543, p = .055). BR-adaptive MM was added in the second step of the model. In this step, BR-adaptive MM (β = -0.148, p < .001) accounted for a statistically significant amount of variance in *d'* (R^2 = 0.030, F(4, 880) = 6.863, p < .001) and explained 2.2% of the unique variance in *d'* after accounting for age and gender (F(1, 880) = 19.662, p < .001). BR-maladaptive MM was added in the third step of the model. In this step, BR-maladaptive MM (β = -0.126, p = .001) accounted for a statistically significant amount of variance in *d'* (R^2 = 0.042, F(5, 879) = 7.680, p < .001) and explained 1.2% of the unique variance in *d'* after accounting for age, gender and BR-adaptive MM (F(1, 879) = 10.646, p = .001).

Table 4

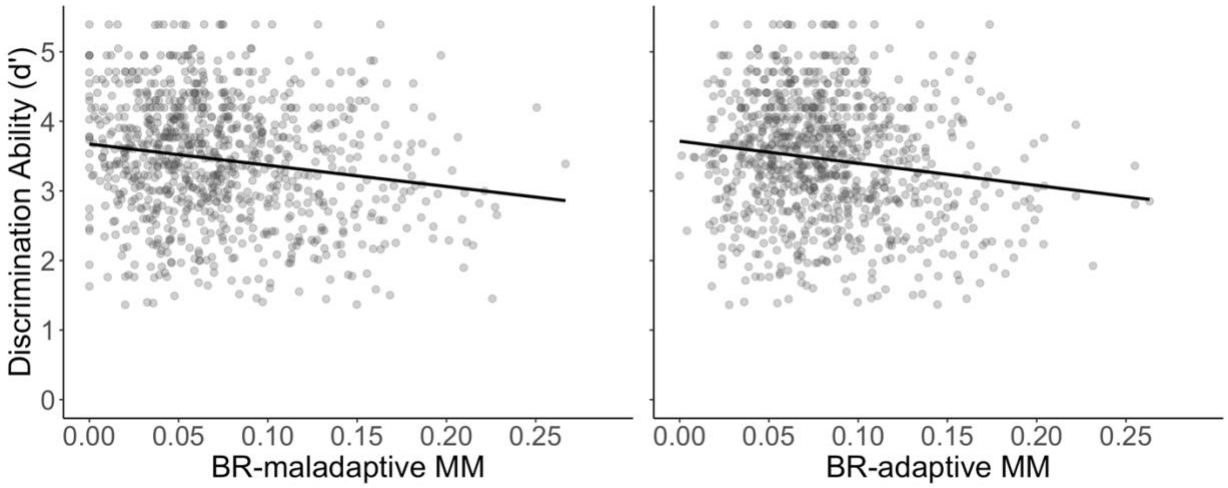
Regression Summary Table for the Behavioral Response Dimension

	Model 1			Model 2			Model 3		
Variable	*B*	*SE(B)*	β	*B*	*SE(B)*	β	*B*	*SE(B)*	β
Age	0.010	0.008	0.044	0.009	0.008	0.041	0.008	0.008	0.037
Gender (Male)	0.108	0.060	0.124	0.104	0.059	0.119	0.119	0.059	0.136
Gender (Non-binary)	0.379	0.244	0.435	0.291	0.243	0.335	0.268	0.241	0.308
BR-adaptive MM				-3.072	0.693	-0.148**	-1.724	0.803	-0.083
BR-maladaptive MM							-2.282	0.699	-0.126*
R^2		0.009			0.030			0.042	
F for change in R^2					19.662**			10.646*	

Note. *p < .0167, **p <.001. B = effect size, SE(B) = standard error for effect size, β = standardized effect size, BR-adaptive MM = the tendency to media multitask with pairs that require no more than one behavioral response, BR-maladaptive MM = the tendency to media multitask with pairs that requires two behavioral responses. Gender was coded as 0 = Female, 1 = Male, 2 = Other, with female as the reference group.

Figure 7

Maladaptive vs. Adaptive Behavioral Response Media Multitasking and Discrimination Ability (d')



Note. BR-adaptive MM = the tendency to media multitask with pairs that require no more than one behavioral response. BR-maladaptive MM = the tendency to media multitask with pairs that requires two behavioral responses.

Post Analysis Screening

Post analysis screening was conducted to test the assumptions of normality and homoscedasticity of residuals, assess potential collinearity of the predictor variables, and identify any influential cases (Field et al., 2012). Measures of collinearity suggested the relationships between predictor variables were not problematic, as tolerance values were high (>0.1) and variance inflation factors (VIF) were low (<10). The standardized residuals were plotted and appeared to be normally distributed. The assumption of homoscedasticity of residuals was met for the predictor variables across the three regression models. The residuals appeared to be uniformly distributed across the range of predicted values. Cook's distance was employed to assess the influence of individual data points on the regression model (Field et al., 2012). No individual data points were above the threshold of 1 (Field et al., 2012). Overall, the results are

unlikely to have been influenced in a meaningful way by collinearity, heteroscedasticity, failed assumptions of normality, or influential cases.

Exploratory Post-Hoc Analysis

Regression results suggested that while hypothesized maladaptive MM across all cognitive dimensions (sensory processing, information flow, and behavioral response) were negatively associated with *d'*, hypothesized adaptive MM for the information flow and behavioral response dimensions were also negatively associated with *d'* before correction for multiple comparisons. The relationship between adaptive MM and *d'* in the information flow dimension was also significant after correction for multiple comparisons. Hypothesized adaptive MM for both information flow and behavioral response dimensions involved combining different MM pairs that may in fact be differentially associated with *d'*. Specifically, I originally classified static-static MM and transient-static MM pairs as adaptive, and transient-transient MM as maladaptive, for the information flow dimension because transient media inputs were hypothesized to carry a higher cognitive, perceptual and motor demand relative to static input sources. Similarly, passive-passive MM and response-passive MM pairs were classified as adaptive, and response-response MM as maladaptive, for the behavioral response dimension because inputs that require a behavioral response carried a higher cognitive, perceptual and motor demand than passive input sources.

As an exploratory endeavor, I repeated regressions predicting *d'* with age, gender and MM measures representing the specific characteristics of the inputs for the information flow and behavioral response dimensions. Specifically, the measures for information flow were transient-transient (TT), transient-static (TS), and static-static (SS) MM. The measures for behavioral response were response-response (RR), response-passive (RP), and passive-passive (PP) with

response indicating a required behavioral response and passive indicating no required behavioral response. I utilized Bonferroni correction for multiple comparisons (Bland & Altman, 1995) to account for the risk of false-positive findings for the addition of two exploratory analyses ($p_{adj} <$ .01).

Post-Hoc Data Screening

Preliminary post-hoc analyses were completed to assess the distribution of the continuous outcome variables and identify outliers. First, I assessed descriptive statistics for the outcome variable discrimination ability (*d'*). Next, I tested if the data sampled from a normal distribution by examining histograms, Q-Q plots, and skewness and kurtosis values. Histograms and Q-Q plots revealed that the dependent variable *d'* followed a normal distribution. Post-hoc predictors for transient-static (TS) MM exhibited a normal distribution. Static-static (SS) MM, response-passive (RP) MM, and response-response (RR) MM predictors exhibited a relatively normal distribution with a moderate right skew. Transient-transient (TT) MM and passive-passive (PP) MM predictors exhibited a significant right skew and did not exhibit a normal distribution.

I explored bivariate relationships between the predictors and *d'* through an ocular assessment of the scatter plots along with statistical assessments using Pearson correlations for predictors with a normal or relatively normal distribution and Spearman correlations for predictors with a skewed distribution. Scatterplots and correlations revealed a significant relationship between *d'* and the following: TT MM ($rho(883) = -.113$, $p < .001$), TS MM ($r(883) = -.149$, $p < .001$), SS MM ($r(883) = -.158$, $p < .001$), RR MM ($r(883) = -.169$, $p < .001$), RP MM ($r(883) = -.130$, $p < .001$), and PP MM ($rho(883) = -.171$, $p < .001$). Based on data screening, as well as evaluation of univariate and bivariate relationships between the predictors and outcomes, I did not exclude any participants in the subsequent analyses.

Post-hoc Sequential Multiple Linear Regression Models

Post-hoc Information Flow Dimension. Post-hoc information flow regression results are summarized in Table 5 and visualized in Figure 8. For this regression model predicting *d',* I entered age and gender into the first step of the model. In this step, age (β = 0.044, p = .198) and gender (male relative to female, β = 0.124, p = .071, non-binary relative to female, β = 0.435, p = .121), did not account for a significant amount of variance in *d'* (R^2 = 0.009, $F(3, 881) = 2.543$, p = .055). SS and TS MM were added in the second step of the model. In this step, SS MM (β= -0.107, p =.013) and TS MM (β= -0.074, p = .085) accounted for a statistically significant amount of variance in *d'* (R^2 = 0.035, $F(5, 879) = 6.401$, $p < .001$). SS MM and TS MM explained 2.7% of the unique variance in *d'* after accounting for age and gender ($F(2, 879) = 12.093$, $p < .001$). TT MM was added in the third step of the model. In this step, TT MM (β = -0.175, $p < .001$) accounted for a statistically significant amount of variance in *d'* (R^2 = 0.053, $F(6, 878) = 8.253$, $p < .001$) and explained 1.8% of the unique variance in *d'* after accounting for age, gender, SS MM, and TS MM ($F(1, 878) = 16.931$, $p < .001$).

Table 5

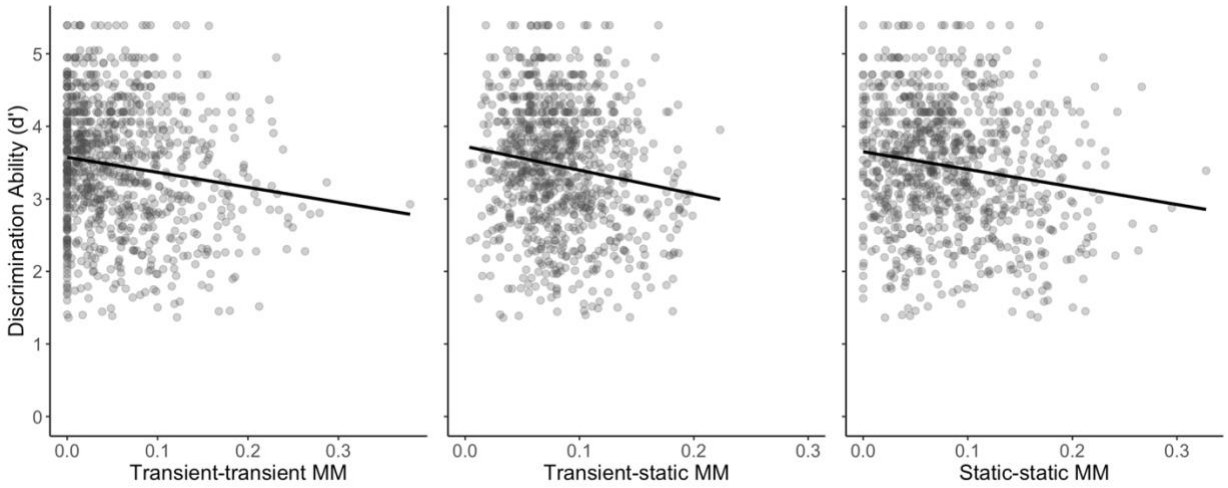
(Post-hoc) Exploratory Regression Summary Table for the Information Flow Dimension

	Model 1			Model 2			Model 3		
Variable	*B*	*SE(B)*	β	*B*	*SE(B)*	β	*B*	*SE(B)*	β
Age	0.010	0.008	0.044	0.009	0.008	0.038	0.010	0.008	0.044
Gender (Male)	0.108	0.060	0.124	0.098	0.059	0.113	0.169	0.061	0.193*
Gender (Non-binary)	0.379	0.244	0.435	0.269	0.242	0.309	0.299	0.240	0.343
Static-static MM				-1.641	0.656	-0.107	-2.687	0.698	-0.175**
Transient-static MM				-1.628	0.944	-0.074	1.315	1.177	0.060
Transient-Transient MM							-2.595	0.631	-0.175**
R^2		0.009			0.035			0.053	
F for change in R^2					12.093**			16.932**	

Note. *p < .01, **p<.001. B = effect size, MM = media multitasking, SE(B) = standard error for effect size, β = standardized effect size. Gender was coded as 0 = Female, 1 = Male, 2 = Other, with female as the reference group.

Figure 8

Information Flow Media Multitasking Measures and Discrimination Ability (d')



Note. MM = media multitasking.

Post-hoc Behavioral Response Dimension. Post-hoc behavioral response regression results are summarized in Table 6 and Figure 9. For this regression model predicting *d',* I entered age and gender into the first step of the model. In this step, age (β = 0.044, p = .198) and gender (male relative to female, β = 0.124, p = .071, non-binary relative to female, β = 0.435, p = .121), did not account for a significant amount of variance in *d'* (R^2 = 0.009, $F(3, 881) = 2.543$, p = .055). PP MM and RP MM were added in the second step of the model. In this step, PP MM (β = -0.176, $p < .001$) and RP MM (β = -0.017, p = .689) accounted for a statistically significant amount of variance in *d'* (R^2 = 0.043, $F(5, 879) = 7.936$, $p < .001$) and together explained 3.5% of the unique variance in *d'* after accounting for age and gender ($F(2, 879) = 15.897$, $p < .001$). RR MM was added in the third step of the model. In this step, RR MM (β = -0.186, $p < .001$) accounted for a statistically significant amount of variance in *d'* (R^2= 0.066, $F(6, 878) = 10.327$, $p < .001$) and explained 2.3% of the unique variance in *d'* after accounting for age, gender, PP MM, and RP MM ($F(1,878) = 21.360$, $p < .001$).

Table 6

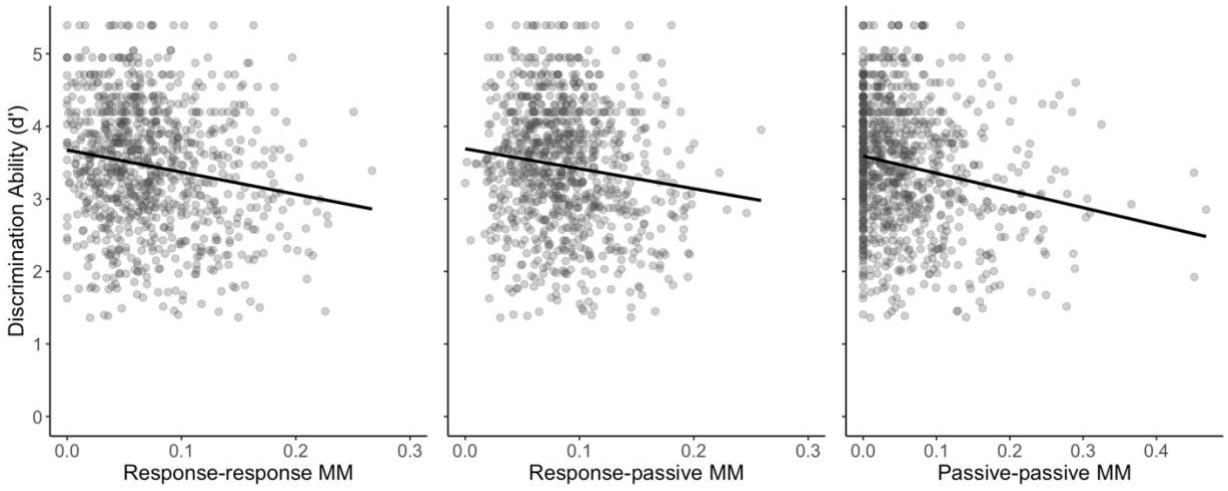
(Post-hoc) Exploratory Regression Summary Table for the Behavioral Response Dimension

	Model 1			Model 2			Model 3		
Variable	*B*	*SE(B)*	β	*B*	*SE(B)*	β	*B*	*SE(B)*	β
Age	0.010	0.008	0.044	0.012	0.008	0.051	0.012	0.008	0.052
Gender (Male)	0.108	0.060	0.124	0.095	0.059	0.109	0.113	0.058	0.129
Gender (Non-binary)	0.379	0.244	0.435	0.318	0.241	0.365	0.295	0.238	0.339
Passive-passive MM				-2.228	0.528	-0.176**	-2.724	0.533	-0.215**
Response-passive MM				-0.354	0.886	-0.017	2.340	1.052	0.110
Response-response MM							-3.361	0.723	-0.186**
R^2		0.009			0.043			0.066	
F for change in R^2					15.897**			21.360**	

Note. **p < .01, **p <.001. B = effect size, MM = media multitasking, SE(B) = standard error for effect size, β = standardized effect size. Gender was coded as 0 = Female, 1 = Male, 2 = Other, with female as the reference group.

Figure 9

Behavioral Response Media Multitasking Measures and Discrimination Ability (d')



Note. MM = media multitasking.

Post-hoc Analysis Screening

Post analysis screening was conducted to test the assumptions of normality and homoscedasticity of residuals, assess potential collinearity of the predictor variables, and identify any influential cases for post-hoc analyses. Measures of collinearity suggested the relationships between predictor variables were not problematic, as tolerance values were high (>0.1) and variance inflation factors (VIF) were low (<10). I then plotted the standardized residuals, and these appeared to be normally distributed. The assumption of homoscedasticity of residuals was met for the predictor variables across the three regression models. The residuals appeared to be uniformly distributed across the range of predicted values. Cook's distance was employed to assess the influence of individual data points on the regression model (Field et al., 2012). No individual data points were above the Cook's distance threshold of 1 (Field et al., 2012). Overall, the results are unlikely to have been influenced in a meaningful way by collinearity, heteroscedasticity, failed assumptions of normality, or influential cases.

Discussion

This study aimed to better characterize the role of cognitive and perceptual resource utilization in the relationship between MM and sustained attention. Specifically, this study is the first to investigate whether maladaptive MM pairs, hypothesized to be inefficient, exhibit a differential relationship with task-based sustained attention relative to adaptive MM pairs, hypothesized to be efficient. I categorized MM pairs as adaptive and maladaptive across cognitive dimensions proposed in previous work, specifically: (1) sharing a specific sensory processing modality (visual, auditory, or motor), (2) transmitting information in a static or transient manner, and (3) requiring a behavioral response (Baumgartner & Wiradhany, 2022). I

hypothesized that media pairs were adaptive if media inputs: (1) did not both require a specific sensory modality, (2) did not both transmit information transiently, and (3) did not both require a behavioral response. I predicted that a greater tendency to maladaptively MM would be negatively associated with sustained attention, but there would be no relationship between adaptive MM and sustained attention when included in the same model.

In line with my hypotheses, a greater tendency to media multitask with inputs that shared sensory processing (S-maladaptive MM) was negatively associated with *d',* while tendency to media multitask with inputs that did not require the same sensory input (S-adaptive MM) was not associated with *d'*. This aligns with prior work that found that MM pairs that likely utilize shared sensory processing across visual, auditory, or motor senses, were less likely to be chosen that MM pairs that utilize diverse, non-shared sensory resources (Baumgartner & Wiradhany, 2022; Wang et al., 2015). In line with my hypothesis, a greater tendency to media multitask with inputs that both transmitted information in a transient manner (IF-maladaptive MM) was negatively associated with *d'* for the dimension of information flow. Contrary to my hypothesis, a greater tendency to media multitask with at least one static input (IF-adaptive MM) was also negatively associated with *d'.* Consistent with my hypothesis, a greater tendency to media multitask with inputs that both required a behavioral response (BR-maladaptive) was also negatively associated with *d'*. Consistent with my hypothesis, a greater tendency to media multitask with at least one input that did not require a behavioral response (BR-adaptive) was not associated with *d'* after correction for multiple comparisons.

In response to these mixed findings, I conducted exploratory post-hoc analyses to avoid classifications of adaptive and maladaptive for the information flow and behavioral response dimensions. Instead, I included specific qualitative types of MM pairs in regression analyses to

avoid assumptions of whether these classifications of specific inputs intrinsically carry a higher cognitive or perceptual load based on the original Baumgartner classification. Specifically for the information flow dimension, a greater tendency to media multitask with transient-transient pairs and static-static pairs were both negatively associated with *d'* while a tendency to media multitask with transient-static pairs was not associated with *d'*. For the behavioral response dimension, a greater tendency to media multitask with response-response pairs and passive-passive pairs were both negatively associated with *d'*, while a tendency to media multitask with response-passive pairs was not associated with *d'*.

I propose two plausible contributing factors that may account for these findings. First, it's possible that interference caused by simultaneously processing two media inputs with shared characteristics is the key differentiator in classify whether a MM pair is adaptive or maladaptive in its relation to sustained attention. Conversely, theoretical cognitive and perceptual demand from specific media inputs may be less meaningful or get lost in translation when individuals MM in their daily lives. This is consistent with findings that a greater tendency to media multitask with inputs with dissimilar processing requirements (e.g., one input requires transient processing, and one requires static processing) is more efficient due to less cognitive and perceptual interference and more effective information processing. This theory is in line with the threaded cognition theory, in which completing two tasks that require similar cognitive and perceptual resources leads to interference and ineffective information processing (Salvucci & Taatgen, 2008).

Second, it's possible that my original hypotheses for the information flow dimension did not account for two important constructs that play an important role in how people practically engage with media inputs at the same time. Specifically, my original hypotheses did not account

for task intentionality and relevance, due to the limitations of measuring these constructs from existing survey data (Zamanzadeh & Rice, 2021). MM does not occur in a vacuum, and MM inputs are not necessarily prioritized equally. For instance, many transient-static MM pairs include pairing a low priority passive media input (such as TV or music), and a high priority input that likely carries high relevance and intentionality (specifically coding, photo or video editing, or other computer-based work). In these instances, one engages with a static input that carries consequences for performance, while the transient input carries no such consequences. The difference in functional consequences for these inputs may lead to an individual prioritizing and attending to the highly relevant and intentional static input and ignore the irrelevant transient input when cognitive or perceptual demands are too high. In contrast, transient-transient and static-static pairs may carry no inherent hierarchy, leading to no clear prioritization and an individual attempting to attend to both inputs. Attempting to MM with pairs with no clear hierarchy, regardless of whether the input is theoretically cognitively demanding, may lead to more frequent attentional switching and shallow, inefficient processing relative to MM in which one primary input can be prioritized over a second input during periods of high perceived mental effort.

Study Two: Does Situational Media Multitasking Influence Sustained Attention?

Media multitasking (MM), the simultaneous use of two or more media inputs, has been previously linked to individual differences in sustained attention (Rioja et al., 2023). As previously described, research suggests that people with a greater tendency to habitually media multitask exhibit poorer sustained attention (Chen et al., 2025; Madore et al., 2020; Rioja et al., 2023). Researchers hypothesize heavy habitual MM biases a user's style of information processing away from top-down goal-directed processing toward "breadth-biased" processing of both relevant and irrelevant information across multiple inputs in one's environment (Ophir et al., 2009; Parry & Le Roux, 2021; Ralph et al., 2014). While several studies have explored whether habitual MM is linked to sustained attention, no studies have explored whether situational MM influences one's ability to subsequently sustain attention (Chen et al., 2025). Researchers propose that frequent MM over time influences attentional mechanisms through conditioning, neuroplastic changes in the brain, and habituation (Parry & Fisher, 2024). Considering the proposed mechanisms linking habitual MM and sustained attention, it's unlikely situational MM would influence sustained attention the same way. These are underlying mechanisms that rely on a dose-response effect on a timescale of months and years, not hours (Davidson & McEwen, 2012). Instead, research on the malleable of attentional states throughout the day suggest that an activity like MM may influence subsequent sustained attention through attentional residue (Leroy, 2009), distraction fatigue (Snider et al., 2023), as well as shifts in attentional preferences and motivation (Kurzban et al., 2013; Mark et al., 2015).

Situational Media Multitasking and Potential Carry-over Effects on Sustained Attention

Efficient cognitive resource utilization has been demonstrated to be pivotal for successful sustained attention (Guidetti et al., 2023). Specifically, sustained attention requires available

cognitive resources and the motivation to deploy those resources (Esterman et al., 2014; Kurzban et al., 2013). Based on this, situational MM may influence subsequent sustained attention through several different mechanisms. First, it's possible that the cognitive resources allocated for MM continue to be consumed after an individual mores on to another task, a concept described as attentional residue (Leroy, 2009). Attentional residue from a preceding task has been demonstrated to diminish performance on subsequent task (Leroy, 2009). The effects of attentional residue are particularly salient when participants perceive no time pressure for the preceding task or feel the preceding task was left unfinished (Leroy, 2009). Attentional residue causes a misallocation of cognitive and perceptual resources, recruiting available resources away from the current task in the direction of processing the preceding task (Leroy, 2009).

Snider et al. (2023) has extended the underlying idea of attentional residue into the applied world of simulated driving. Specifically, researchers demonstrated that voice call and text-based distractions during simulated driving causes a "distraction hangover", in which distractions impair driving performance up to 25 seconds after the distraction has ended (Snider et al., 2023). Based on these studies, it's possible that MM may exert acute carry-over effects on subsequent sustained attention. Also, if MM does influence subsequent sustained attention, it's likely that the degree of influence varies based on the specific characteristics of the MM engagement. MM with inputs that are inherently more distracting may lead to a greater "distraction hangover" relative to less distracting inputs (Snider et al., 2023). Further, perceptions of the MM experience may also influence the degree of attentional residue on subsequent sustained attention (Leroy, 2009). If individuals perceive their MM experience as having no time pressure or perceive the MM experience was left incomplete, attentional residue on subsequent sustained attention may be exacerbated (Leroy, 2009).

In addition to inefficient cognitive and perceptual resource utilization, situational MM may influence underlying attentional preferences and motivation during subsequently sustained attention (Kurzban et al., 2013; Mark et al., 2015). Previous work suggests that how individuals deploy their attentional directly influences subsequent preferences for in-person conversations, using social media, or answering emails (Mark et al., 2015). Researchers specifically found participants were more likely to use social media and have in-person conversations after periods of non-challenging but engaging rote work, while participants were more likely to engage with email after periods of challenging and engaging focused work (Mark et al., 2015). These findings may have important implications for the relationship between situational MM and subsequent sustained attention. Specifically, it suggests that rote MM may prime individuals to prefer some aspect of social engagement immediately after the activity. In contrast, focused MM may prime individuals to prefer a more rote task, such as email. These differences may have a considerable effect on sustained attention, considering the important role that motivation plays in both predicting MM behaviors and successfully sustaining attention (Kurzban et al., 2013; Wiradhany et al., 2021). Based on this work, rote MM may prime participants to seek social or emotional gratification, needs that are functionally not met while performing a sustained attention task. This imbalance in motivation may lead participants to get bored during sustained attention more quickly and mind-wander, allocating cognitive and perceptual resources away from task and hindering performance (Kurzban et al., 2013; Pattyn et al., 2008; Wiradhany et al., 2021). Conversely, focused MM may prime participants to seek out cognitive gratification in line with the experience of sustained attention (Wiradhany et al., 2021). In these circumstances, focused MM may have no influence on subsequent sustained attention, or even improve

performance due to situational motivation aligning with task demands (Esterman et al., 2014; Kurzban et al., 2013).

Despite evidence of situational attentional deployment influencing subsequent cognitive preferences and performance, no study to date has explicitly explored whether situational MM influences subsequent sustained attention. To address currently knowledge gaps in literature, I designed a study to assess if and how situational MM influences subsequent sustained attention. In Study Two, I specifically explored whether 1) situational MM was associated with subsequent sustained attention relative to situational single media usage, 2) situational MM with pairs theorized to be maladaptive was associated with subsequent sustained attention relative to situational MM with pairs theorized to be adaptive, and 3) whether perceived mental effort during situational MM was associated with subsequent sustained attention. Perceived mental effort exerted during the situational media use manipulation was also used to validate that perceived demand was higher during MM relative to single media usage.

Hypotheses

Hypothesis 2a. Multitasking is generally considered to be more cognitively and perceptually demanding than single-tasking due to task switching costs (Salvucci & Taatgen, 2008; Wickens, 2002). Specifically, multitasking requires an individual to switch their attention between two tasks, resulting in the potential for interference, inefficiency, and performance costs. I hypothesized inefficiency and interference from multitasking with two media inputs would impair subsequent sustained attention relative to single media usage through mechanisms similar to attentional residue and distraction hangover (Leroy, 2009; Snider et al., 2023). Based on this, I predicted that individuals who situationally media multitasked would exhibit lower

subsequent *d'* on the gradCPT relative to individuals who situationally engaged with single media.

Hypothesis 2b. Previous work suggests that individuals can media multitask in ways that are efficient and adaptive, or inefficient and maladaptive (Baumgartner & Wiradhany, 2022). Specifically, MM with inputs that are both demanding and likely to cause cognitive or sensory interference is considered maladaptive (Baumgartner & Wiradhany, 2022). Based on previous work that demonstrated how individuals deploy their attention influences subsequent attentional preferences and motivations (Mark et al., 2015), I hypothesized participants who situationally media multitasked with maladaptive MM pairs would exhibit poorer subsequent sustained attention relative to participants who media multitasked with adaptive MM pairs. Specifically, I predicted that individuals who situationally media multitasked with maladaptive MM pairs would exhibit lower subsequent *d'* relative to individuals who situationally media multitasked with adaptive MM pairs across cognitive dimensions of 1) sensory processing, 2) information flow, and 3) behavioral response. Further, I hypothesized these findings extended to two novel cognitive dimensions introduced in Study Two, receptive and productive verbal processing (Salvucci & Taatgen, 2008; Wickens, 2002). These dimensions were added to better characterize the role of interference in the relationship between situational MM and subsequent sustained attention.

Receptive verbal processing refers to the processing required to receive language, regardless of whether the language is written or said aloud. Productive verbal processing refers to the processing required to create language, regardless of whether the language is written or said aloud. Specifically, I predicted that individuals who media multitasked with inputs that both require receptive verbal processing (RVP-maladaptive MM) would exhibit lower subsequent *d'*

relative to individuals who media multitasked with pairs in which at least one input does not require verbal processing (RVP-adaptive MM). Further, I predicted that individuals who media multitasked with inputs that both required productive verbal processing (PVP-maladaptive MM) would exhibit lower *d'* relative to individuals who media multitasked with pairs in which at least one input does not require productive verbal processing (PVP-adaptive MM).

Hypothesis 2c. Perceived mental effort is hypothesized to represent the felt output of internal deliberations around opportunity cost during task performance (Kurzban et al., 2013). Greater perceived mental effort is thought to represent a shift in motivation away from the current task toward an alternative task or activity (Kurzban et al., 2013). Similarly, researchers propose that media multitasking occurs naturally as task engagement fluctuates, where individuals begin to explore alternative tasks when primary task engagement declines (Wiradhany et al., 2021). Based on previous work, it's unclear whether situationally MM in ways perceived to be mentally effortful would influence subsequent sustained attention. Situationally MM with high perceived mental effort may prime individuals to be less motivated to sustain attention to a single task, impairing subsequent performance. Situationally MM with high perceived mental effort may also indicate inefficient resource utilization, which may influence subsequent performance based on mechanisms of attentional residue and distraction hangover (Leroy, 2009; Snider et al., 2023). Alternatively, situationally MM with high perceived mental effort may prime individuals to desire a task dissimilar to MM. This may result in greater motivation to subsequently sustain attention, improving subsequent performance. I hypothesized that perceived mental effort represents a situational tendency in which individuals are less motivated to subsequently sustained attention. I predicted that greater perceived mental effort during situational MM would be associated with lower subsequent *d'*.

Methods

Participants

This study was deployed online using Prolific's data collection platform (www.prolific.co). Previous research suggests superior data quality when utilizing prolific compared to MTurk and alternative recruitment techniques (Douglas et al., 2023). Qualtrics was utilized for survey responses (www.qualtrics.com). The study was approved by the Tufts IRB for before data collection. Participants were compensated $12 an hour for their time. I recruited 300 participants between the ages of 18-35 years old. The estimated effect size is based on previous work demonstrating medium to large effect size across MM and sequential media conditions on perceptual processing style (d = .65) and conceptual processing style (d = 0.76) (Kazakova et al., 2015). The sample size was determined by an a priori power analysis in G*Power (Two-tailed independent group t-test, Effect size d = 0.5, α err probability = 0.05, Power (1-β err probability) = .95, allocation ratio N2/N1 = 1), which determined 210 participants were needed. An additional 90 participants were recruited to account for potential data loss from technical issues and participant non-compliance.

Qualitative Coding of Media Inputs across Cognitive Dimensions

The first step I took for coding cognitive dimensions was to create an exploratory committee to independently score cognitive dimensions based on previous work (Baumgartner & Wiradhany, 2022). The exploratory committee included myself and eight researchers not involved with data collection or analysis on this project. This committee was instructed to take notes on media inputs and cognitive dimensions that were unclear to allow for eventual revision.

Members of the committee were provided a draft of media inputs: (1) video chatting, (2) print media (including print books, print newspapers, etc.), (3) texting, instant messaging, email, (4) text-based social sites (e.g., Facebook, X, Threads, etc., except games), (5) video-based social media (Instagram Reels, TikTok, Snapchat), (6) Non-social text-oriented sites (e.g., online news, blogs, eBooks), (7) Telephone chatting, (8) Music (with lyrics) and non-music audio (podcasts, audiobooks, etc.), (9) Instrumental music (without lyrics), (10) Computer-based work (word processing, writing, coding, etc.), (11) Online videos, streaming, Youtube, movies, and (12) Video games or online games.

The exploratory committee was also provided with initial prompts for qualitatively coding of media inputs across modalities. This included two new modalities: (1) Receptive verbal processing: “Is this media input likely to require receptive verbal processing (i.e., taking in language)?”, and (2) Productive verbal processing: “Is this media input likely to require productive verbal processing (i.e., producing language)?”. These modalities address cognitive and perceptual load varying as a function of verbal processing interference (Schaeffner et al., 2018). I further included three modalities detailed in Baumgartner et al. (2022): (3) Visual: “Is this media input likely to engage the visual modality?”, (4) Audio: “Is this media input likely to engage with the audio modality?”, (5) Motor: “Is this media input likely to engage with the motor modality?”, (6) Information flow: “Is this media input likely to communicate information in a rather static or transient way?”, (7) Behavioral response: “Is this media input likely to require a behavioral response”. The committee was asked to independently code each dimension in a binary way with a 0 suggesting the media input was unlikely to engage the cognitive dimension, and a 1 suggesting the media input was likely to engage the cognitive dimension. The

one exception was for the information flow dimension, in which 0 indicated the media input was rather static and a 1 indicated the media input was rather transient.

I then used these responses to calculate percentage agreement for each dimension. The analyses revealed an agreement of the following for each dimension: (1) Receptive verbal processing [98%], (2) Productive verbal processing [89%], (3) Visual [99%], (4) Auditory [97%], (5) Motor [86%], (6) Information flow [73%], and (7) Behavioral response [83%].

Based on initial percentage agreement and qualitative feedback, I then modified specific media input items to minimize ambiguity and improve rater agreement. The final media inputs were as follows: (1) video chatting, (2) reading print media or text-oriented websites (e.g., print books, print newspapers, eBooks, online news, blogs, etc.), (3) texting, instant messaging, email, (4) scrolling text-based social sites (e.g., Facebook, X, Threads, etc., except games), (5) watching video-based social media (Instagram Reels, TikTok, Snapchat) or short Youtube videos, (6) Talking on the telephone, (7) Listening to music (with lyrics) or non-music audio (podcasts, audiobooks, etc.), (8) Listening to instrumental music (without lyrics), (9) Doing computer-based work (word processing, writing, coding, etc.), (10) Watching movies, TV, or streaming and (11) Playing video games (mobile, console, computer, cloud-based, etc.) without speaking with another person.

A subset of raters was then organized, which consisted of myself and three of the original independent evaluators. I asked all raters to read the introduction of Baumgartner and Wiradhany (2022) to provide an initial framework for understanding the goals and prior framework for coding cognitive dimensions across media inputs. After reading this, raters independently rated each media input across cognitive dimensions with the same instructions as before. After these modifications, there was perfect agreement among raters across cognitive dimensions except for

"reading print media or text-oriented websites" for the motor and behavioral response dimensions. After a brief discussion and weighing arguments, we agreed to code "reading print media or text-oriented websites" as being unlikely to require a motor or behavioral response due to responses likely being required intermittently rather than consistently. The final coding structure for media inputs across cognitive dimensions is demonstrated in Table 7.

Table 7

Qualitative Coding Structure for Adapted Media Use Questionnaire in Study Two

Media	Receptive Verbal Processing 0 = unlikely, 1 = likely	Productive Verbal Processing 0 = unlikely, 1 = likely	Visual 0 = unlikely, 1 = likely	Audio 0 = unlikely, 1 = likely	Motor 0 = unlikely, 1 = likely	Information Flow 0 = rather static, 1 = rather transient	Behavioral Response Requirement 0 = unlikely, 1 = likely
(1) Video chatting	1	1	1	1	1	1	1
(2) Reading print media or non-social text-oriented websites (e.g., print books, print newspapers, eBooks, online news, blogs, etc.)	1	0	1	0	0	0	0
(3) Texting, instant messaging, emailing	1	1	1	0	1	0	1
(4) Scrolling text-based social sites (e.g., Facebook, X, Threads etc., except games)	1	0	1	0	1	0	1
(5) Watching video-based social media (Instagram Reels, TikTok, snapchat) or short Youtube videos	1	0	1	1	1	1	1
(6) Talking on a telephone	1	1	0	1	1	1	1
(7) Listening to music (with lyrics) and non-music audio (podcasts, audiobooks, etc.)	1	0	0	1	0	1	0
(8) Listening to instrumental music (without lyrics)	0	0	0	1	0	1	0
(9) Doing computer-based work (word processing, writing, coding, etc.)	1	1	1	0	1	0	1
(10) Watching movies, TV, or streaming	1	0	1	1	0	1	0
(11) Playing video games (mobile, console, computer, cloud, etc.) without speaking with another person	1	0	1	1	1	1	1

Measures

Adapted Media Use Questionnaire (A-MUQ). This study utilized a modified version of the MUQ used in Ophir et al. (2009). Modifications were made to modernize and extend the survey. Specific modifications were made to better distinguish media items across cognitive dimensions and assess the perceived mental effort individuals experience when habitually engaging with each specific MM pair. The final media inputs were as follows: (1) video chatting, (2) reading print media or text-oriented websites (e.g., print books, print newspapers, eBooks, online news, blogs, etc.), (3) texting, instant messaging, email, (4) scrolling text-based social

sites (e.g., Facebook, X, Threads, etc., except games), (5) watching video-based social media (Instagram Reels, TikTok, Snapchat) or short Youtube videos, (6) talking on the telephone, (7) listening to music (with lyrics) or non-music audio (podcasts, audiobooks, etc.), (8) listening to instrumental music (without lyrics), (9) doing computer-based work (word processing, writing, coding, etc.), (10) watching movies, TV, or streaming and (11) playing video games (mobile, console, computer, cloud-based, etc.) without speaking with another person. Participants were asked to provide both the total number of hours per week spent on the primary media and the frequency in which they concurrently use other media types along with the primary media during a typical media-consumption hour assessed on a four-point Likert scale with values ranging from 0 "Never" to 1 "Most of the time." New to this study, participants were also asked to estimate their perceived mental effort exerted when multitasking with primary and secondary media inputs on a 6-point Likert scale ranging from 0 “None At All” to 5 “Complete/Full (Doolittle et al., 2024). The order of media inputs presented was randomized to minimize fatigue effects (Jeong et al., 2023). One attention check was embedded within the randomization between media inputs that asked the participant “Which of the following is an animal” with response options as a “desk” or “dog”.

Gradual Onset Continuous Performance Task (gradCPT). The gradCPT is a go/no-go continuous performance task designed to measure sustained attentional control (Esterman et al., 2013). During the 8-minute version of the task, participants view a series of gray-scale scene images that gradually transition from one to the next approximately every 800 ms using linear pixel-by-pixel interpolation. This task version is slightly faster than the version used in Rioja et al. (2023) and did not automatically pause due to participant non-responsiveness. The gradCPT requires participants to respond via button press to frequently occurring city images (90%) and

withhold responses to rare mountain images (10%). The primary measure of sustained attention ability on the gradCPT is discrimination ability (*d'*), a measure that applies signal detection analyses to quantify the ability to discriminate between targets/non-targets independent of response strategy (Esterman et al., 2013, 2019; Fortenbaugh et al., 2015). Secondary measures of sustained attention ability on the gradCPT include *d'* slope, coefficient of variation in reaction time (CV), and commission error rate. *D'* slope represents the relative change in discrimination ability over the duration of the task. CV represents reaction time variability, and is calculated from correct responses to city scenes using the standard deviation of reaction time divided by mean reaction time (Macmillian & Creelman, 1991). Commission error rate represent the rate of incorrect responses to city scenes.

Visual Analog Scale – Mental Effort. Participants were asked to rate the mental effort they exerted during the media conditions (MM vs. single media) on a 100-point visual analog scale in order to estimate perceived cognitive and perceptual resource utilization during the media condition (Galy et al., 2012; Paas et al., 2003; Paas & Van Merriënboer, 1993).

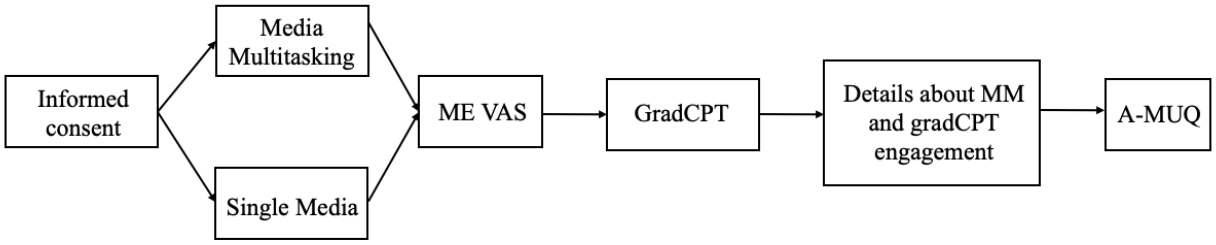
Procedure

This study was conducted online using a between-subjects design to compare how situational MM affects sustained attention relative to single media (Figure 10). Following informed consent, participants were randomly assigned to one of two experimental groups. One group was asked to media multitask for 10 minutes with two media inputs of their choosing out of the following options: (1) video chatting, (2) reading print media or text-oriented websites (e.g., print books, print newspapers, eBooks, online news, blogs, etc.), (3) texting, instant messaging, email, (4) scrolling text-based social sites (e.g., Facebook, X, Threads, etc., except games), (5) watching video-based social media (Instagram Reels, TikTok, Snapchat) or short

Youtube videos, (6) talking on the telephone, (7) listening to music (with lyrics) or non-music audio (podcasts, audiobooks, etc.), (8) listening to instrumental music (without lyrics), (9) Doing computer-based work (word processing, writing, coding, etc.), (10) watching movies, TV, or streaming or (11) playing video games (mobile, console, computer, cloud-based, etc.) without speaking with another person. The single media group was asked to consume only one media input from the same list for 10 minutes and avoid media multitasking. Participants were asked to set an alarm on their phones to avoid over-extending media usage beyond the allotted time. Following the media conditions, participants were asked to rate their perceived mental effort during the media usage period. Subsequently, participants completed the gradCPT. Following completion of the gradCPT, participants completed a questionnaire detailing their experience during the media conditions and gradCPT. Specifically, participants were asked whether they multitasked during the gradCPT and to describe the task instructions in their own words. Participants in both media conditions were asked to select which media they engaged in. Participants were then asked to complete an adapted media use questionnaire (A-MUQ) to characterize habitual MM habits, and an imbedded attention check. At the end of the survey, participants answered a compliance question that asked whether they randomly responded at any point during any of the surveys.

Figure 10

Protocol for Study Two



Note. A-MUQ = Adapted media use questionnaire, GradCPT = Gradual-onset continuous performance task, ME VAS = mental effort exerted during media conditions using visual analog scale.

Statistical Methods

Exclusion Criteria. Three hundred participants (*n* = 300) were recruited for the current study. Of these, 10 were excluded due to missing gradCPT data, likely attributable to technical difficulties. An additional 29 were excluded for self-reporting they multitasked during the gradCPT task. Further exclusions included 11 participants who completed the gradCPT on a mobile device, 3 who spent more than 20 minutes on the media use condition, 4 who reported not using a media device during the media condition, and 29 for failing to respond during the gradCPT for more than 10 seconds (Fortenbaugh et al., 2017). All participants in the final sample (n = 214) reported taking the study seriously and passed the embedded attention check.

Data Analysis. All data processing, statistical analyses, and data visualizations were performed using Rstudio versions 2024.04.1+748, a free and open-source statistical platform. R code generation was assisted using Google Gemini versions 1.5 and 2 (Google, 2025), as well as Jamovi (Şahin & Aybek, 2019). Outcome variables were assessed for normality using Shapiro-Wilk tests and ocular assessment of histograms. Analyses are listed in Table 8. I conducted a between-subjects t-test (MM/single media) to assess differences across media conditions for *d'*, and *d'* slope. Cohen's *d* was reported as a measure of effect size. Means and standard deviations for *d'* across groups were reported. Due to violations of normality, I conducted a Mann-Whitney U test for CV and CE rate. Cliff's delta was used as a non-parametric measure of effect size (Meissel & Yao, 2024). Median and interquartile range (IQR) values for *d'* across groups were reported. I used Bonferroni multiple comparisons correction to adjust the p-value for significance from $p < .05$ to $p < .0125$ for these analyses.

To check if perceived mental effort was higher during the MM condition relative to the single media condition, I conducted a Mann-Whitney U test across conditions. The Mann-Whitney U test was used as an alternative to the independent sample t-test due to the distribution of perceived mental effort exhibiting a violation of normality. Median and IQR values for subjective cognitive load ratings across groups were reported. Cliff's delta was used as a non-parametric measure of effect size (Meissel & Yao, 2024).

To test the influence of cognitive and perceptual resource utilization during situational MM on gradCPT performance, I created groups based on media inputs reported in the in-experiment MM questionnaire and coding system described in Study One (Figure 3). I performed Mann-Whitney U tests to compare the influence of maladaptive and adaptive MM pairs on *d'*, *d'* slope, CV, and CE rate across each cognitive dimension of (1) shared sensory processing, (2) information flow, (3) behavioral response, (4) productive verbal processing, and (5) receptive verbal processing. Mann-Whitney U tests were utilized due to outcome measures exhibiting non-normal distributions within either the maladaptive or adaptive groups. I used Bonferroni multiple comparisons correction to adjust the p-value for significance from $p < .05$ to $p < 0.0125$ for these analyses. Means and standard deviation for *d'* across groups are reported. Cliff's delta was used as a non-parametric measure of effect size (Meissel & Yao, 2024).

To test the influence of subjective cognitive load during media usage and performance on the gradCPT, I performed a linear regression in which independent variables were age, gender, and subjective mental effort during the media condition while the dependent variables were *d'*, *d'* slope, CV, and CE rate. R^2, F-statistics, and p-values are reported across steps for the regression model. Outcome measures appeared to be approximately normally distributed.

Regression coefficients, standard error for regression coefficients, and standardized regression coefficients are reported for all independent variables across models.

Table 8

Study Two Analyses

Purpose	Approach	Independent Measures	Dependent Measures	# Tests
Test: Effect of MM on gradCPT performance	Between-subjects t-test / Mann-Whitney U test	Media Condition: (MM vs. single media)	*d*', *d'* slope, CV, CE rate	4
Manipulation check: perceived mental effort exerted during media condition	Mann-Whitney U test	Media Condition: (MM vs single media)	Visual analog score (mental effort)	1
Test: Effect of adaptive vs. maladaptive MM on gradCPT performance	Mann-Whitney U test	Situational MM Condition: adaptive vs. maladaptive MM	*d*', *d'* slope, CV, CE rate	20 (5 per dependent measure)
Test: Relationship between perceived mental effort during media conditions and gradCPT performance	Linear regression	Age, gender, perceived mental effort during situational MM	*d*', *d'* slope, CV, CE rate	4

Note. CE rate = commission error rate, CV = coefficient of variation in reaction time to correct commissions, *d'* = Discrimination ability, *d'* slope = slope of decline in discrimination ability, MM = media multitasking.

Results

Sample characteristics

The final sample included 214 participants (age: M = 27.62, SD = 4.87). Of these, 114 were male, 94 were female, and 6 identified as non-binary. In terms of reported ethnicity, 104 identified as White, 90 identified as Black or African American, 3 identified as American Indian

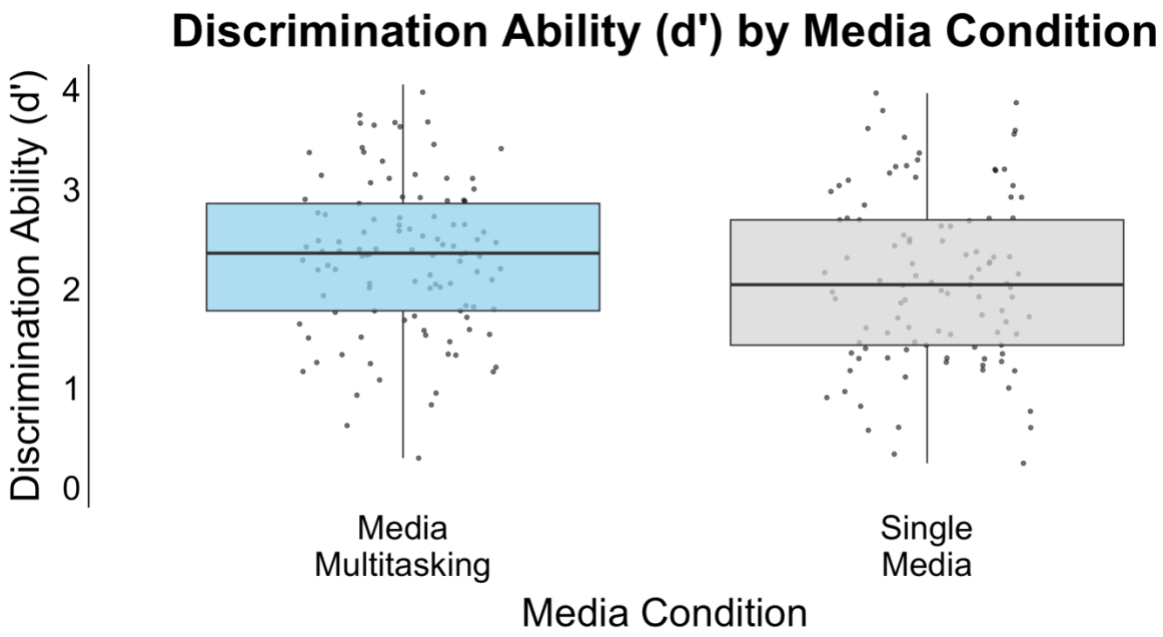
or Alaska Native, 11 identified as Asian, 12 identified Hispanic or Latino/a, and 1 preferred not to answer.

The Influence of Situational Media Multitasking on Subsequent Sustained Attention relative to Single Media Use

There were no violations of homogeneity across media use groups for *d'* ($F(1, 212) = 2.080$, $p = .151$), *d'* slope ($F(1, 212) = 0.746$, $p = .389$), CV, $F(1, 212) = 3.415$, $p = .066$, and CE rate ($F(1, 212) = 1.038$, $p = .310$). An independent samples t-test was conducted to compare *d'* across participants who media multitasked relative to participants who engaged with a single media input during the media use portion of the study. The results indicated a non-significant difference after Bonferroni correction ($p < .0125$) between single media and MM groups, $t(212) = -2.174$, $p = .031$, $d = -0.297$, Figure 11. Specifically, participants in the single media group ($M = 2.09$, $SD = 0.85$) exhibited a lower *d'* relative to the MM group ($M = 2.33$, $SD = 0.77$). No differences were demonstrated between the single media group and MM group for the outcome measure of *d'* slope, $t(212) = -0.238$, $p = .812$, $d = -0.033$), CV ($U = 5036$, $p = .130$, Cliff's Delta = 0.120) or CE rate ($U = 4851.5$, $p = .055$, Cliff's Delta = 0.152).

Figure 11

Comparison of Discrimination Ability (d') Across Multitasking and Single Media Conditions

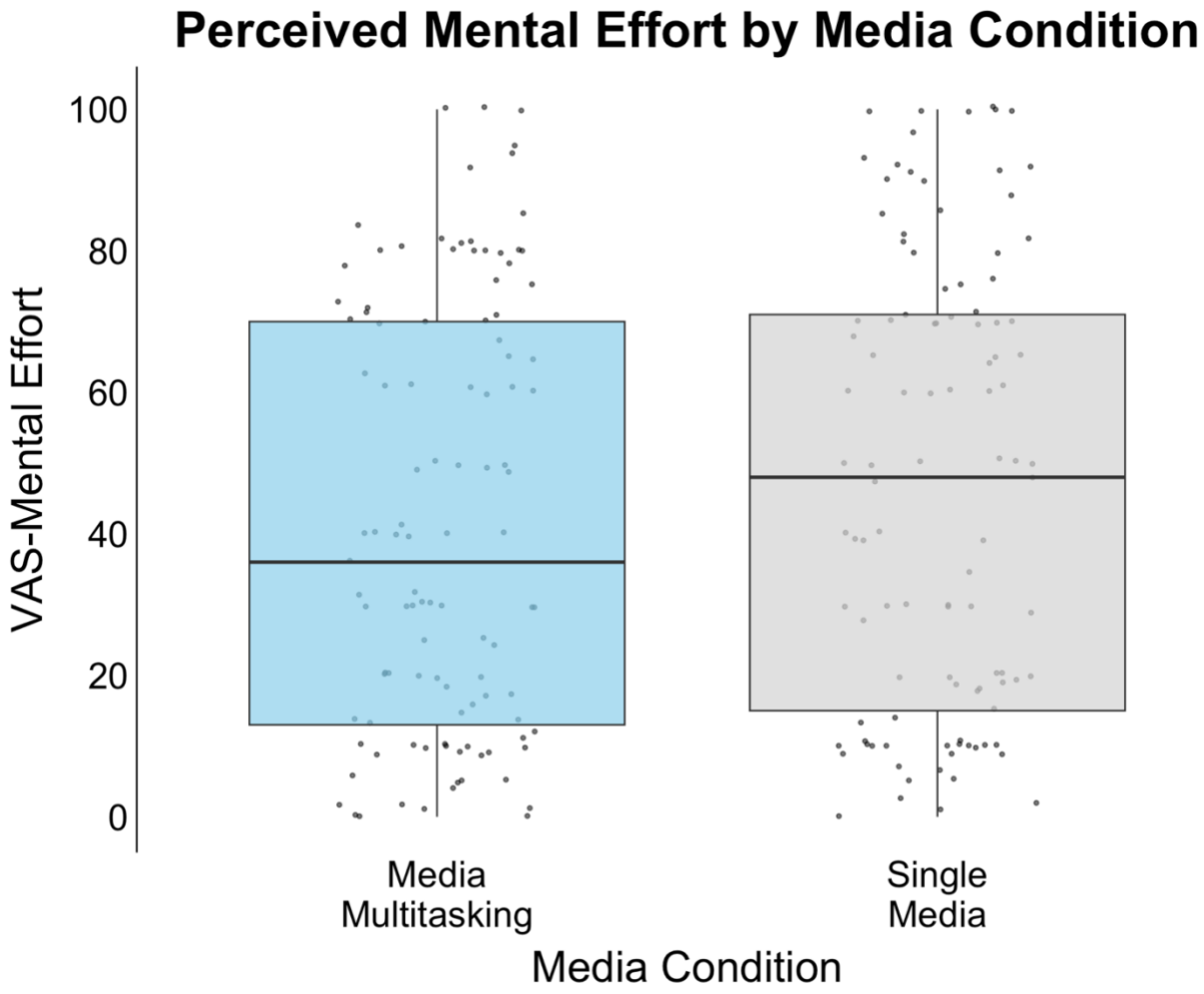


Comparison of perceived mental effort during media use condition across single media use and media multitasking groups:

There were no violations of homogeneity across groups $F(1, 212) = 0.515$, $p = .474$. A between-subjects t-test was conducted to compare perceived mental effort across participants who media multitasked relative to those who engaged with a single media input during the media use portion of the study. A Mann-Whitney U test indicated no significant differences in perceived mental effort among participants in the single media group (Mdn = 48, IQR = 15 – 71) and MM group (Mdn = 36, IQR = 13 – 70), $U = 5229$, $p = .276$, Cliff's Delta = 0.086, Figure 12.

Figure 12

Comparison of Perceived Mental Effort Across Single Media and Media Multitasking Conditions



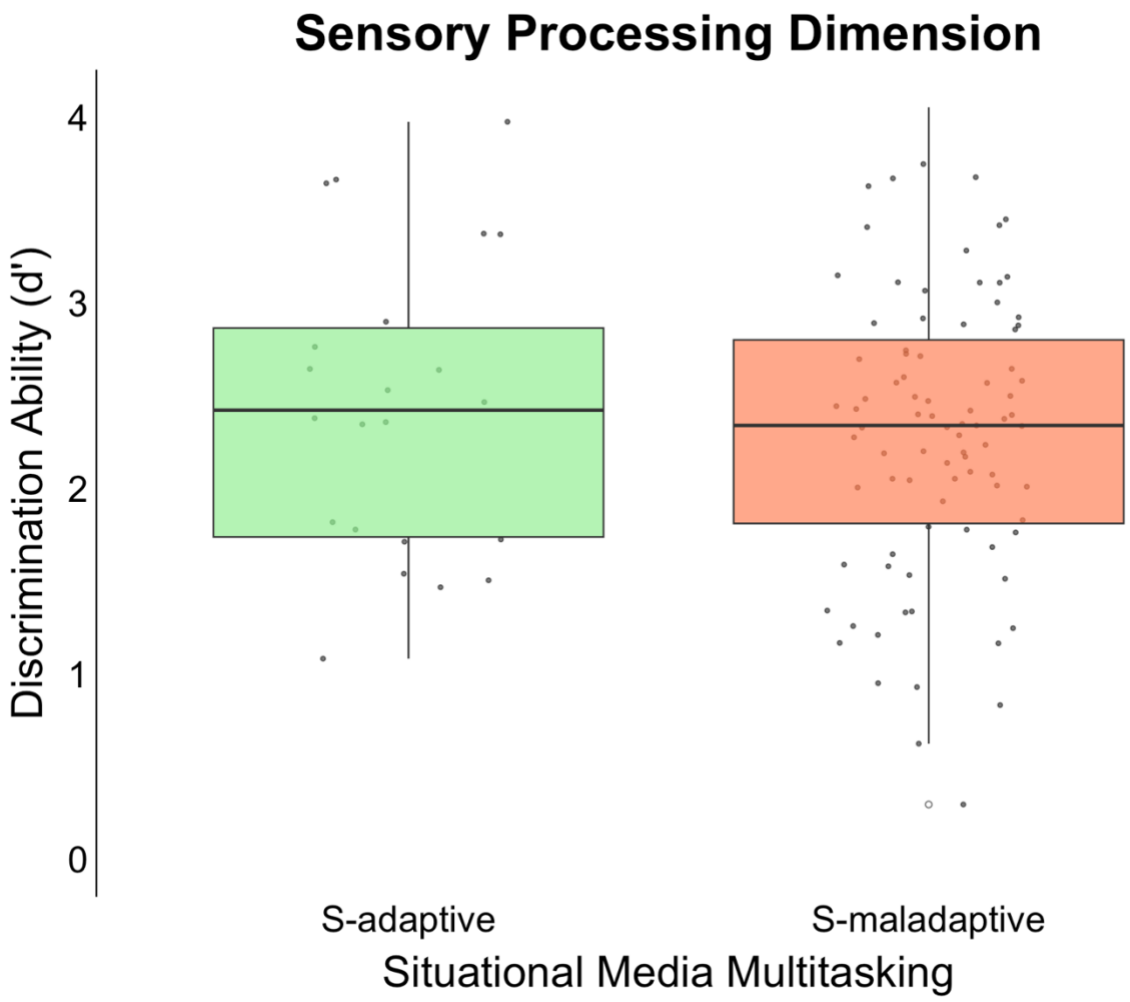
Note. VAS-Mental Effort = Visual Analog Scale of Perceived Mental Effort during Media Condition.

Comparison of Sustained Attention across Adaptive and Maladaptive Sensory Media Multitasking During Media Use Condition Within Participants Assigned to Media Multitasking Condition

There were no violations of homogeneity across groups for *d'* (F(1, 107) = 0.273, p = .603), *d'* slope (F(1, 107) = 0.072, *p* = .790), CV (F(1, 107) = 0.145, *p* = .704), CE rate (F(1, 107) = 0.041, *p* = .841). Mann-Whitney U tests were conducted to compare *d'*, *d'* slope, CV, and CE rate across participants who media multitasked with maladaptive sensory MM pairs relative to participants who media multitasked with adaptive sensory MM pairs during the media use portion of the study. The results indicated no significant difference in *d'* between participants who utilized adaptive (Mdn = 2.42, IQR = 1.74 – 2.86) compared to maladaptive (Mdn = 2.34, IQR = 1.81 – 2.80) sensory MM pairs (U = 880, *p* = .564, Cliff's Delta = 0.080), Figure 13. Further, there were no differences among participants who utilized adaptive relative to maladaptive sensory MM pairs in *d'* slope (U = 754, *p* = .126, Cliff's Delta = 0.212), CV (U = 868, *p* = .504, Cliff's Delta = -0.093), CE rate (U = 805.5, *p* = .254, Cliff's Delta = -0.158).

Figure 13

Comparison of Discrimination Ability (d') Across Adaptive and Maladaptive Situational Media Multitasking for the Sensory Processing Dimension During the Media Multitasking Condition



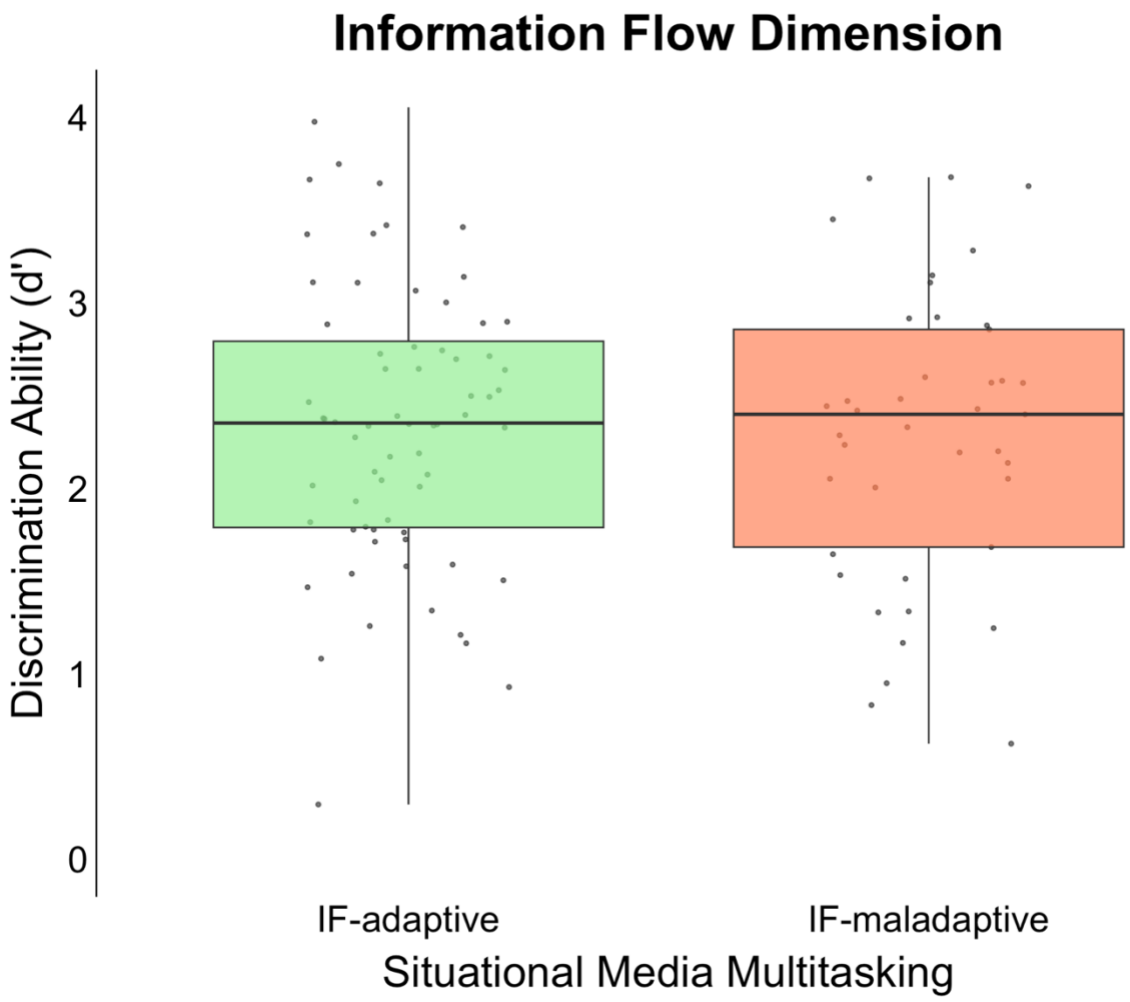
Note. S-adaptive = media multitasking pairs that do not share a specific sensory input, S-maladaptive = media multitasking pairs that share a specific sensory input.

Comparison of Sustained Attention Across Adaptive and Maladaptive Information Flow Media Multitasking During Media Multitasking Condition

There were no violations of homogeneity across groups for *d'* ($F(1, 107) = 0.016$, $p = .900$), *d'* slope ($F(1, 107) = 0.165$, $p = .685$), and CV ($F(1, 107) = 0.804$, $p = .372$). There was a violation of homogeneity across groups for CE rate ($F(1, 107) = 10.919$, $p = .001$). Mann-Whitney U tests were conducted to compare *d'*, *d'* slope, CV, and CE rate across participants who media multitasked with maladaptive information flow MM pairs relative to participants who media multitasked with adaptive information flow MM pairs during the media use portion of the study. The results indicated no significant difference in *d'* between participants who utilized adaptive (Mdn = 2.35 IQR = 1.79 – 2.79) and maladaptive (Mdn = 2.40, IQR = 1.68 – 2.86) information flow MM pairs ($U = 1354$, $p = .805$, Cliff's Delta = 0.029), Figure 14. Further, there were no significant difference among participants who utilized adaptive and maladaptive information flow MM pairs on *d'* slope ($U = 1248$, $p = .363$, Cliff's Delta = 0.105), CV ($U = 1367$, $p = 868$, Cliff's Delta = 0.019) and CE rate ($U = 1251.5$, $p = .374$, Cliff's Delta = -0.102).

Figure 14

Comparison of Discrimination Ability (d') Across Adaptive and Maladaptive Situational Media Multitasking for the Information Flow Dimension During the Media Multitasking Condition



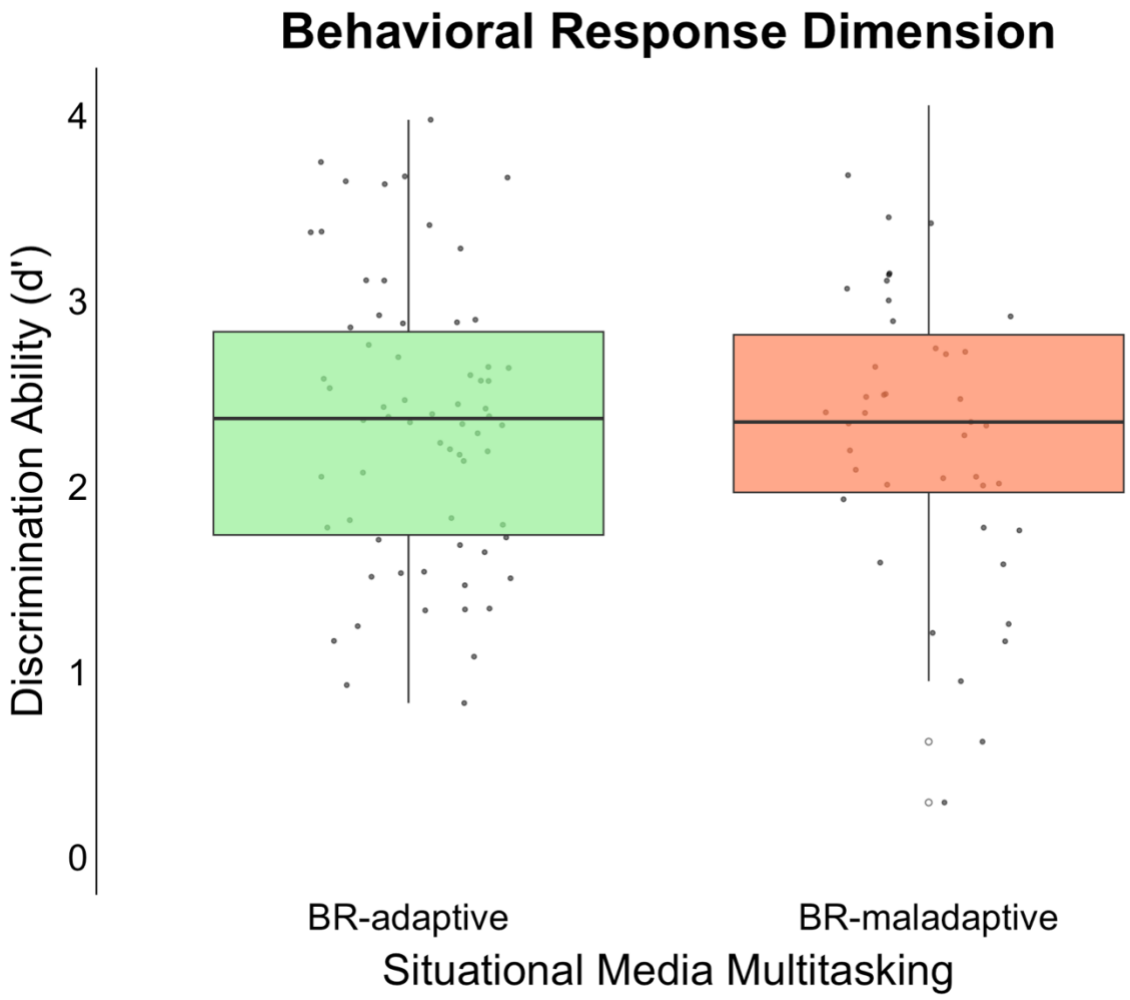
Note. IF-adaptive = media multitasking pairs that contain at least one static media input, IF-maladaptive = media multitasking pairs with two transient media inputs.

Comparison of Sustained Attention Across Adaptive and Maladaptive Behavioral Response Media Multitasking During Media Multitasking Condition

There were no violations of homogeneity across groups for *d'* (F(1, 107) = 0.009, *p* = .924), *d'* slope (F(1, 107) = 0.015, *p* = .902), CV (F(1, 107) = 2.425, *p* = .122), CE rate (F(1,107) = 0.635, *p* = .427). Mann-Whitney U tests were conducted to compare *d', d'* slope, CV, and CE rate across participants who media multitasked with maladaptive behavioral response MM pairs relative to participants who media multitasked with adaptive behavioral response MM pairs during the media use portion of the study. The results indicated no significant difference in *d'* between participants who utilized adaptive (Mdn = 2.37, IQR = 1.74 – 2.83) and maladaptive (Mdn = 2.35, IQR = 1.97 – 2.82) information flow MM pairs (U = 1417, *p* = .993, Cliff's Delta = -0.001), Figure 15. Further, there were no significant difference among participants who utilized adaptive and maladaptive behavioral response MM pairs on *d'* slope (U = 1391, *p* = .865, Cliff's Delta = 0.020), CV (U = 1389, *p* = .855, Cliff's Delta = 0.021) and CE rate (U = 1334, *p* = .600, Cliff's Delta = -0.060).

Figure 15

Comparison of d' Across Adaptive and Maladaptive Behavioral Response Media Multitasking During Media Use Condition Within Participants Assigned to Media Multitasking Condition



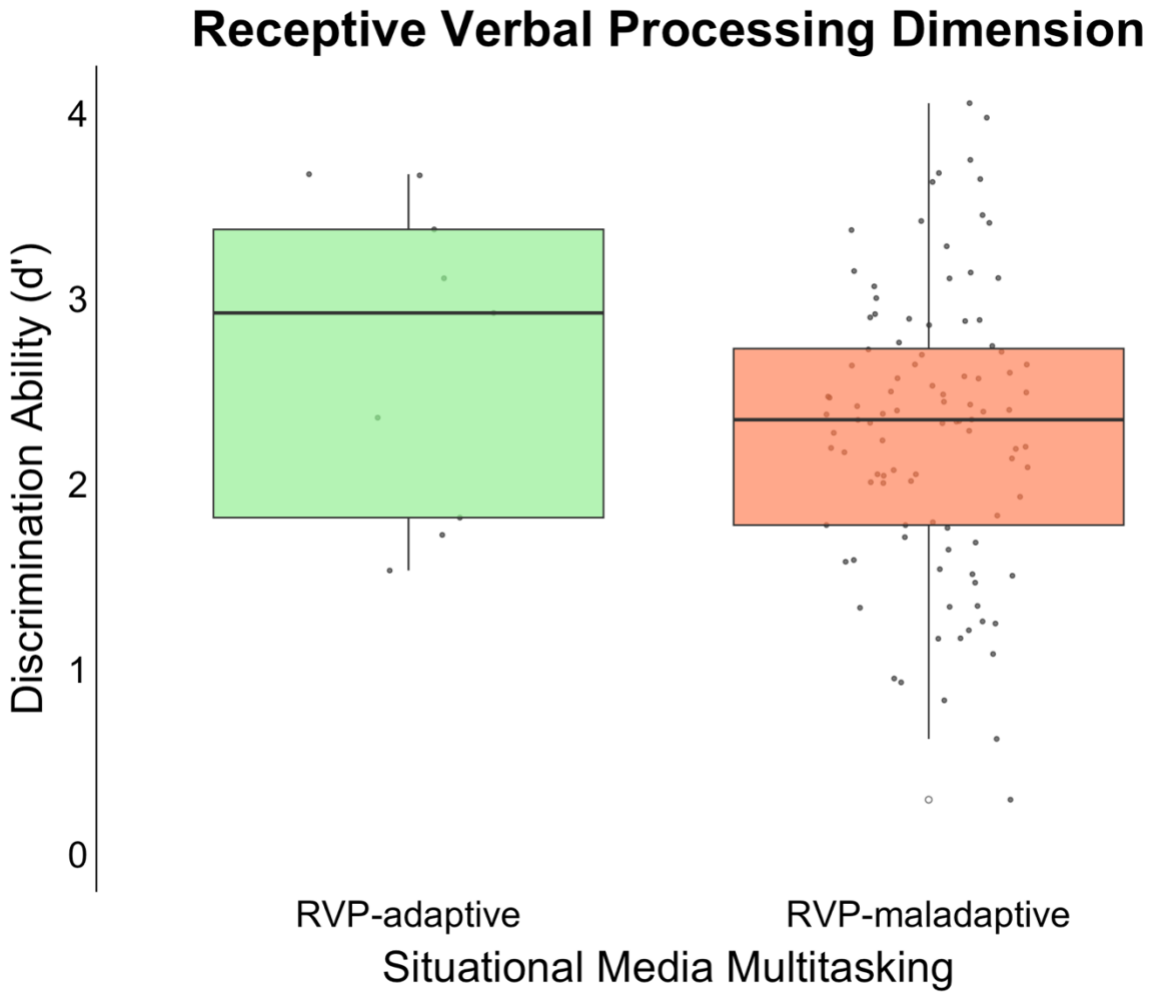
Note. BR-adaptive = media multitasking pairs that require no more than one behavioral response, BR-maladaptive = media multitasking that requires two behavioral responses.

Comparison of Sustained Attention Across Adaptive and Maladaptive Receptive Verbal Processing Media Multitasking During Media Multitasking Condition

There were no violations of homogeneity across groups for *d'* (F(1, 107) = 0.835, *p* = .363), *d'* slope (F(1, 107) = 2.392, *p* = .125), CV (F(1, 107) = 0.025, *p* = .875), CE rate (F(1, 107) = 0.033, *p* = .855). Mann-Whitney U tests were conducted to compare *d'*, *d'* slope, CV, and CE rate across participants who media multitasked with maladaptive receptive verbal processing MM pairs relative to participants who media multitasked with receptive verbal processing MM pairs during the media use portion of the study. The results indicated no significant difference in *d'* between participants who utilized adaptive (Mdn = 2.92, IQR = 1.82 – 3.37) and maladaptive (Mdn = 2.35, IQR = 1.78 – 2.73) receptive verbal processing MM pairs (U = 330, *p* = .188, Cliff's Delta = 0.267), Figure 16. Further, there were no significant differences among participants who utilized adaptive and maladaptive receptive verbal processing MM pairs on *d'* slope (U = 425, *p* = .787, Cliff's Delta = 0.056), CV (U = 440, *p* = .917, Cliff's Delta = 0.022) and CE rate (U = 305, *p* = .112, Cliff's Delta = -0.322).

Figure 16

Comparison of d' Across Adaptive and Maladaptive Receptive Verbal Processing Media Multitasking During Media Use Condition Within Participants Assigned to Media Multitasking Condition



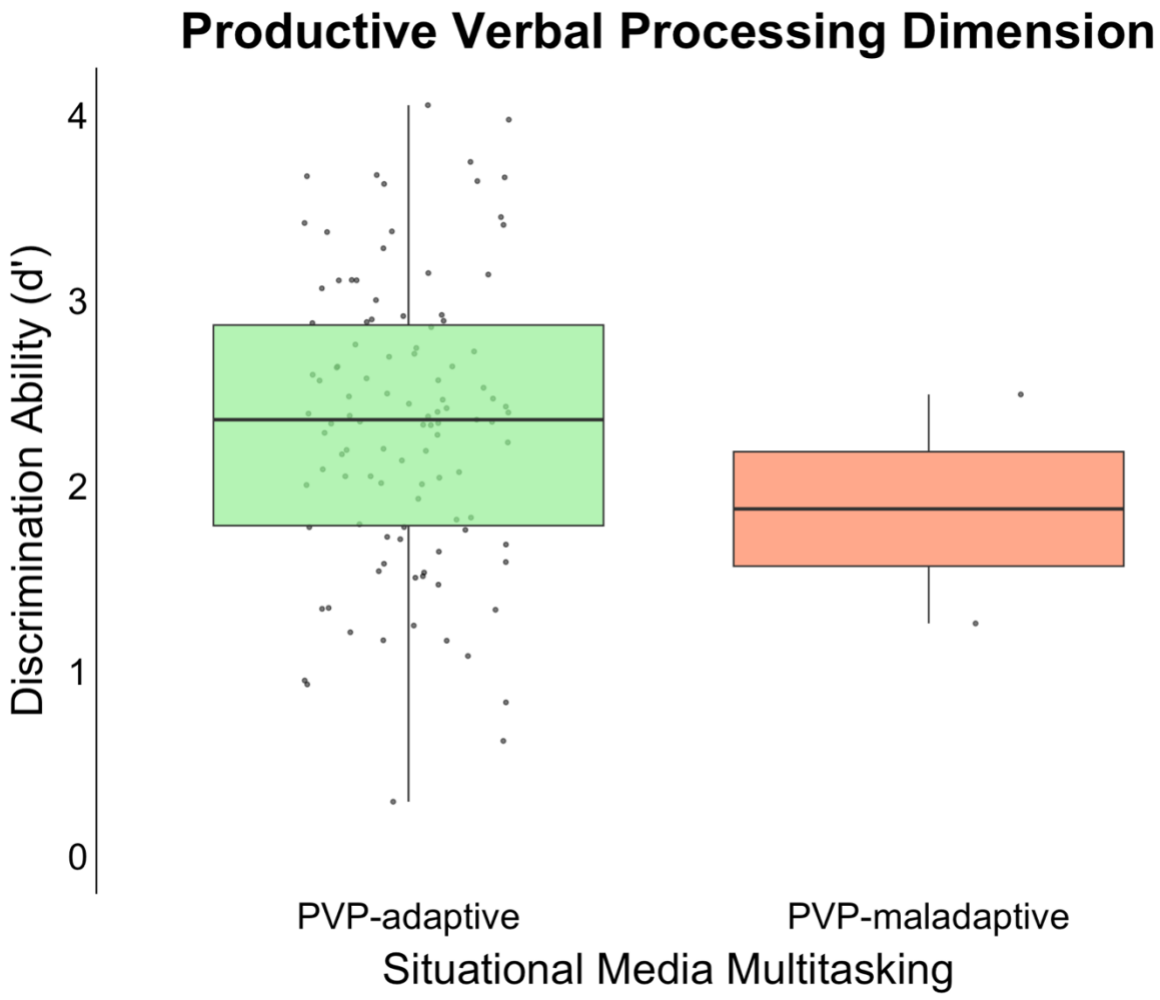
Note. RVP-adaptive = media multitasking pairs with one input that does not require receptive verbal processing, RVP-maladaptive = media multitasking pairs in which both inputs require receptive verbal processing.

Comparison of Sustained Attention Across Adaptive and Maladaptive Productive Verbal Processing Media Multitasking During Media Multitasking Condition

There were no violations of homogeneity across groups for *d'* ($F(1, 107) = 0.003$, $p = .958$), *d'* slope ($F(1, 107) = 1.236$, $p = .269$), CV ($F(1, 107) = 2.775$, $p = .099$), CE rate ($F(1, 107) = 1.916$, $p = .169$). An independent samples t-test was conducted to compare *d'* across participants who media multitasked with maladaptive productive verbal processing MM pairs relative to participants who media multitasked with productive verbal processing MM pairs during the media use portion of the study. The results indicated no significant difference in *d'* between participants who utilized adaptive (Mdn = 2.36, IQR = 1.78 – 2.87) and maladaptive (Mdn = 1.88, IQR = 1.57 – 2.18) productive verbal processing MM pairs ($U = 75$, $p = .477$, Cliff's Delta = 0.299), Figure 17. Further, there were no significant differences among participants who utilized adaptive and maladaptive productive verbal processing MM pairs on *d'* slope ($U = 49$, $p = .194$, Cliff's Delta = -0.542), CV ($U = 37$, $p = 0.117$, Cliff's Delta = -0.654) and CE rate ($U = 103.5$, $p = .946$, Cliff's Delta = -0.033).

Figure 17

Comparison of d' Across Adaptive and Maladaptive Productive Verbal Processing Media Multitasking During Media Use Condition Within Participants Assigned to Media Multitasking Condition



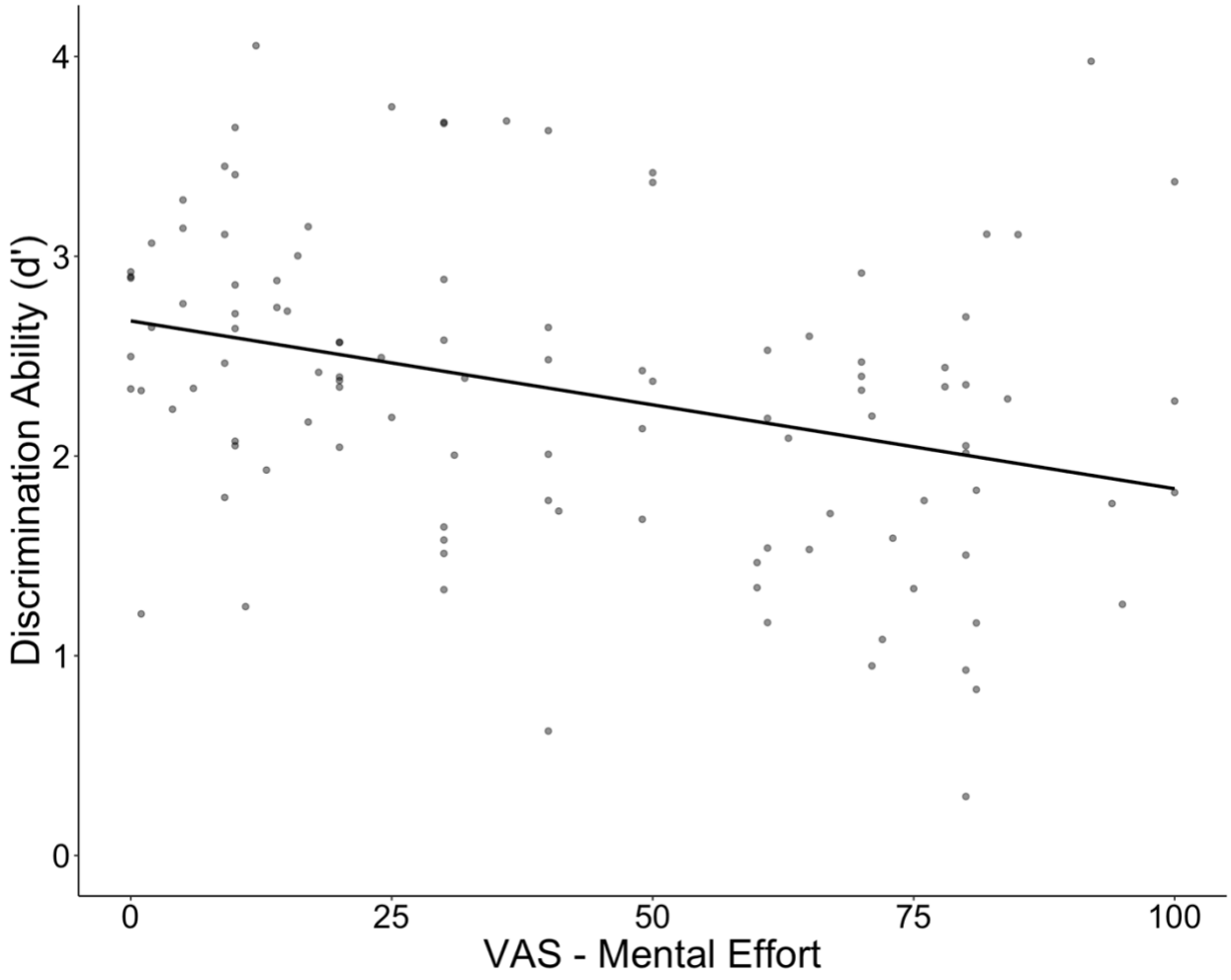
Note. PVP-adaptive = media multitasking pairs with one input that does not require productive verbal processing. PVP-maladaptive = media multitasking pairs in which both inputs require productive verbal processing.

Linear Regression Predicting Sustained Attention with Perceived Mental Effort During Media Multitasking Condition and Demographic Variables

For this regression model predicting *d',* I entered age and gender into the first step of the model. In this step, age (β = 0.028, $p = .778$) and gender (male relative to female, β = -0.207, $p = .295$, non-binary relative to female, β = 0.173, $p = .774$), did not account for a significant amount of variance in *d'* ($R^2 = 0.013$, $F(3, 105) = 0.458$, $p = .712$). Perceived mental effort during the MM condition (VAS-ME) was added in the second step of the model. In this step, VAS-ME (β = -0.331, $p < .001$) accounted for a statistically significant amount of variance in *d'* ($R^2 = 0.120$, $F(4, 104) = 3.539$, $p = .009$). VAS-ME explained 10.7% of the unique variance in *d'* after accounting for age and gender ($F(1, 104) = 12.632$, $p < .001$), Figure 18**.**

Figure 18

Scatterplot of Perceived Mental Effort During Media Multitasking Condition of Media Use Condition and Discrimination Ability (d')



Note. VAS-Mental Effort = Visual Analog Scale of Perceived Mental Effort during Media Condition.

For this regression model predicting *d'* slope, I entered age and gender into the first step of the model. In this step, age (β = -0.085, p = .385) and gender (male relative to female, β = 0.127, p = .519, non-binary relative to female, β = 0.267, p = .658), did not account for a significant amount of variance in *d'* slope (R^2 = 0.012, $F(3, 105) = 0.429$, p = .732). VAS-ME

was added in the second step of the model. In this step, VAS-ME during the MM condition (β = 0.082, p = .407) did not account for a statistically significant amount of variance in *d'* slope (R^2 = 0.0187, F(4, 104) = 0.494, p = .740). VAS-ME explained 0.7% of the unique variance in *d'* slope after accounting for age and gender (F(1, 104) = 0.693, p = .407).

For this regression model predicting CV, I entered age and gender into the first step of the model. In this step, age (β = -0.133, p = .165) and gender (male relative to female, β = 0.292, p = .131, non-binary relative to female, β = -0.777, p = .189), did not account for a significant amount of variance in CV (R^2 = 0.057, F(3, 105) = 2.114, p = .103). VAS-ME was added in the second step of the model. In this step, VAS-ME (β = 0.236, p = .013) did not account for a statistically significant amount of variance in CV after correction for multiple comparisons (R^2 = 0.111, F(4, 104) = 3.252, p = .015). VAS-ME explained 5.4% of the unique variance in CV after accounting for age and gender (F(1, 104) = 6.344, p = .013).

For this regression model predicting CE rate, I entered age and gender into the first step of the model. In this step, age (β = 0.046, p = .636) and gender (male relative to female, β = -0.045, p = .820, non-binary relative to female, β = -0.553, p = .378), did not account for a significant amount of variance in CE rate (R^2 = 0.010, F(3, 105) = 0.358, p = .783). VAS-ME was added in the second step of the model. In this step, VAS-ME (β = 0.103, p = .295) did not account for a statistically significant amount of variance in CE rate (R^2 = 0.021, F(4, 104) = 0.545, p = .703). VAS-ME explained 1% of the unique variance in CE rate after accounting for age and gender (F(1, 104) = 1.107, p = .295).

Post-hoc Analyses

First, I attempted to better characterize differences in perceived cognitive and perceptual load for categories of MM across cognitive dimensions. Specifically, I computed the average

of perceived mental effort required for habitually MM with different pairs across the (1) sensory (shared, no shared), (2) information flow (transient, mixed, static), behavioral response (response, mixed, no response), (4) receptive verbal processing (shared, no shared), (5) productive verbal processing (shared, no shared). Participants reported perceived effort requirements for only pairs they engage in during an average week. Perceived mental effort MM scores were computed ignoring missing values (i.e., values were included if they engaged in at least one MM pair in the category, and were excluded only if a participant did not engage in any MM pairs for a given category). Thus, sample size varied across comparisons, dependent on participant responses. Paired sample t-tests were used to compare perceived mental effort required for MM pairs across cognitive dimensions with two levels (sensory and verbal processing dimensions), while repeated-measures ANOVAs were used to compare perceived mental required for MM pairs across cognitive dimensions with three levels (information flow and behavioral response dimensions). Follow-up paired sample t-tests were conducted for information flow and behavioral response dimensions if the repeated-measures ANOVAs indicated significant differences. Histograms of relative difference measures for each dimension were inspected and suggested assumptions of normality were met across comparisons. Significance thresholds were adjusted using Bonferroni correction for multiple comparisons for each dimension (adjusted alpha value = .01). Descriptive statistics (Mean and SD) were reported for all categories across cognitive dimensions.

Based on findings from Study One, I hypothesized that participants would perceive more mental effort would be required when MM with pairs that (1) both require shared sensory processing, (2) both communicate information in the same fashion (e.g., transient or static), (3) exhibit similar behavioral response requirements (e.g., both require a behavioral response or

neither require a behavioral response), (4) both require receptive verbal processing, and (5) both require productive verbal processing, relative to MM pairs with mixed processing demands.

Second, I attempted to replicate and extend sequential regressions finding from Study One for the (1) sensory processing, (2) information flow, (3) behavioral response, (4) receptive verbal processing, and (5) productive verbal processing. Habitual MM measures were calculated similarly to those in Study One, with a minor change. Specifically, I utilized the original Fisher et al. (2023) equation below in Figure 19 to calculate MM measures for individual pairs.

Figure 19

The Equation For Calculating Weighted Frequency Measures Of Individual Media Multitasking Pairs (J. T. Fisher et al., 2023)

$$MM_{ij} = \frac{(m_{ij} \times h_i) + (m_{ji} \times h_j)}{h_{total}}$$

Note. MM_{ij} = weighted frequency of two specific media inputs; m_{ij} = the frequency that a participant reports multitasking between the media task i and media task j; m_{ji} = the frequency that a participant reports multitasking between the media task j and media task i; h_i= the total number of hours a participant reports using media task i during a typical week; h_j= the total number of hours a participant reports to use media task j during a typical week; h_{total} = the total number of hours a participant reports to use media in a given week across all media inputs.

The dependent variable for the replication of Study One was the primary accuracy-based measure of performance on the gradCPT, discrimination ability (*d'*). For the dimensions of information flow and behavioral response, I aimed to replicate the post-hoc analyses instead of the primary analyses to not assume "adaptive" and "maladaptive" classifications based on findings that a greater tendency to media multitask with inputs that share characteristics (static-

static MM in the information flow dimension, and passive-passive MM in the behavioral response domain) were associated with lower *d'*. Significance thresholds were adjusted using Bonferroni correction for multiple comparisons for each dimension (adjusted alpha value = .01). I hypothesized that findings from Study One would replicate in the sensory, information flow, and behavioral response dimensions, as well as extend to the novel verbal processing dimensions. Specifically, I hypothesized that greater habitual MM with pairs that require similar cognitive and perceptual resources would be associated with lower *d'*, while habitual MM with pairs that require distinct cognitive and perceptual resources would not be associated with sustained attention. I hypothesized the follow significant predictors across regression analyses: (1) shared sensory processing (S-maladaptive MM) (2) static-static MM and transient-transient MM for the information flow dimension, (3) behavior response MM and no behavioral response MM for the behavioral response dimension, (4) shared receptive verbal processing, and (5) shared productive verbal processing.

Third, I attempted to complement the replication of linear regressions in Study Two by conducting binomial logistic regression analyses replacing the dependent variable of *d'*, with "tune-out" (i.e., a binary classification of whether participants failed to respond to the task for a period of 10 seconds or more). This was used as an exclusion criteria for all other analyses, as tune-outs indicate non-compliance on the task (Fortenbaugh et al., 2017). When including participants originally excluded for tune-outs, the total sample size is 241 participants. I specifically conducted five logistic regression analyses, one each for the (1) sensory processing, (2) information flow, (3) behavioral response, (4) receptive verbal processing, and (5) productive verbal processing dimensions. Predictors in each model were as follows: (1) sensory processing dimension: age, gender, S-adaptive MM, S-maladaptive MM (2) information flow: age, gender,

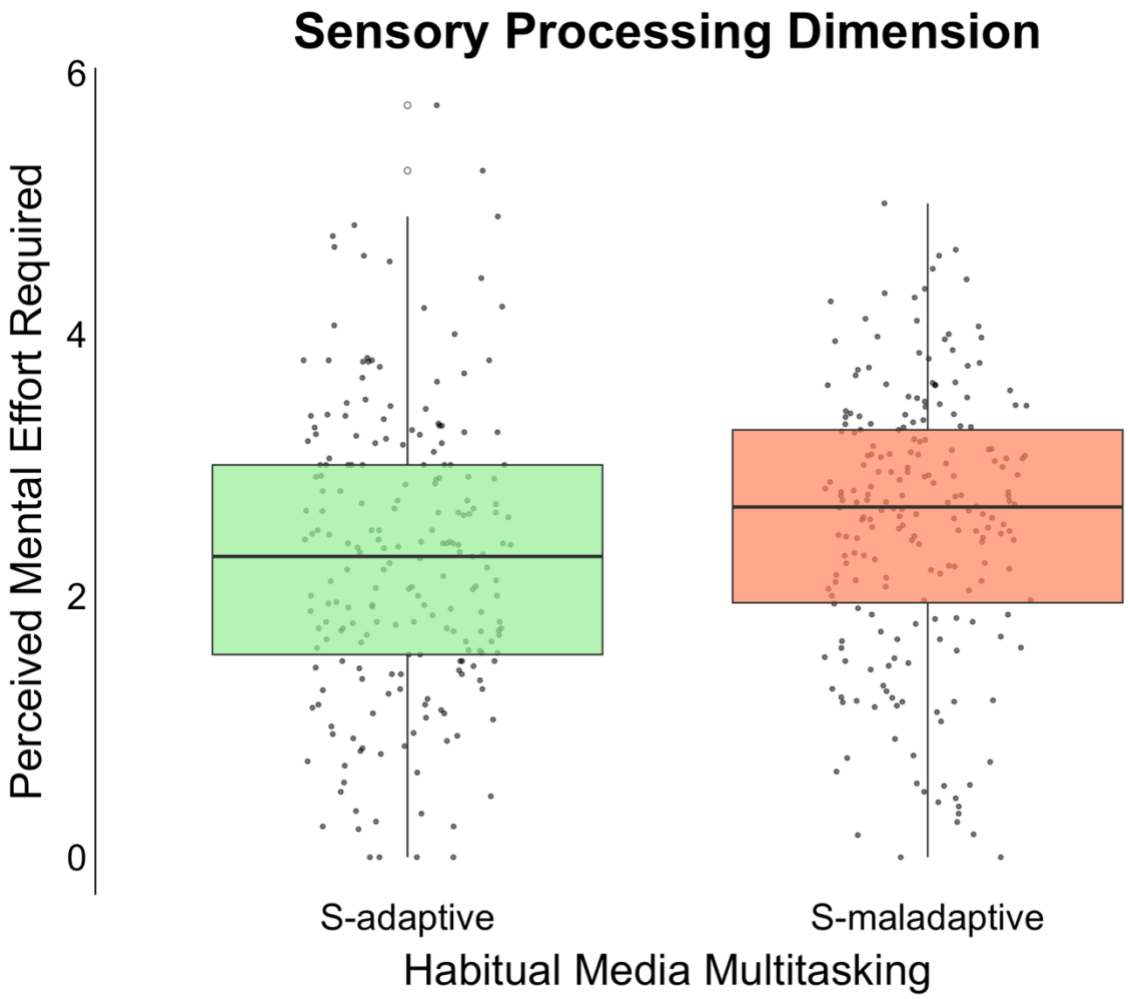
transient-transient MM, transient-static MM, and transient MM, (3) behavioral response: age, gender, response-response MM, response-passive MM, and passive-passive MM, (4) receptive verbal processing: age, gender, RVP-adaptive MM, RVP-maladaptive MM, (5) productive verbal processing: age, gender, PVP-adaptive MM, PVP-maladaptive MM. Significance thresholds were adjusted using Bonferroni correction for multiple comparisons for each dimension (adjusted alpha value = .01). I hypothesized that a greater tendency to media multitask with inputs that require similar cognitive and perceptual resources would be associated with participants tuning out during the gradCPT. Specifically, I hypothesized the following significant predictors across regression analyses: (1) shared sensory MM (2) static-static MM and transient-transient MM for the information flow dimension, (3) response-response MM and passive-passive MM for the behavioral response dimension, (4) shared receptive verbal processing (RVP-maladaptive), and (5) shared productive verbal processing (PVP-maladaptive).

Perceived Mental Effort During Habitual MM Across Cognitive Dimensions.

For the sensory dimension, participants perceived less mental effort was required during habitual S-adaptive MM (M = 2.28, SD = 1.10) relative to S-maladaptive MM (M = 2.57, SD = 1.02), t(210) = -5.768, $p < .001$, $d = -0.397$, Figure 20.

Figure 20

Perceived Mental Effort Required During Habitual Media Multitasking for the Sensory Dimension



Note. S-adaptive = media multitasking pairs that do not share sensory processing. S-maladaptive = media multitasking pairs that share sensory processing.

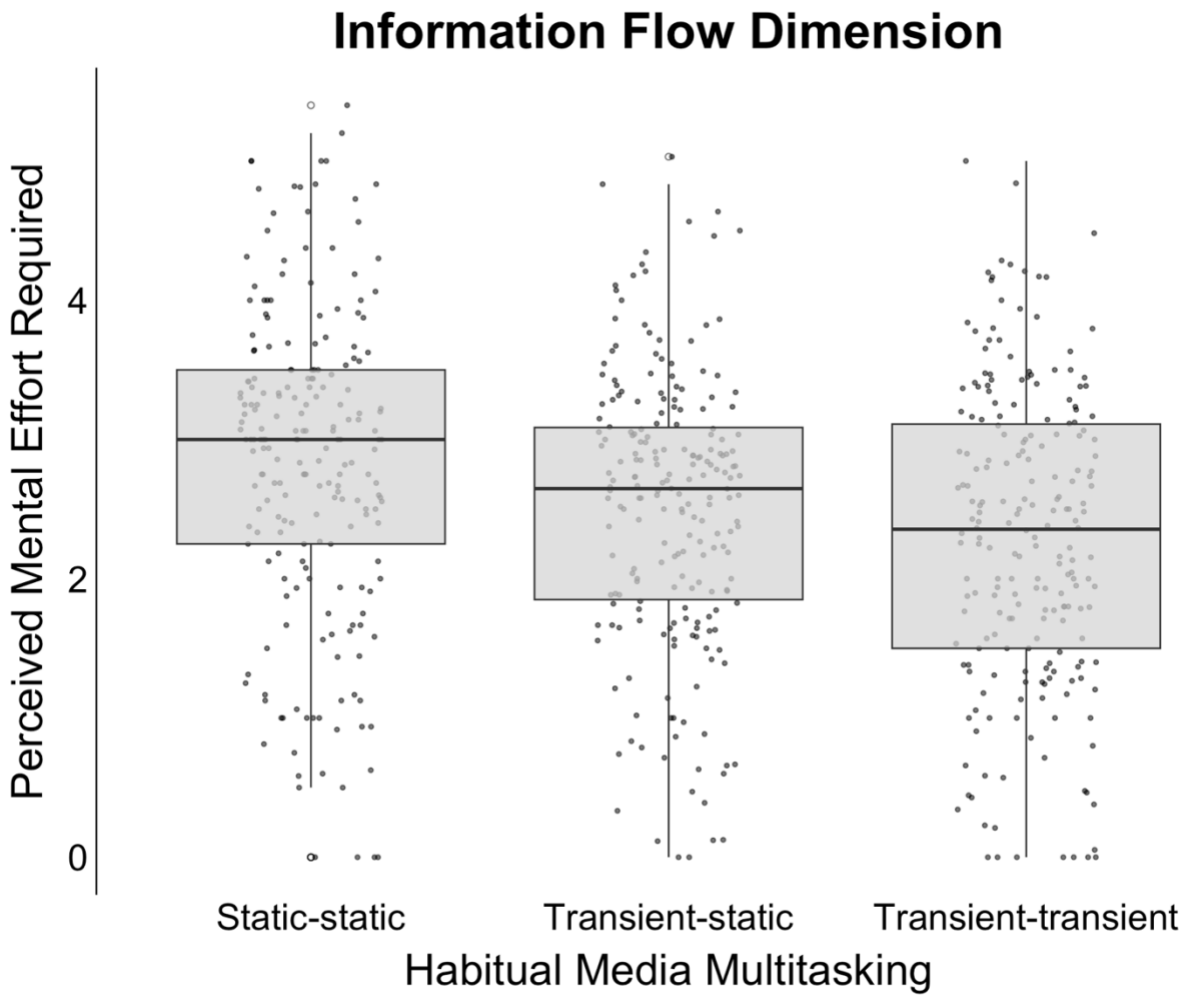
For the information flow dimension, I conducted a repeated measures ANOVA to compare the perceived mental effort across information flow MM pairs (transient-transient, transient-static, and static-static). There was a violation of sphericity across groups according to the Mauchly's Test, $W(2) = .585$, $p < .001$. To account for this, I applied Greenhouse-Geiser

correction. Information flow MM pairs differed in perceived mental effort, $F(1.4, 295.5) = 60.056$, $p < .001$, $n^2 = .04$, Figure 21.

Based on the subsequent paired t-tests, participants perceived less mental effort was required during transient-transient MM (M = 2.29, SD = 1.09) relative to transient-static MM (M = 2.50, SD = 0.99), $t(213) = -5.681$, $p < .001$, $d = -0.388$. Participants perceived less mental effort was required during transient-static MM (M = 2.51, SD = 0.99) relative to static-static MM (M = 2.83, SD = 1.13), $t(209) = 7.230$, $p < .001$, $d = 0.499$. Finally, participants perceived less mental effort was required during transient-transient MM (M = 2.29, SD = 1.09) relative to static-static MM (M = 2.83, SD = 1.13), $t(209) = 8.534$, $p < .001$, $d = 0.589$.

Figure 21

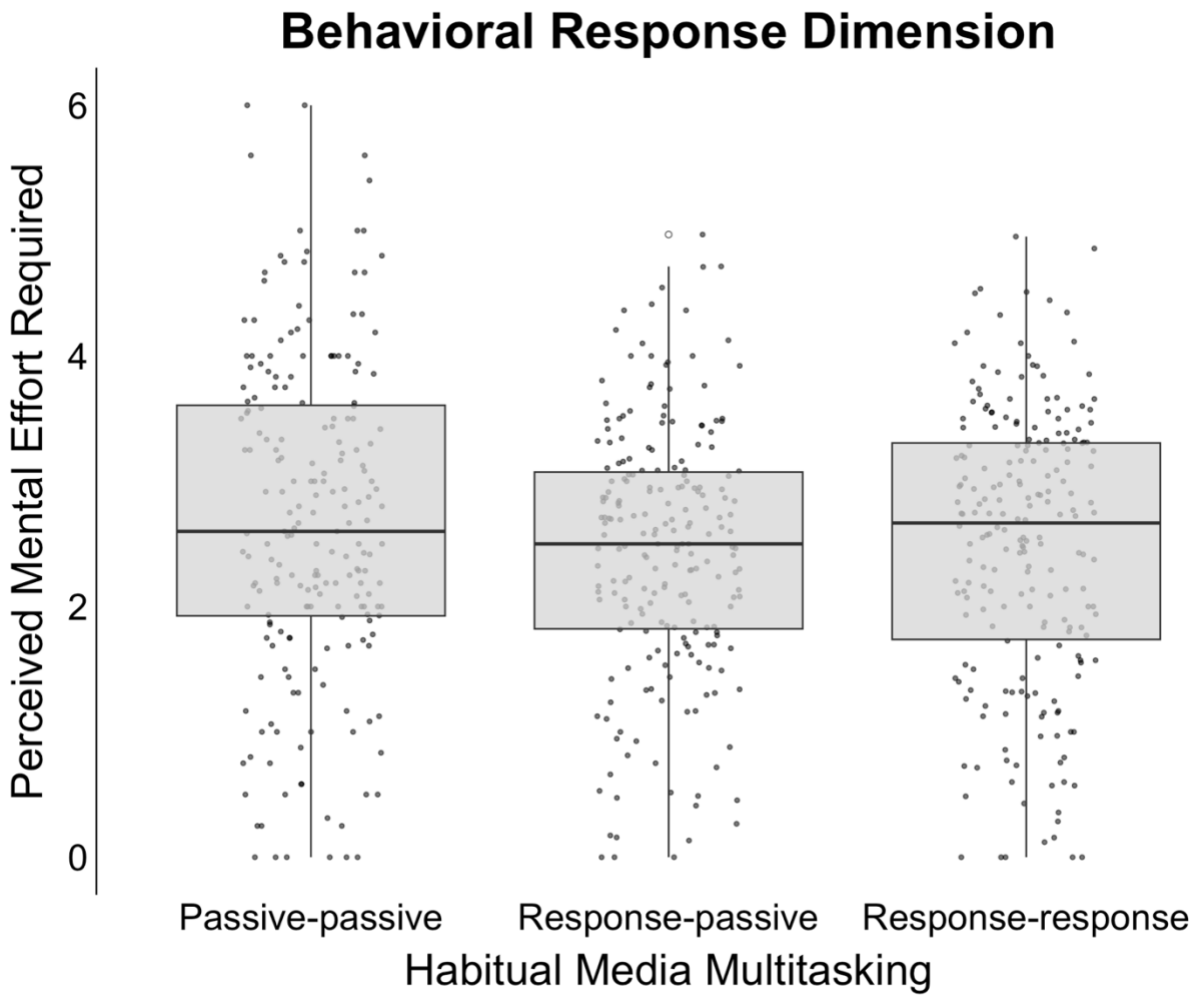
Perceived Mental Effort Required During Habitual Media Multitasking for the Information Flow Dimension



For the behavioral response dimension, I conducted a repeated measures ANOVA to compare the perceived mental effort required across information flow MM pairs (response-response MM, response-passive MM, and passive-passive MM). There was a violation of sphericity across groups according to the Mauchly's Test, $W(2) = .57$, $p < .001$. To account for this, I applied Greenhouse-Geiser correction. MM pairs did not differ significantly in perceived mental effort required after correction for multiple comparisons, $F(1.4, 283.96) = 5.547$, $p = .011$, $n^2 = .006$, Figure 22.

Figure 22

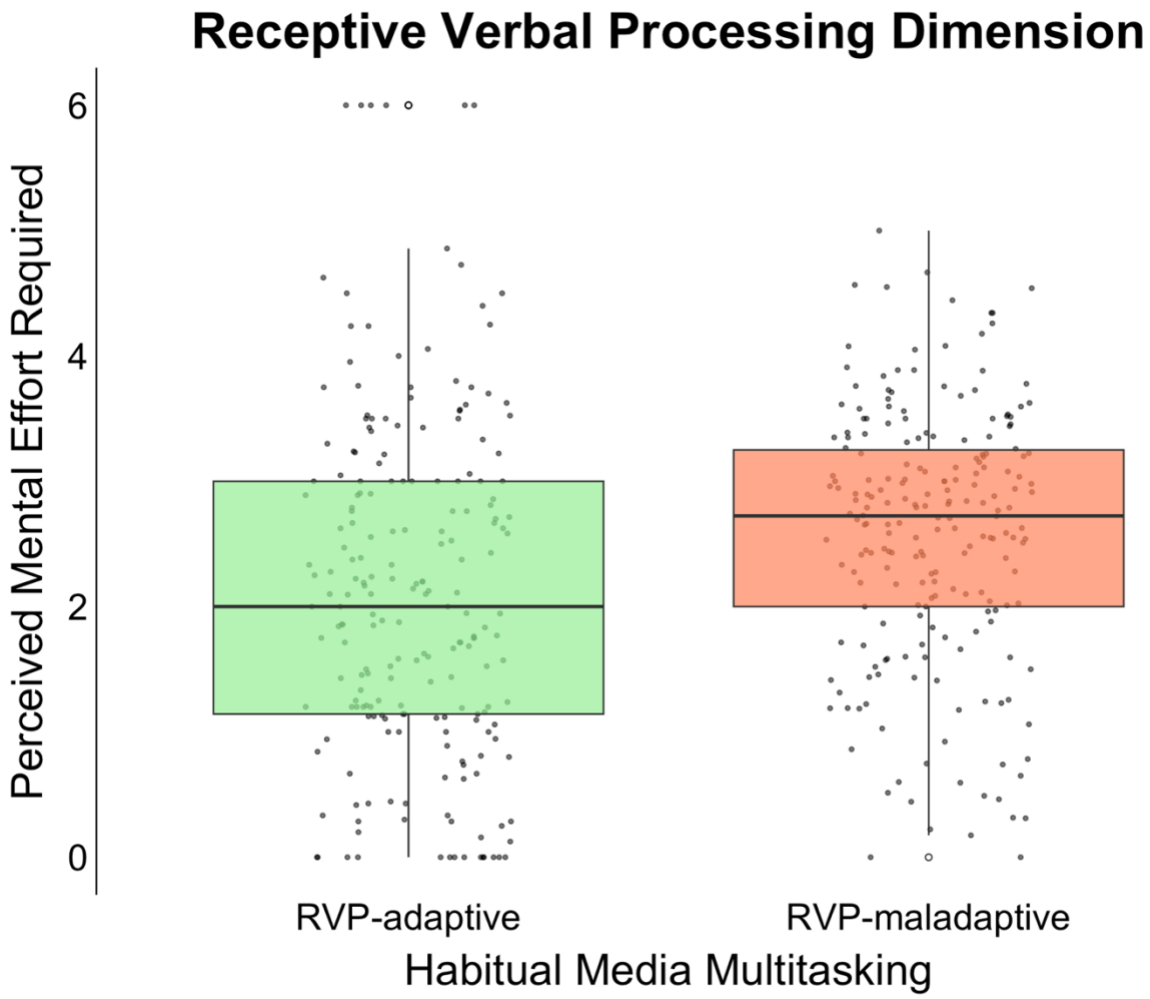
Perceived Mental Effort Required During Habitual Media Multitasking for the Behavioral Response Dimension



For the receptive verbal processing dimension, participants perceived less mental effort was required during MM with at least one input that did not require receptive verbal processing (M = 2.12, SD = 1.36) relative to MM with media inputs that both required receptive verbal processing (M = 2.59, SD = 1.02), t(209) = 6.583, $p < .001$, $d = 0.454$, Figure 23.

Figure 23

Perceived Mental Effort Required During Habitual Media Multitasking for the Receptive Verbal Processing Dimension

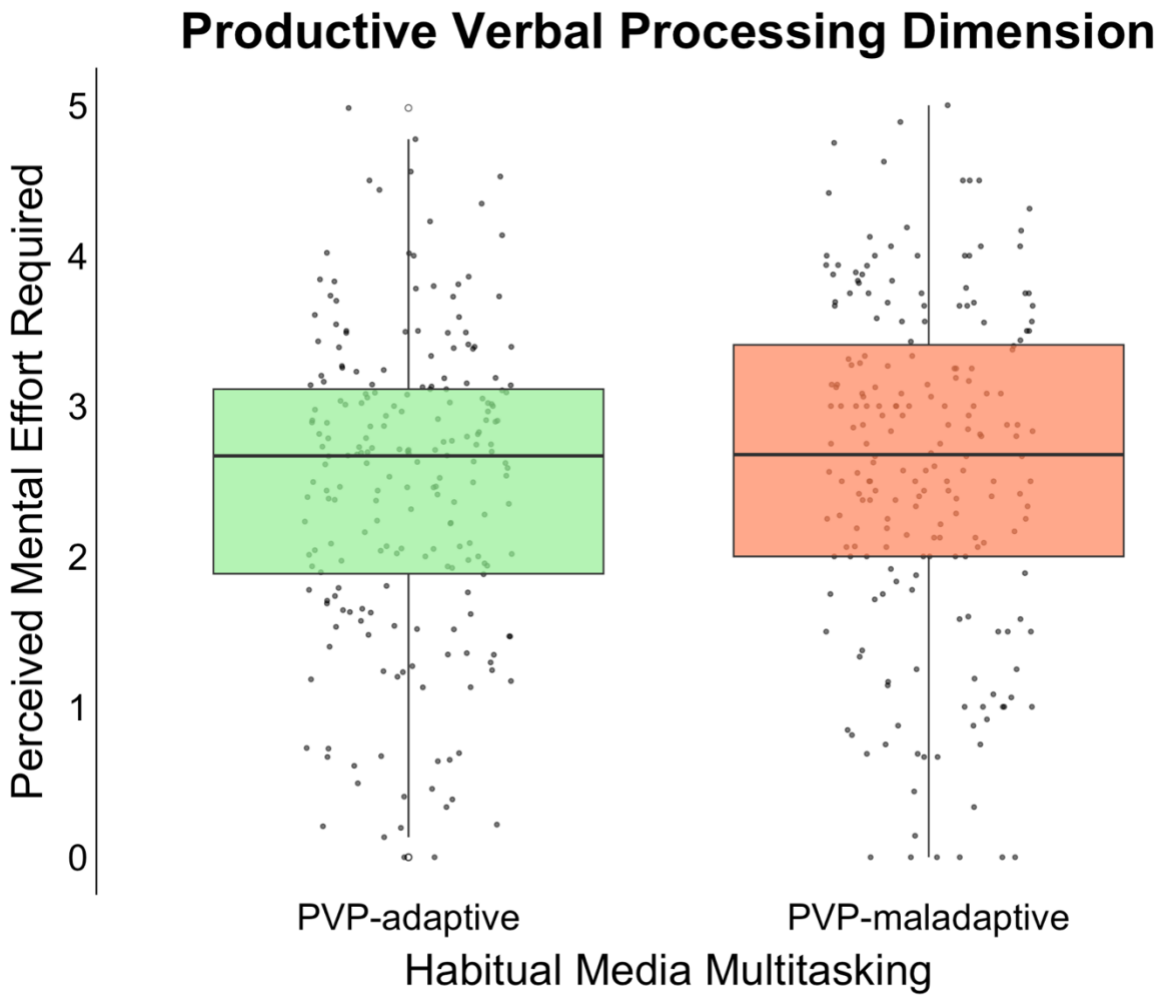


Note. RVP-adaptive = media multitasking pairs with at least one input that does not require receptive verbal processing. RVP-maladaptive = media multitasking pairs in which both inputs require receptive verbal processing.

For the productive verbal processing dimension, there was no difference in perceived mental effort required between MM with inputs that both required productive verbal processing (M = 2.60, SD = 1.11) relative to MM with at least one input that did not require productive verbal processing (M = 2.50, SD = 1.00), t(207) = 1.90, $p = 0.059$, $d = 0.132$, Figure 24.

Figure 24

Perceived Mental Effort Required During Habitual Media Multitasking for the Productive Verbal Processing Dimension



Note. PVP-adaptive = media multitasking pairs with one input that does not require productive verbal processing, PVP-maladaptive = media multitasking pairs in which both inputs require productive verbal processing.

Replication and Extension of Linear Regressions from Study One. Data screening procedures were identical to those described in Study One and can be found in Appendix A. Based on data screening, as well as evaluation of univariate and bivariate relationships between the predictors and outcomes, no participants were excluded in these analyses.

Sensory Processing Dimension. Regression results are summarized in Table 9 and visualized in Figure 25. For this regression model predicting *d',* I entered age and gender into the first step of the model. In this step, age (β = 0.008, p = .904) and gender (male relative to female, β = 0.031, p = .823, non-binary relative to female, β = 0.636, p = .135) did not account for a significant amount of variance in *d'* (R^2 = 0.011, $F(3, 210) = 0.774$, p = .510). S-adaptative MM was added in the second step of the model. In this step, adaptive sensory MM (β = -0.044, p = .523) did not account for a statistically significant amount of variance in *d'* (R^2 = 0.013, $F(4, 209) = 0.681$, p = .606). S-adaptative MM explained 0.2% of the unique variance in *d'* after accounting for age and gender ($F(1, 209) = 0.410$, p = .523). S-maladaptive MM was added in the third step of the model. In this step, S-maladaptive MM (β = -0.249, p < .001) accounted for a statistically significant amount of variance in *d'* (R^2 = 0.066, $F(5, 208) = 2.948$, p = .0136). S-maladaptive MM explained 5.3% of the unique variance in *d'* after accounting for age, gender and S-adaptive MM ($F(1, 208) = 11.876$, p < .001).

Table 9

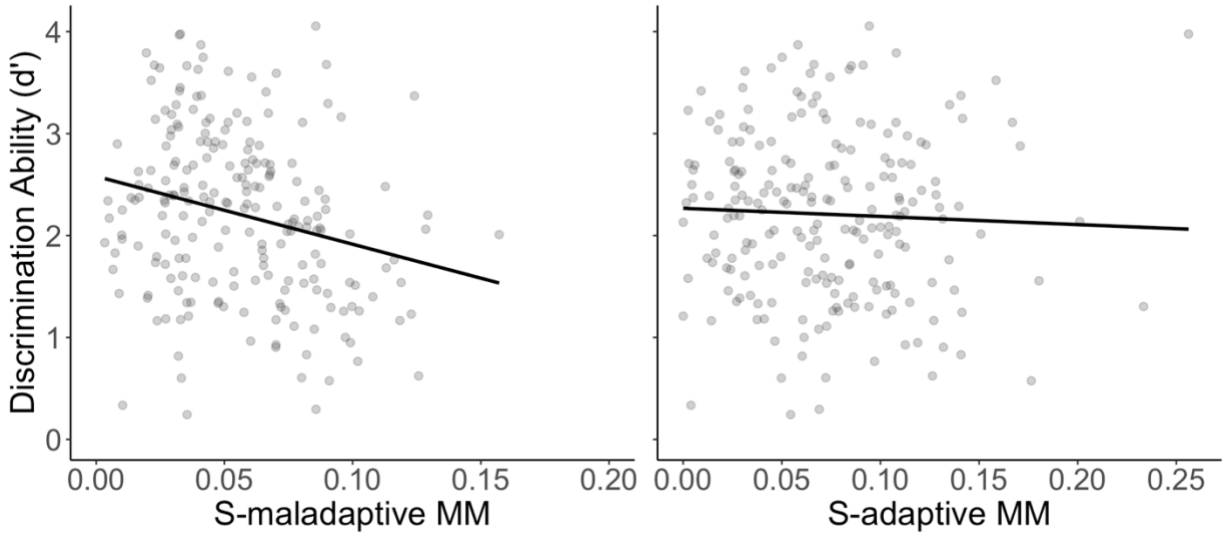
(Post-hoc) Regression Summary Table for the Sensory Modality Replication

	Model 1			Model 2			Model 3		
Variable	*B*	*SE(B)*	β	*B*	*SE(B)*	β	*B*	*SE(B)*	β
Age	0.001	0.012	0.008	0.002	0.012	0.009	3.70e-04	0.011	0.002
Gender (Male)	0.026	0.114	0.031	0.029	0.114	0.036	0.048	0.112	0.059
Gender (Non-binary)	0.519	0.346	0.636	0.519	0.346	0.636	0.371	0.340	0.455
S-adaptive MM				-0.807	1.261	-0.044	0.741	1.308	0.040
S-maladaptive MM							-6.832	1.982	-0.249**
R^2		0.011			0.013			0.066	
F for change in R^2					0.410			11.876**	

Note. *p < .01, **p <.001. B = effect size, SE(B) = standard error for effect size, β = standardized effect size. S-adaptive MM = the tendency to media multitask with pairs that do not share sensory processing. S-maladaptive MM = the tendency to media multitask with pairs that do share sensory processing. Gender was coded as 0 = Male, 1 = Female, 2 = Non-binary, with female as the reference group.

Figure 25

Sensory Media Multitasking and Discrimination Ability (d') Replication



Note. S-adaptive MM = the tendency to media multitask with pairs that do not share sensory processing. S-maladaptive MM = the tendency to media multitask pairs that share sensory processing.

Information Flow Dimension. Regression results are summarized in Table 10 and visualized in Figure 26. For this regression model predicting *d',* I entered age and gender into the first step of the model. In this step, age (β = 0.008, *p* = .904) and gender (male relative to female, β = 0.031, *p* = .823, non-binary relative to female, β = 0.636, *p* = .135) did not account for a significant amount of variance in *d'* (R^2 = 0.011, *F*(3, 210) = 0.774, *p* = .510). Static-static MM and transient-static MM were added in the second step of the model. In this step, static-static MM (β = -0.203, *p* =.027) and transient-static MM (β = -0.012, *p* = .892) did not account for a statistically significant amount of variance in *d'* (R^2= 0.054, *F*(5, 208) = 2.396, *p* = .039). Static-static MM and transient-static MM explained 4.4% of the unique variance in *d'* after accounting for age and gender (*F*(2, 208) = 4.787, *p* = .009). Transient-transient MM was added in the third step of the model. In this step, transient-transient MM (β= -0.292, *p* = .001)

accounted for a statistically significant amount of variance in *d'* (R^2= 0.096, $F(6, 207) = 3.668$, $p = .002$). Transient-transient MM explained 4.2% of the unique variance in *d'* after accounting for age, gender, static-static MM, and transient-static MM ($F(1, 207) = 9.537$, $p = .002$).

Table 10

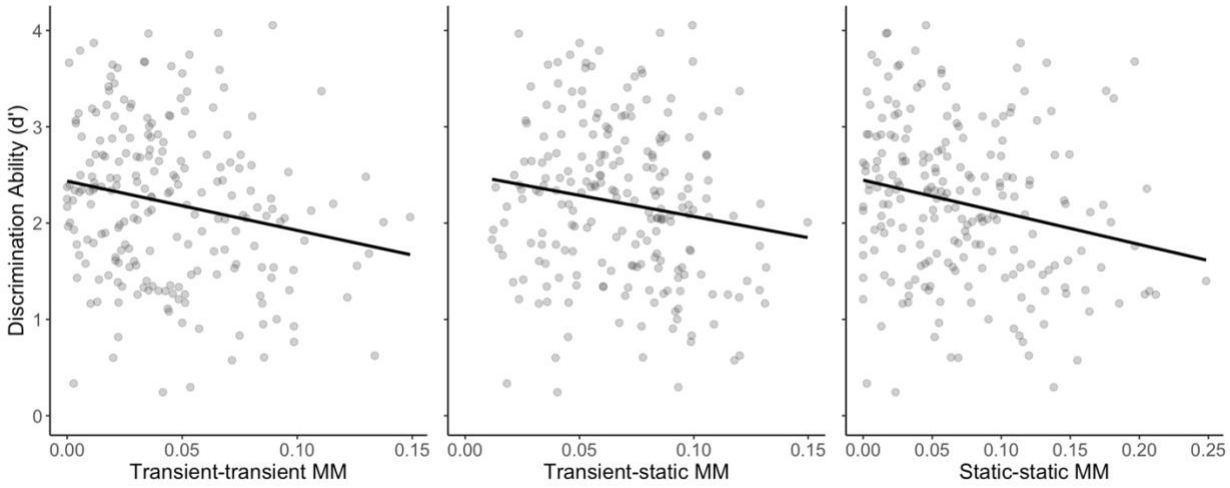
(Post-hoc) Regression Summary Table for the Information Flow Dimension Replication

	Model 1			Model 2			Model 3		
Variable	*B*	*SE(B)*	β	*B*	*SE(B)*	β	*B*	*SE(B)*	β
Age	0.001	0.012	0.008	0.004	0.012	0.026	0.006	0.011	0.038
Gender (Male)	0.026	0.114	0.031	0.025	0.112	0.031	0.055	0.110	0.068
Gender (Non-binary)	0.519	0.346	0.636	0.380	0.343	0.466	0.335	0.336	0.411
Transient-static MM				-0.351	2.581	-0.012	7.088	3.493	0.250
Static-static MM				-3.103	1.397	-0.203	-4.787	1.474	-0.313**
Transient-transient MM							-7.398	2.395	-0.292**
R^2		0.011			0.054			0.096	
F for change in R^2					4.787*			9.537*	

Note. *p < .01, **p < .001. B = effect size, SE(B) = standard error for effect size, β = standardized effect size, MM = media multitasking. Gender was coded as 0 = Male, 1 = Female, 2 = Non-binary, with female as the reference group.

Figure 26

Information Flow Media Multitasking and Discrimination Ability (d') Replication



Note. MM = media multitasking.

Behavioral Response Dimension. Regression results are summarized in Table 11 and visualized in Figure 27. For this regression model predicting *d',* I entered age and gender into the first step of the model. In this step, age (β = 0.008, *p* = .904) and gender (male relative to female, β = 0.031, *p* = .823, non-binary relative to female, β = 0.636, *p* = .135) did not account for a significant amount of variance in *d'* (R^2 = 0.011, *F*(3, 210) = 0.774, *p* = .510). Passive-passive MM and response-passive MM were added in the second step of the model. In this step, passive-passive MM (β= -0.219, *p* = .028) and response-passive MM (β = 0.053, *p* = .596) did not account for a statistically significant amount of variance in *d'* (R^2 = 0.045, *F*(5, 208) = 1.955, *p* = .087). Passive-passive MM and response-passive MM explained 3.4% of the unique variance in *d'* after accounting for age and gender (*F*(2, 208) = 3.697, *p* = .026). Response-response MM was added in the third step of the model. In this step, response-response MM (β = -0.287, *p* < .001) accounted for a statistically significant amount of variance in *d'* (R^2 = 0.101, *F*(6, 207) =

3.888, $p = .001$). Response-response MM explained 5.6% of the unique variance in *d'* after accounting for age, gender, passive-passive MM, and response-passive MM ($F(1, 207) = 12.990$, $p < .001$).

Table 11

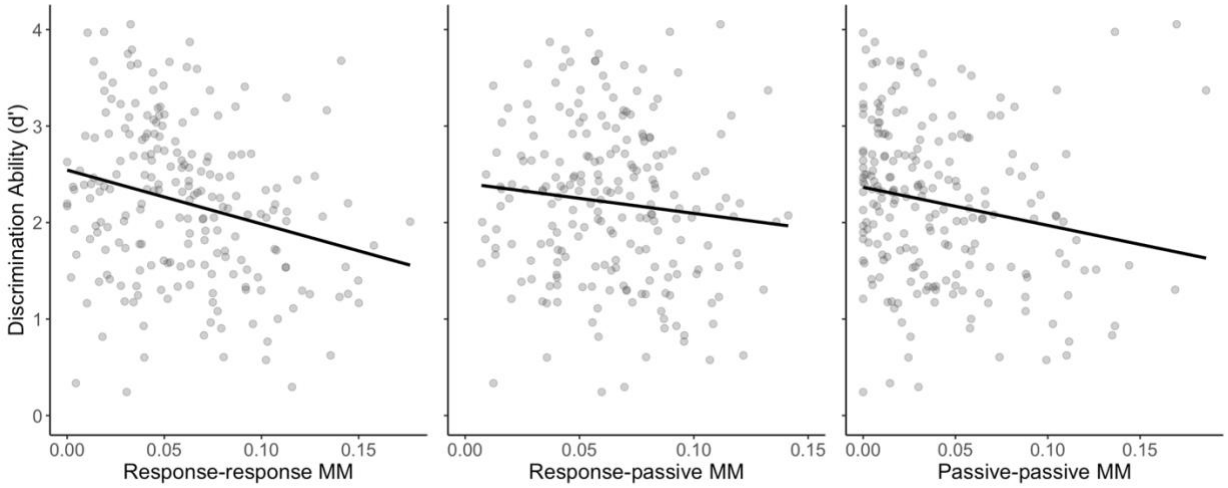
(Post-hoc) Regression Summary Table for the Behavioral Response Dimension Replication

	Model 1			Model 2			Model 3		
Variable	*B*	*SE(B)*	β	*B*	*SE(B)*	β	*B*	*SE(B)*	β
Age	0.001	0.012	0.008	0.003	0.011	0.021	0.003	0.011	0.019
Gender (Male)	0.026	0.114	0.031	0.021	0.113	0.026	0.040	0.110	0.049
Gender (Non-binary)	0.519	0.346	0.636	0.468	0.342	0.573	0.282	0.336	0.345
Passive-passive MM				-4.689	2.116	-0.219	-5.577	2.072	-0.261*
Response-passive MM				1.484	2.796	0.053	6.587	3.065	0.233
Response-response MM							-6.332	1.757	-0.287**
R^2		0.011			0.045			0.101	
F for change in R^2					3.697			12.990**	

Note. **p < .01, **p < .001. B = effect size, SE(B) = standard error for effect size, β = standardized effect size, MM = media multitasking. Gender was coded as 0 = Male, 1 = Female, 2 = Non-binary, with female as the reference group.

Figure 27

Behavioral Response Media Multitasking and Discrimination Ability (d') Replication



Note. MM = media multitasking.

Receptive Verbal Processing Dimension. Receptive verbal processing dimension regression results are summarized in Table 12 and visualized in Figure 28. For this regression model predicting *d',* I entered age and gender into the first step of the model. In this step, age (β = 0.008, p = .904) and gender (male relative to female, β = 0.031, p = .823, non-binary relative to female, β = 0.636, p = .135) did not account for a significant amount of variance in *d'* (R^2 = 0.011, $F(3, 210) = 0.774$, p = .510). Adaptive receptive verbal processing MM (RVP-adaptive MM) was added in the second step of the model. In this step, RVP-adaptive MM (β = -0.130, p = .060) did not account for a statistically significant amount of variance in *d'* (R^2 = 0.028, $F(4, 209) = 1.483$, p = .208). RVP-adaptive MM explained 1.7% of the unique variance in *d'* after accounting for age and gender ($F(1, 209) = 3.584$, p = .060). Maladaptive receptive verbal processing MM (RVP-maladaptive MM) was added in the third step of the model. In this step, RVP-maladaptive MM (β = -0.189, p = .010) accounted for a statistically significant amount of variance in *d'* (R^2 = 0.058, $F(5, 208) = 2.577$, p = .028). RVP-maladaptive MM explained 3.1%

of the unique variance in *d'* after accounting for age, gender and RVP-adaptive MM ($F(1, 208) = 6.785$, $p = .010$).

Table 12

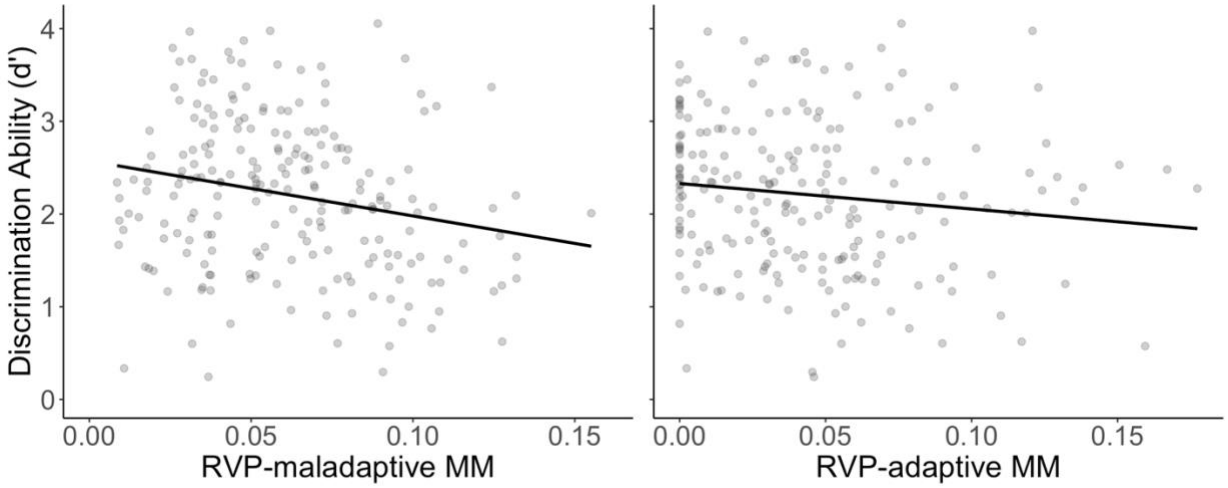
(Post-hoc) Regression Summary Table for the Receptive Verbal Processing Dimension

	Model 1			Model 2			Model 3		
Variable	*B*	*SE(B)*	β	*B*	*SE(B)*	β	*B*	*SE(B)*	β
Age	0.001	0.012	0.008	0.002	0.011	0.010	0.001	0.011	0.006
Gender (Male)	0.026	0.114	0.031	0.056	0.114	0.068	0.053	0.113	0.065
Gender (Non-binary)	0.519	0.346	0.636	0.513	0.343	0.628	0.406	0.341	0.498
RVP-adaptive MM				-2.780	1.468	-0.130	-1.334	1.551	-0.063
RVP-maladaptive MM							-5.092	1.955	-0.189*
R^2		0.011			0.028			0.058	
F for change in R^2					3.584			6.785*	

Note. *p < .01, **p <.001. B = effect size, SE(B) = standard error for effect size, β = standardized effect size, RVP-adaptive MM = the tendency to media multitask with pairs in which one input does not require receptive verbal processing, RVP-maladaptive MM= the tendency to media multitask with pairs with inputs that both require receptive verbal processing. Gender was coded as 0 = Male, 1 = Female, 2 = Non-binary, with female as the reference group.

Figure 28

Receptive Verbal Processing Media Multitasking and Discrimination Ability (d')



Note. RVP-adaptive MM = the tendency to media multitask with pairs in which one input does not require receptive verbal processing, RVP-maladaptive MM= the tendency to media multitask with pairs with inputs that both require receptive verbal processing.

Productive Verbal Processing Dimension. Productive verbal processing dimension regression results are summarized in Table 13 and visualized in Figure 29. For this regression model predicting *d',* I entered age and gender into the first step of the model. In this step, age (β = 0.008, *p* = .904) and gender (male relative to female, β = 0.031, *p* = .823, non-binary relative to female, β = 0.636, *p* = .135) did not account for a significant amount of variance in *d'* (R^2 = 0.011, *F*(3, 210) = 0.774, *p* = .510). Adaptive productive verbal processing MM (PVP-adaptive MM) was added in the second step of the model. In this step, PVP-adaptive MM (β= -0.203, *p* = .003) accounted for a statistically significant amount of variance in *d'* (R^2= 0.052, F(4, 209) = 2.847, *p* = .025). PVP-adaptive MM explained 4.1% of the unique variance in *d'* after accounting for age and gender (*F*(1, 209) = 8.977, *p* = .003). Maladaptive productive verbal processing MM (PVP-maladaptive MM) was added in the third step of the model. In this step, PVP-maladaptive MM (β= -0.108, *p* = .178) did not account for a statistically significant amount of variance in *d'*

(R^2= 0.060, F(5, 208) = 2.652, p = .024). PVP-maladaptive MM explained 0.8% of the unique variance in *d'* after accounting for age, gender and PVP-adaptive MM (F(1, 208) = 1.828, p = .178).

Table 13

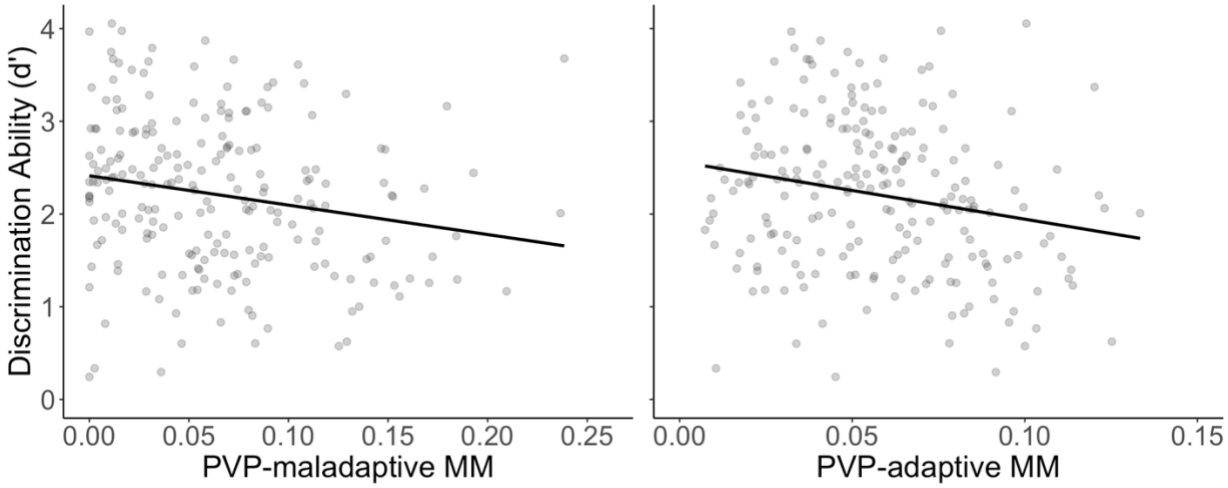
(Post-hoc) Regression Summary Table for the Productive Verbal Processing Dimension

	Model 1			Model 2			Model 3		
Variable	*B*	*SE(B)*	β	*B*	*SE(B)*	β	*B*	*SE(B)*	β
Age	0.001	0.012	0.008	0.001	0.011	0.005	0.001	0.011	0.006
Gender (Male)	0.026	0.114	0.031	0.051	0.112	0.063	0.048	0.112	0.058
Gender (Non-binary)	0.519	0.346	0.636	0.440	0.340	0.539	0.379	0.343	0.464
PVP-adaptive MM				-6.027	2.011	-0.203*	-4.338	2.364	-0.146
PVP-maladaptive MM							-1.743	1.289	-0.108
R^2		0.011			0.052			0.060	
F for change in R^2					8.978*			1.828	

Note. *p < .01, **p <.001. B = effect size, SE(B) = standard error for effect size, β = standardized effect size, PVP-adaptive MM = the tendency to media multitask with pairs in which one input does not require productive verbal processing, PVP-maladaptive MM= the tendency to media multitask with pairs with inputs that both require productive verbal processing. Gender was coded as 0 = Male, 1 = Female, 2 = Non-binary, with female as the reference group.

Figure 29

Productive Verbal Processing Media Multitasking and Discrimination Ability (d')



Note. PVP-adaptive MM = the tendency to media multitask with pairs in which one input does not require productive verbal processing, PVP-maladaptive MM= the tendency to media multitask with pairs with inputs that both require productive verbal processing.

Logistic Regressions Predicting Tune-outs with Age, Gender, and Habitual Media Multitasking Measures. Initial logistic regression analyses were conducted to predict tune-outs during the gradCPT with age, gender, and MM predictors across each cognitive dimension. Model fit was extremely poor across all analyses, likely driven by the class imbalance of no tune outs (n = 214) relative to tune-outs (n = 29).

Sensory Processing Dimension. A binomial linear regression was conducted with age, gender, S-adaptive MM, and S-maladaptive MM as predictors and tune outs (a binary variable denoting whether participants failed to respond during the gradCPT for at least 10 seconds) as the dependent variable. Model coefficients are presented in Table 14. The overall model fit was poor (deviance = 134.371, AIC =146.371, R^2-N = 0.265, $\chi^2(5) = 34.688$, $p < .001$), accuracy = 0.888, specificity = 0.986, sensitivity = 0.111, and area under the curve (AUC) = 0.831). S-

maladaptive MM was a significant predictor of tune-outs (b = 32.679, SE = 7.587, z = 4.307, $p <$ .001). Age, gender, and S-adaptive MM were not associated with tune-outs.

Table 14

(Post-hoc) Logistic Regression Summary Table for the Sensory Processing Dimension

Predictor	b	SE	z	Odds Ratio	95% CI [OR]
Intercept	-3.999	1.418	-2.82	0.018	[0.001, 0.296]
Age	-0.046	0.047	-0.979	0.955	[0.872, 1.047]
Gender (Male)	-0.152	0.460	-0.330	0.859	[0.349, 2.115]
Gender (Non-binary)	-14.356	1496.183	-0.010	5.82E-07	[0.000, Inf]
S-maladaptive MM	32.679	7.587	4.307	1.56E+14**	[5.4E+7, 4.47E+20]
S-adaptive MM	9.846	4.726	2.083	18891.796	[1.793, 1.99E+8]

Note. *p < .01, **p <.001. CI = confidence interval, OR = odds ratio, S-adaptive MM = the tendency to media multitask with pairs that do not share sensory processing. S-maladaptive MM = the tendency to media multitask pairs that share sensory processing. Gender was coded as 0 = Male, 1 = Female, 2 = Non-binary, with female as the reference group.

Information Flow Dimensions. A binomial linear regression was conducted with age, gender, transient-transient MM, transient-static MM, and static-static MM as predictors and tune out (a binary variable denoting whether participants failed to respond during the gradCPT for at least 10 seconds) as the dependent variable. Model coefficients are presented in Table 15. The overall model fit was poor (deviance = 128.070, AIC = 142.070, R^2-N = 0.310, $\chi^2(6) = 40.989$, $p <$ .001, accuracy = 0.900, specificity = 0.981, sensitivity = 0.259, and AUC of 0.838). Transient-transient MM was a significant predictor of tune-outs (b = 30.954, SE = 8.325, z = 3.718, $p <$ .001). Age, gender, transient-static MM, and static-static MM were not associated with tune-outs.

Table 15

(Post-hoc) Logistic Regression Summary Table for the Information Flow Dimension

Predictor	b	SE	z	Odds Ratio	95% CI [OR]
Intercept	-3.527	1.493	-2.362	0.029	[0.002, 0.549]
Age	-0.035	0.047	-0.747	0.965	[0.879, 1.059]
Gender (Male)	-0.195	0.476	-0.411	0.822	[0.324, 2.089]
Gender (Non-binary)	-14.328	1522.592	-0.009	5.99E-7	[0.000, Inf]
Static-static MM	4.644	7.037	0.660	103.941	[1.06E-4, 1.02E+08]
Transient-static MM	0.976	16.026	0.061	2.653	[6.06E-14, 1.16E+14]
Transient-transient MM	30.954	8.325	3.718	2.77E+13**	[2.27E+5, 3.39E+20]

Note. *p < .01, **p <.001. CI = confidence interval, MM = media multitasking, OR = odds ratio. Gender was coded as 0 = Male, 1 = Female, 2 = Non-binary, with female as the reference group.

Behavioral Response Dimension. A binomial linear regression was conducted with age, gender, response-response MM, passive-passive MM, and response-passive MM as predictors and tune out (a binary variable denoting whether participants failed to respond during the gradCPT for at least 10 seconds) as the dependent variable. Model coefficients are presented in Table 16. The overall model fit was poor (deviance = 130.874, AIC = 144.874, R^2-N = 0.291, $\chi^2(6) = 38.185$, $p < .001$, accuracy = 0.892, specificity = 0.986, sensitivity = 0.148, and AUC = 0.837). Response-response MM (b = 24.361, SE = 7.299, z = 3.338, p <.001) and passive-passive MM (b = 21.367, SE = 7.867, z = 2.716, p =.006) were significant predictors of tune-outs. Age, gender, and response-passive MM were not associated with tune-outs.

Table 16

(Post-hoc) Logistic Regression Summary Table for the Behavioral Response Dimension

Predictor	b	SE	z	Odds Ratio	95% CI [OR]
Intercept	-3.018	1.472	-2.050	0.049	[0.003, 0.875]
Age	-0.053	0.047	-1.129	0.949	[0.866, 1.040]
Gender (Male)	-0.331	0.471	-0.701	0.718	[0.285, 1.810]
Gender (Non-binary)	-13.975	1527.214	-0.009	8.53E-07	[0.000, Inf]
Response-response MM	24.361	7.299	3.338	3.80E+10**	[2.33E+4, 6.21E+16]
Passive-passive MM	21.367	7.867	2.716	1.90E+09*	[3.83E+2, 9.45E+15]
Response-passive MM	-8.64	14.593	-0.592	1.77E-04	[6.70E-17, 4.67E+8]

Note. *p < .01, **p <.001. BR = behavioral response, CI = confidence interval, MM = media multitasking, OR = odds ratio. Gender was coded as 0 = Male, 1 = Female, 2 = Non-binary, with female as the reference group.

Receptive Verbal Processing Dimension. A binomial linear regression was conducted with age, gender, shared receptive verbal processing, and no shared receptive verbal processing MM as predictors and tune-out (a binary variable denoting whether participants failed to respond during the gradCPT for at least 10 seconds) as the dependent variable. Model coefficients are presented in Table 17. The overall model fit was poor (deviance = 130.853, AIC = 142.853, and R^2-N of 0.291, $\chi^2(5) = 38.207$, $p < .001$, accuracy = 0.896, specificity = 0.986, sensitivity = 0.185, and AUC = 0.833). RVP-maladaptive MM (b = 28.905, SE = 7.605, z = 3.801, $p < .001$) and RVP-adaptive MM (b = 13.301, SE = 4.158, z = 3.199, $p = .001$) were significant predictors of tune-outs. Age and gender were not associated with tune-outs.

Table 17

(Post-hoc) Logistic Regression Summary Table for the Receptive Verbal Processing Dimension

Predictor	b	SE	z	Odds Ratio	95% CI [OR]
Intercept	-3.679	1.433	-2.567	0.025	[0.002, 0.419]
Age	-0.052	0.047	-1.105	0.949	[0.865, 1.041]
Gender (Male)	-0.123	0.469	-0.262	0.885	[0.353, 2.217]
Gender (Non-binary)	-14.260	1507.860	-0.009	6.41E-07	[0.000, Inf]
RVP-maladaptive MM	28.905	7.605	3.801	3.57E+12**	[1.20E+5, 1.06E+19]
RVP-adaptive MM	13.301	4.158	3.199	597803.4**	[172.694, 2.07E+9]

Note. *p < .01, **p <.001. CI = confidence interval, OR = odds ratio, RVP-adaptive MM = the tendency to media multitask with pairs that do not share receptive verbal processing, RVP-maladaptive MM = the tendency to media multitask with pairs that share receptive verbal processing. Gender was coded as 0 = Male, 1 = Female, 2 = Non-binary, with female as the reference group.

Productive Verbal Processing Dimension. A binomial linear regression was conducted with age, gender, shared productive verbal processing, and no shared productive verbal processing MM as predictors and tune-out (a binary variable denoting whether participants failed to respond during the gradCPT for at least 10 seconds) as the dependent variable. Model coefficients are presented in Table 18. The overall model fit was poor (deviance = 135.023, AIC = 147.023, and R^2-N of 0.261, $\chi^2(5) = 34.036$, $p < .001$, accuracy = 0.896, specificity = 0.991, sensitivity = 0.148, and AUC = 0.825). PVP-adaptive MM was a significant predictor of tune-outs (b = 34.516, SE = 8.590, z = 4.018, $p < .001$). Age, gender, and PVP-maladaptive MM were not associated with tune-outs.

Table 18

(Post-hoc) Logistic Regression Summary Table for the Productive Verbal Processing Dimension

Predictor	b	SE	z	Odds Ratio	95% CI [OR]
Intercept	-3.931	1.438	-2.733	0.020	[0.001, 0.329]
Age	-0.040	0.047	-0.864	0.960	[0.876, 1.053]
Gender (Male)	-0.192	0.463	-0.415	0.825	[0.333, 2.043]
Gender (Non-binary)	-14.290	1517.121	-0.009	6.22E-07	[0.000, Inf]
PVP-maladaptive MM	6.192	3.813	1.624	488.738	[0.278, 859965.922]
PVP-adaptive MM	34.516	8.590	4.018	9.77E+14**	[4.77E+7, 2.00E+22]

Note. *p < .01, **p <.001. CI = confidence interval, OR = odds ratio, PVP-adaptive MM = the tendency to media multitask with pairs in which one input does not require productive verbal processing, PVP-maladaptive MM= the tendency to media multitask with pairs with inputs that both require productive verbal processing. Gender was coded as 0 = Male, 1 = Female, 2 = Non-binary, with female as the reference group.

Discussion

This study aimed to explore whether situational MM influences subsequent sustained attention. Further, this study aimed to characterize how adaptive and maladaptive forms of situational MM may differentially influence subsequent sustained attention based on underlying cognitive and perceptual resource utilization during MM. The findings of Study Two paint a complex and nuanced relationship between situational MM and sustained attention. Contrary to my hypotheses, participants who engaged in situational MM before the gradCPT performed better than those who engaged in single media use. Specifically, participants who situationally media multitasked exhibited greater *d'* relative to single media use; however, these differences did not survive correction for multiple comparisons. Further, there were no differences in perceived mental effort during media use across participants who engaged in MM relative to single media, suggesting MM was not subjectively more demanding than single media use for

participants in the study. Participants in the MM condition may have interacted with media in ways to conserve mental effort and cognitive resources, consistent with theories of the law of less work (Baumgartner & Wiradhany, 2022; Kool et al., 2010). Participants in the MM condition may capture this by choosing specific pairs classified as adaptive based on my qualitative framework (Baumgartner & Wiradhany, 2022). It's also possible other factors of media engagement were at play in the MM condition to avoid inefficient resource utilization or interference, such as prioritization of one input over the other to minimize the frequency of attentional switching (Zamanzadeh & Rice, 2021).

Further, I also did not find significant differences in sustained attention across participants who media multitasked in ways considered maladaptive rather than adaptive across all cognitive dimensions. For verbal processing modalities, the lack of significance may have been influenced by the relatively small sample sizes of "adaptive" media multitaskers for the receptive verbal processing dimension and the "maladaptive" media multitaskers for the productive verbal processing dimension. These analyses may have been underpowered overall, as the a priori power analysis was conducted to compare sustained attention across situational MM and single media use, which was approximately double the sample size of situational MM alone.

Yet, there was a statistically significant relationship between greater perceived mental effort while situationally MM and poorer subsequent *d'*. This suggests that situational MM with a high degree of perceived mental effort may prime individuals to be in an exploratory state, in which individuals are more prone to task disengagement and exploring alternative tasks to meet situational gratification (Wiradhany et al., 2021). Alternatively, high perceived mental effort during MM may indicate participants feel cognitively overloaded or stressed, impairing their

ability to adapt to the situational demands of the gradCPT subsequently (Zamanzadeh & Rice, 2021). This interpretation is less likely considering previous work that found no difference in biological or subjective stress responses across situational MM and single media use (Wannagat et al., 2025).

Post-hoc analyses explored perceived mental effort requirements across habitual MM pairs for each cognitive dimension. I found that participants perceived that MM required more mental effort with pairs that shared sensory processing relative to MM pairs that did not share sensory processing. For the information flow dimension, participants perceived the most mental effort required when habitually MM with static-static MM pairs relative to transient-transient and transient-static MM inputs. Participants perceived requiring more mental effort habitually MM with pairs that both required receptive verbal processing relative to MM pairs that did not both require verbal processing (i.e., included instrumental music as one of the inputs). I did not see differences in perceived mental effort required when habitually MM with different pairs for the behavioral response and productive verbal processing dimensions after correction for multiple comparisons.

These findings help further characterize the relationship between habitual MM and perceived mental effort. Specifically, findings in the sensory processing and receptive verbal processing dimensions suggest that MM with qualitatively similar inputs are perceived to require more mental effort than MM with inputs with dissimilar characteristics. This likely reflects that participants are subjectively aware of the likely cognitive and perceptual interference experienced when MM with inputs that likely require similar cognitive and perceptual resources. However, findings in the information flow dimension add nuance to this understanding. Specifically, transient-transient MM was perceived to require less effort than transient-static

MM. This is unexpected, considering transient-transient MM was hypothesized to be highly demanding and induce cognitive and perceptual interference due to shared characteristics between the inputs.

Further, I utilized post-hoc regression analyses to replicate regression findings from Study One and extend these findings in the dimensions of receptive and productive verbal processing. Specifically, I aimed to replicate that a greater tendency to habitually media multitask with pairs that carry similar cognitive and perceptual processing requirements (i.e., maladaptive MM) is associated with poorer sustained attention. Conversely, I hypothesized habitual MM with inputs that carry unique processing requirements would not be related to sustained attention. I hypothesized these findings would replicate for the three cognitive dimensions in Study One (sensory processing, information flow, and behavioral response), and to the cognitive dimensions of receptive and productive verbal processing. Findings from Study One did indeed replicate in Study Two. Specifically, a greater tendency to habitually MM with pairs that required shared sensory processing, communicated information in the same manner (transient-transient MM and static-static MM) , or required similar behavioral response demands (response-response MM and passive-passive MM) was associated with lower *d'*. Conversely, habitual MM with pairs that did not share sensory processing, communicated information in different ways (transient-static MM), and required different behavioral response demands (response-passive MM) was not associated with *d'*. These findings extended to the receptive verbal processing modality, in which a greater tendency to media multitask with inputs that both require receptive verbal processing was associated with lower *d'*, while MM in which one input did not require receptive verbal processing (i.e., instrumental music), was not associated with *d'*. Contrary to my hypotheses, a greater tendency to habitually MM with inputs that both required

productive verbal processing did not explain additional variance in *d'* after accounting for a tendency to media multitask with pairs in which one input did not require productive verbal processing.

Finally, post-hoc binomial logistic regressions were conducted to assess whether habitual MM habits predicted the likelihood an individual would tune-out during the gradCPT (i.e., fail to respond for more than ten seconds during the task). These analyses were conducted to assess whether adaptive and maladaptive habitual MM differentiated whether participants exhibited the sustained attention necessary to comply with the task demands of the gradCPT, irrespective of performance. Binomial logistic regressions included identical predictors as those included in linear regressions predicting *d'* in studies one and two. Analyses demonstrated a greater tendency to media multitask with inputs that shared sensory processing requirements was associated with a greater likelihood of tune-outs, while no relationship was found between a tendency to media multitask with inputs that did not share sensory processing requirements. A greater tendency to media multitask with transient-transient pairs was associated with a greater likelihood of tune-outs, while no relationships were found between tune-outs and a tendency to media multitask with static-static or transient-static pairs. A greater tendency to media multitask with response-response and passive-passive pairs were both associated with a greater likelihood of tune-outs, while no relationships were found between tune-outs and a tendency to media multitask with response-passive pairs. A greater tendency to media multitask with pairs in which both inputs required receptive verbal processing and pairs in which one input did not require receptive verbal processing were both associated with a greater likelihood of tune-outs. A greater tendency to media multitask with pairs in which one input did not require productive verbal processing was associated with a greater likelihood of tune-outs, while a tendency to media multitask with pairs

that both required productive verbal processing was not associated with tune-outs. These results suggest that MM characteristics may play a significant role in task non-compliance. Yet, all five logistic regressions exhibited poor model fit, suggesting findings be taken with caution. Poor model fit was likely influenced by the class imbalance between participants who did not tune out (n = 214) and participants who tuned out (n = 27).

General Discussion

Studies one and two aimed to characterize the role of cognitive and perceptual resource utilization during MM and sustained attention by differentiating MM pairs hypothesized to be maladaptive and adaptive. Studies one and two suggest a nuanced relationship between MM and sustained attention. Study One and its replication in Study Two found that the relationship between habitual MM and sustained attention differed as a function of cognitive and perceptual resource utilization. Specifically, these studies found that a greater tendency to habitually media multitask with qualitatively similar inputs was associated with poorer sustained attention, operationalized by accuracy on the gradCPT, *d'.* These findings were consistent across three cognitive dimensions representing different aspects of information processing and behavior, specifically sensory processing, information flow, and behavioral response. A greater tendency to media multitask with inputs that shared sensory processing requirements was associated with lower *d'*, while there was no relationship between a tendency to media multitask with inputs that did not share sensory processing requirements and *d'*. A greater tendency to media multitask with inputs that communicate information in similar ways (transient-transient MM and static-static MM) was associated with lower *d'*, while there was no relationship between a tendency to media multitask with inputs that communicate information in different ways (transient-static MM) and *d'*. A greater tendency to media multitask with inputs that exhibited similar behavioral

response requirements (response-response MM and passive-passive MM) was associated with lower *d'*, while there was no relationship between a tendency to media multitask with inputs that exhibited different behavioral response requirements (response-passive MM) and *d'*.

These findings partially aligned with my initial hypothesis, which proposed that poorer sustained attention would be associated with a greater tendency to maladaptively media multitask but not adaptively media multitask. The core discrepancy between my initial hypothesis and these findings may be attributed to how I initially characterized maladaptive and adaptive MM. Based on previous work, I hypothesized MM pairs were maladaptive if two conditions were met: 1) media inputs within the MM pair were both cognitively and perceptually demanding, and 2) media inputs within the MM pair were likely to cause cognitive and perceptual interference due to reliance on shared cognitive and perceptual resources (Baumgartner & Wiradhany, 2022). Based on this original classification, static-static MM and transient-static MM were considered adaptive for the information flow dimension due to the assumption that transient information flow is inherently more cognitively and perceptually demanding than static information flow. Similarly for the behavioral response dimension, passive-passive MM and response-passive MM were considered adaptive due to the assumption that a media input that requires a behavioral response is inherently more cognitively and perceptually demanding than an input that does not require a behavioral response. These assumptions were based on previous work (Baumgartner & Wiradhany, 2022) and supported by existing frameworks on cognitive architectures (Kahneman, 1973; L. Li et al., 2022; Salvucci & Taatgen, 2008; Wickens, 2002, 2020). Based on this classification, a tendency to media multitask with maladaptive and adaptive pairs was associated with *d'* in the information flow dimension. Post-hoc analyses provided context and clarification to my initial mixed findings. Specifically, post-hoc analyses found that two types of MM

hypothesized to be adaptive, static-static MM and passive-passive MM, were negatively associated with *d'*. I found no relationship between a tendency to MM with transient-static or response-passive pairs and *d'*. Considering static and passive media inputs were theorized be less demanding than transient and response media inputs, this suggests that theoretical cognitive and perceptual demand assigned to specific media inputs may not be meaningful for determining whether a MM pair is adaptive or maladaptive. Instead, cognitive and perceptual interference may be the key differentiator in determining whether a tendency to media multitask is associated with poorer sustained attention. Based on this understanding, one would predict that a greater tendency to MM with static-static and passive-passive pairs would be related to poorer performance due to similar characteristics and processing requirements between media inputs.

When considering the strength of these key findings, it is important to note key differences between Study One and Study Two. For instance, the adapted media use questionnaire (A-MUQ) utilized in studies one and two varied in the number of media inputs, the media inputs themselves, and the framing of media inputs. The A-MUQ used in Study One also removed redundant pairs to truncate the survey, whereas the A-MUQ used in Study Two did not. The A-MUQ used in Study Two was more extensive than the A-MUQ used in Study One. Specifically, the A-MUQ in Study Two asked participants to rate their perceived mental effort required when MM with specific inputs habitually. This allowed us to characterize perceptions of MM and mental effort in a novel way but likely increased the acute cognitive burden on participants while completing the survey. Further, studies one and two followed protocols that differed in meaningful ways. Perhaps the most meaningful protocol difference was the implementation of a situational MM manipulation unique to Study Two. Finally, Study One utilized a variant of the gradCPT that automatically paused in response to inactivity and was

slower than the traditional version I used in Study Two (Fortenbaugh et al., 2015; Rioja et al., 2023). Despite these considerable differences, regression findings across studies one and two were nearly identical. Taken together, both studies suggest that underlying cognitive and perceptual resource utilization during MM is a key determinant in the relationship between habitual MM and sustained attention.

In addition to their similarities, the goals of Study One and Study Two differed in important ways. Study Two explored the relationship between MM and sustained attention from a different perspective than Study One. Specifically, Study Two explored whether situational MM influences subsequent sustained attention. The idea for Study Two was inspired primarily by research that suggests cognitive and perceptual resource utilization during a task can influence performance on a subsequent task (Leroy, 2009; Snider et al., 2023). Study Two was further inspired by research demonstrating that how an individual deploys their attention influences subsequent task preferences (Mark et al., 2015). These potential carry-over effects on task preferences may be meaningful due to motivation's central role in successful sustained attention (Kurzban et al., 2013).

Interestingly, findings from Study Two broadly did not support the hypotheses that situational MM and underlying cognitive and perceptual resource utilization influence subsequent sustained attention. First, I found no evidence to support the notion that situational MM impairs subsequent sustained attention relative to single media use. Participants assigned to the single media use condition exhibited lower *d'* than participants assigned to the MM condition, a finding that was not significant after correction for multiple comparisons. Participants also did not perceive exerting more mental effort during the MM relative to single media use. While somewhat unexpected, this turned out to be similar to previous work that found

no differences in subjective and objective stress during situational MM relative to single media use (Wannagat et al., 2025).

Second, cognitive and perceptual resource utilization during situational MM did not appear to influence subsequent sustained attention. More specifically, I found no differences in *d'* following MM when comparing performance across hypothesized adaptive and maladaptive types of MM across cognitive dimensions of sensory processing, information flow, behavioral response, receptive verbal processing, and productive verbal processing. This did not support my hypothesis that situational MM with maladaptive pairs would impair subsequent *d'* relative to MM with adaptive pairs. With that said, these analyses may have been underpowered to detect meaningful differences, particularly for the dimensions of sensory processing, receptive verbal processing, and productive verbal processing.

Third, I found that greater perceived mental effort during MM was associated with poorer subsequent *d'*. Higher perceived effort during MM may represent inefficient resource utilization (Kool et al., 2010; Kurzban et al., 2013). Performance may be impaired if this inefficient resource utilization promotes further inefficiency during sustained attention. Alternatively, higher perceived effort during MM may represent a preference to explore the environment rather than stay engaged with a single task (Wiradhany et al., 2021). Based on this understanding, MM may impair subsequent sustained attention by priming individuals to be less motivated to sustain attention to a single task. Considering null findings regarding adaptive and maladaptive situational MM and subsequent *d'* discussed above, it is more likely that perceived mental effort represents situational attentional preferences and underlying motivations rather than resource utilization (Kurzban et al., 2013; Mark et al., 2015).

Studies one and two demonstrated *how* individuals habitually media multitask is a crucial predictor for differentiating whether MM is associated with sustained attention. Specifically, media multitasking habitually with inputs that rely on similar cognitive and perceptual resources may promote interference and inefficient information processing over time. Further, interference and inefficient information processing during MM may be the key link between MM and altered attentional processing, such as increased perceptual sensitivity to irrelevant stimuli, impaired attentional control, and habituation to high levels of stimulation (Baumgartner, 2022; Ophir et al., 2009; Ralph et al., 2014).

These findings may have important implications for translational interventions. Previous work has demonstrated that interventions restricting screen time and phone internet capabilities effectively improve sustained attention (Castelo et al., 2025; Perrault et al., 2019). However, these interventions are becoming increasingly difficult in the modern world. Participants willing to go without internet on their phone for a week or two may be a non-representative sample, in which they actively understand the potential negative consequences of their technology engagement and want to change. Designing interventions that target particularly problematic media habits may be more feasible and just as effective in improving underlying sustained attention. For instance, about half of the MM pairs in the information flow dimension were transient-static pairs, representing habits that had no relationship with sustained attention. Similarly, about half of the MM pairs in the behavioral response dimension were response-passive pairs, representing habits that had no relationship with sustained attention. Further, previous work suggests that individuals choose adaptive MM pairs over maladaptive pairs to minimize cognitive demand (Baumgartner & Wiradhany, 2022; Kool et al., 2010). Based on this, interventions that target screen time and phone internet capabilities may be unnecessarily broad.

Instead, interventions that target specific maladaptive media habits for a given individual represent a more personalized and potentially effective approach.

Limitations

The present work carries several limitations. First and foremost, studies one and two relied on variations of the media use questionnaire (MUQ) utilized in previous work. The MUQ is a retrospective self-report questionnaire that asks participants to report media habits during an average week. Researchers argue that individuals' responses on the MUQ do not accurately capture their habitual MM habits (Parry & Fisher, 2024; Parry & Le Roux, 2021). This inaccuracy is influenced by question-wording about "typical" habits (J. Dang et al., 2020) and difficulty with evaluating one's own multitasking habits (Guo et al., 2024). Further, the MUQ requires researchers to make a fundamental trade-off. On the one hand, researchers can capture many different MM behaviors by including many items. However, longer surveys undermine the reliability and validity of responses due to participant fatigue (Parry & Fisher, 2024). Due to this tradeoff, researchers tend to limit the number of items in the MUQ, resulting in a narrower scope of MM and limiting the generalizability of study findings (Ophir et al., 2009; Parry & Fisher, 2024; Rioja et al., 2023). This suggests that the length of the adapted MUQ (A-MUQ) utilized in Study Two may undermine confidence in participant responses. Specifically, the Study Two A-MUQ asked participants to report MM habits and perceptions of mental effort required during habitual MM, almost doubling the length of an already long survey. While modifications were made to the survey to minimize the burden on participants (e.g., incorporating skip logic when participants reported not engaging with a specific media input), the length of the A-MUQ was still much longer than the truncated version used in Study One administered by Rioja et al. (2023).

Also, the MUQ typically only captures multitasking using two media inputs simultaneously, with some exceptions (Parry & Fisher, 2024). This ignores the variety of ways individuals multitask when using more than two media inputs and pairing media with non-media activities, such as listening to music while running. This limited characterization may be critical in relation to the sensory processing dimension across studies one and two, in which only 14-15% of MM pairs qualified as being adaptive (i.e., they did not share sensory processing requirements). In practice, most individuals frequently multitask with media in ways that limit sensory interference that were not captured through the MUQ, such as listening to music or podcasts while driving a car or exercising.

Another limitation of the current study was that I did not adequately account for the role of prioritization during MM across studies one and two. Individuals may prioritize certain media habits differentially based on a complex mix of dispositional and situational motivations (Wiradhany et al., 2021). Prioritization likely significantly impacts cognitive and perceptual resource utilization in the real world because it can functionally alter the degree of attentional switching and resource allocation (Zamanzadeh & Rice, 2021). For instance, if an individual is watching TV while working on their computer, prioritization predicts situational resource utilization beyond the characteristics of the media inputs. Suppose the individual prioritizes their work based on achieving goals. In that case, they may functionally ignore the visual processing requirements of TV and instead use it as background noise like a podcast or lyrical music. In this scenario, the individual can effectively minimize attentional switching to reduce acute performance costs to their work. Conversely, if the individual prioritizes TV and computer-based work equally, cognitive and perceptual interference may occur due to shared visual processing requirements. Further, an individual will likely rapidly switch their attention between media

inputs, functionally impairing the effectiveness and efficiency of their work. Simultaneously, the individual is likely to receive less situational emotional gratification while MM with TV than if they were solely watching TV (Park et al., 2019), suggesting a cost to performance and situational gratification.

In order to better understand the role of prioritization in influencing underlying cognitive and perceptual resource utilization during MM, it is important to consider the theory of MM intensity (MMTI) proposed by Zamanzadeh and Rice (2021). MMTI proposes that MM is a multidimensional latent construct that varies in intensity as a function of cognitive and perceptual demands (Zamanzadeh & Rice, 2021). MMTI argues that media multitasking intensity varies based on context and cannot be conceptualized by traditional measures of media usage frequency and percentage of media time multitasking (Zamanzadeh & Rice, 2021). MMTI identifies four dimensions of MM intensity: (1) task relevance, (2) task intentionality, (3) task difficulty, and (4) task co-occurrence and interruption. While the framework I utilized in studies one and two largely accounted for task difficulty, co-occurrence, and interruption, it did not adequately account for two important factors that influence prioritization: task relevance and intentionality. Task relevance refers to the perceived shared purpose of simultaneously engaging with two media inputs. Zamananzadeh and Rice (2021) argue that media inputs with a high degree of task relevance can be combined in a complementary way to accomplish a task while efficiently utilizing cognitive and perceptual resources. For example, it may be beneficial for a student to write a paper on memory distortions and have a textbook chapter accessible to facilitate critical thinking and accurate writing. In this scenario, both writing the paper and reading the textbook passage for that paper would facilitate a more thorough consideration of the literature and more effective communication while writing.

Task intentionality refers to the perceived degree of purpose and motivation when engaging with media inputs. MM with two inputs that share an intention or goal may be less intense than MM with inputs with different intentions. For example, preparing to cook by reading recipes while simultaneously watching video-based instruction on cooking may be less intense relative to reading the recipe and actively watching the news. Intentionality may also influence the level of attentional shifting and subjective immersion experienced during MM. Specifically, when combining an active media input with high intentionality and a passive media input with low intentionality, an individual may actively ignore the passive media input during periods of high intensity to facilitate the successful completion of active media input. For example, journalists may listen to an unrelated podcast while they write a story for their editor. Writing that story is a consequential task with real implications for failure while listening to the podcast carries no such consequences. This distinct difference in intentionality between the media inputs likely leads to fewer attentional shifts and greater focus on the primary task. Conversely, MM with two inputs that exhibit similar intentionality may lead to more frequent attentional shifts and more evenly divided attention between the two inputs. In this scenario, even MM with two media inputs that are less cognitively demanding may be more intense when combined due to constantly shifting between the two inputs.

Task relevance and intentionality may help account for findings from studies one and two that suggested theoretical cognitive and perceptual demand did not differentiate which type of MM was associated with sustained attention and which was not. Specifically, task relevance and intentionality may explain how individuals engage with media inputs in the real world, modulating attentional switching based on underlying motivations that are not captured by underlying characteristics of media inputs.

Another limitation stems from the nature of online data collection in Study Two. Due to the uncontrolled nature of the study, I implemented several quality assurance checks and stringent exclusion criteria. All 300 participants passed the embedded attention check in the survey and responded that they took the study seriously. However, I excluded about 30% of this sample due to condition and task non-compliance. Specifically, I excluded participants who were missing gradCPT data, reported not using media or spent more than 20 minutes on the media use condition, reported media multitasking during the gradCPT, used a mobile device, or failed to respond during the gradCPT for 10 seconds or more. While these exclusions were applied to verify participant compliance, this may have limited my ability to detect meaningful effects in Study Two, particularly for analyses that only included participants assigned to the media multitasking condition.

Beyond the important theoretical limitations mentioned above, Study One and Study Two carry additional practical limitations. Due to the correlational nature of Study One and its replication in Study Two, I cannot make any causal inferences between MM and sustained attention. In other words, studies one and two do not suggest a greater tendency to habitually maladaptively media multitask *causes* poorer sustained attention. Individuals with poorer sustained attention may choose maladaptive MM pairs due to attentional preferences. Study Two carried several other practical limitations. Specifically, I had very little control over participant compliance during Study Two due to the online nature of the study. I could not verify that participants followed instructions during the media manipulation (MM compared to single media use). The media manipulation was also only 10 minutes, which may not have been enough time for MM to exert situational carry-over effects on subsequent sustained attention relative to single media use. Because I allowed participants to choose which media inputs they used during the

media manipulation, there were considerable sample size differences in groups of participants who chose adaptive and maladaptive pairs for sensory processing and verbal processing dimensions. Although this gave the study a degree of ecological validity and participant agency, a key determinant of task performance in previous work (Drody et al., 2024; Parry & Fisher, 2024), it also may have left these analyses underpowered and limited to detect meaningful differences in sustained attention.

Future Directions

To address these limitations, researchers should utilize rigorous, in-depth research methods that may better characterize underlying cognitive and perceptual resource utilization. Specifically, researchers should consider longitudinal studies that characterize the relationship between MM and outcomes over time using experience sampling methods (ESM), ecological momentary assessments (EMAs), and activity logging on smartphones and computers. ESM addresses several limitations with retrospective self-report by allowing participants to characterize the contextual factors surrounding their MM habits. ESM allows participants to describe their MM habits and perceptions of those habits without unintended constraints (Csikszentmihalyi & Larson, 2014; Moreno et al., 2012; Xu & Wang, 2021). Participants can document the number of media devices beyond a primary and secondary device, indicate their subjective cognitive and emotional states during MM, and describe a variety of multitasking habits that involve combining media with non-media activities like driving and exercising. ESMs also allow participants to characterize media content beyond media type, allowing the differentiation of content accessed in the same way that may be beneficial or harmful (e.g., watching educational vs. emotionally distressing and graphic videos on YouTube). Further, ESMs allow participants to characterize these habits shortly after engaging in MM, minimizing

the cognitive burden and fatigue participants experience during arduous surveys and asking participants to perform hundreds of meta-cognitive evaluations quickly (Parry & Fisher, 2024).

Similarly, EMAs allow researchers to characterize subjective and objective performance in a more meaningful and personalized manner than a single cross-sectional assessment (Shiffman et al., 2008). Specifically, EMAs allow researchers to characterize temporal variation in performance throughout the day, demonstrating the relative stability of a participant's abilities and the potential for daily activities to influence performance situationally (Shiffman et al., 2008). For researchers interested in MM and sustained attention, we can capture complexities in the relationship between MM and sustained attention beyond the scope of current work. We can assess the influence of different MM habits on subsequent sustained attention and the potential for different time lags between MM to influence sustained attention to different degrees (Singh et al., 2023). Further, when administering EMAs over time, we may be able to capture the reliability of these situational effects for a given individual (Singh et al., 2023). This allows for individual specificity and behavioral phenotyping that is desperately needed for personalized interventions in a landscape where group-level effects seldomly generalize to individuals in the group (A. J. Fisher et al., 2018).

Finally, activity logging software allows researchers to objectively characterize media habits without concern for issues of recall bias, lack of validity, and low reliability inherent to self-reporting (Kononova et al., 2019; Mark et al., 2015). Activity logging informs researchers of the exact duration individuals use specific applications, the applications they are using simultaneously, the frequency they are actively switching between them, and the type of applications they use (Mark et al., 2015). This approach offers incredible benefits relative to what is accessible using the MUQ. Using these methods, researchers can test the individual

contributions of MM duration relative to attentional deployment, disentangling dose-response mechanisms of media exposure from mechanisms of rapid attentional switching.

In sum, ESM, EMAs, and activity logging allow researchers to characterize MM and outcomes of interest in a valid, reliable, and reproducible way that cannot be accomplished using retrospective self-report. However, it is important to note that these methods are resource-intensive, time-intensive, and complex (Csikszentmihalyi & Larson, 2014; Mark et al., 2015; Shiffman et al., 2008). These methods open the door to issues inherently more difficult in longitudinal data collection than cross-sectional data collection, such as participant recruitment and retention, handling of missing data, and massive data processing requirements. Experience sampling may be particularly time-consuming for participants and even more time-intensive for researchers processing responses to productive qualitative and quantitative data (Hart et al., 2022; Khanshan et al., 2024). To offset these issues, researchers should consider incorporating emerging technologies. Machine learning may help minimize participant burden from ESMs and EMAs by prompting participants to report behaviors and complete assessments at opportune times (Khanshan et al., 2024). This may effectively minimize participant burden by reducing the number of responses required, while still providing researchers with vital longitudinal data (Khanshan et al., 2024). Machine learning may also provide efficient pipelines to process experience sampling data for researchers (Hart et al., 2022). Despite the considerable difficulty with implementing these practices, they offer researchers an innovative and worthwhile path to better characterizing MM and outcomes of interest.

Conclusion

MM is a behavior that is becoming more and more ubiquitous in everyday life. As technology continues to develop exponentially, our understanding of the effects of technology on

our cognition and mental well-being has lagged. Studies one and two in this dissertation aimed to address this lag. Specifically, I aimed to characterize *how* individuals' media multitask was a key determinant in MM's relationship with sustained attention. Across studies one and two, I found that a greater tendency to habitually media multitask with qualitatively similar inputs was associated with poorer sustained attention. At the same time, there was no relationship between a tendency to habitually media multitask with dissimilar inputs and sustained attention. This suggests that how individuals commonly measure MM as a unidimensional behavior misses important context that is integral in distinguishing between signal from noise. MM is a multidimensional behavior that may influence sustained attention in various ways. Studies one and two show that the multidimensional nature of MM can be differentiated and quantified in meaningful ways to understand its relationship with sustained attention. Further, these quantified qualitative differences in MM are likely meaningful for other cognitive abilities, such as executive functioning, memory, and learning, considering the important role of sustained attention in influencing ability in these cognitive domains (Fortenbaugh et al., 2017; Madore et al., 2020; Steinmayr et al., 2010). Future work is warranted to continue characterizing how cognitive and perceptual interference in habitual media habits influence cognition and behavior.

Data Availability

The data supporting the findings of this study are openly available on the Open Science Framework at [https://osf.io/nv9d6/].

Appendix A

Post-Hoc Data Screening

Preliminary post-hoc analyses were completed to assess the distribution of the continuous outcome variables and identify outliers. First, I assessed descriptive statistics for the outcome variable discrimination ability (*d'*). Next, I tested if the data sampled from a normal distribution by examining histograms, Q-Q plots, and skewness and kurtosis values. Histograms and Q-Q plots revealed that the dependent variable *d'* followed a normal distribution. Transient-static (TS) MM and response-passive (RP) MM also exhibited a normal distribution. No shared sensory processing MM (S-adaptive MM), shared sensory processing MM (S-maladaptive MM), transient-transient (TT) MM, transient-static (TS) MM, response-response (RR) MM, response-passive (RP) MM, shared receptive verbal processing MM (RVP-maladaptive MM) and no shared productive verbal processing MM (PVP-adaptive MM) exhibited a relatively normal distribution with a moderate right skew. Static-static (SS) MM, passive-passive (PP) MM, no shared receptive verbal processing MM (RVP-adaptive MM), and shared productive verbal processing MM (PVP-maladaptive MM) exhibited a significant right skew and did not exhibit a normal distribution.

I explored bivariate relationships between the predictors and *d'* through an ocular assessment of the scatter plots along with statistical assessments using Pearson correlations for predictors with a normal or relatively normal distribution and Spearman correlations for predictors with a skewed distribution. Scatterplots and correlations revealed the following relationships between *d'* and the following: S-adaptive MM ($r(212) = -.044$, $p = .526$), S-maladaptive MM ($r(212) = -.242$, $p < .001$), TT MM ($r(212) = -.202$, $p = .003$), TS MM ($r(212) = -.155$, $p = .024$), SS MM ($rho(212) = -.228$, $p < .001$), RR MM ($r(212) = -.253$, $p < .001$), RP MM ($r(212) = -.111$, $p = .106$), PP MM ($rho(212) = -.243$, $p < .001$), RVP-adaptive MM ($rho(212) = -.172$, $p =$

.012), RVP-maladaptive MM ($r(212) = -.221$, $p = .001$), PVP-adaptive MM ($r(212) = -.209$, $p = .002$), PVP-maladaptive MM ($rho(212) = -.223$, $p = .001$).

Based on data screening, as well as evaluation of univariate and bivariate relationships between the predictors and outcomes, I did not exclude any participants in the subsequent analyses.

Post-hoc Analysis Screening

Post analysis screening was conducted to test the assumptions of normality and homoscedasticity of residuals, assess potential collinearity of the predictor variables, and identify any influential cases for post-hoc analyses. Measures of collinearity suggested the relationships between predictor variables were not problematic, as tolerance values were high (>0.1) and variance inflation factors (VIF) were low (<10). I then plotted the standardized residuals, and these appeared to be normally distributed. The assumption of homoscedasticity of residuals was met for the predictor variables across the three regression models. The residuals appeared to be uniformly distributed across the range of predicted values. Cook's distance was employed to assess the influence of individual data points on the regression model (Field et al., 2012). No individual data points were above the Cook's distance threshold of 1 (Field et al., 2012). Overall, the results are unlikely to have been influenced in a meaningful way by collinearity, heteroscedasticity, failed assumptions of normality, or influential cases.

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