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Multimedia-minded

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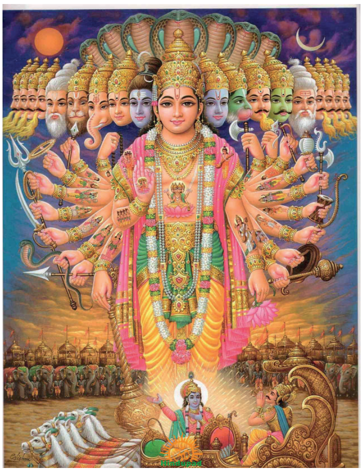
Multimedia-minded

Media Multitasking, Cognition, and Behavior

Wisnu Wiradhany



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Multimedia-minded

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the decision by the College of Deans.

This thesis will be defended in public on
Thursday 18 April 2019 at 09:00 hours

by

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Contents

Chapter 1

General Introduction

One morning, I[1] had seven different tabs opened on my internet browser, and I found myself completely lost. Due to the recent developments of media communications technology, I can afford to have multiple powerful devices. Having one of these devices (e.g., a smartphone) allows me to interleave between multiple activities within a single device (e.g., Yeykelis, Cummings, & Reeves, 2014). Having several of these devices (e.g., a smartphone and a laptop) allows me to interleave across multiple devices (e.g., Judd, 2013). For people like me, the experience of being bombarded with multiple streams of information can be overwhelming[2]. Others, however, may navigate such information-rich environments with ease (see Strayer & Watson, 2012; Watson & Strayer, 2010), while yet others might be inclined to multitask due to their lack of behavioral control. What drives these individual differences? To what extent does the experience in dealing with these devices affect our capabilities in processing information? To what extent are people driven to multitask (or get distracted) due to the presence of these devices? These are some of the main questions addressed in this thesis.

The so-called media multitasking behavior – accessing multiple streams of media-related information – has been shown to be increasingly prevalent over the years (Rideout, Foehr, & Roberts, 2010; Roberts & Foehr, 2008). For instance, adolescents have been estimated to spend about 30% of their media-consumption hours multitasking (Rideout et al., 2010). The frequency of switches is also rather remarkable: It has been estimated that switches between different media streams can occur within minutes (Brasel & Gips, 2011; González & Mark, 2004) to seconds (Yeykelis et al., 2014). Attached to this phenomenon is an interesting puzzle: On the one hand, the human cognitive architecture has been argued to be poorly equipped for multitasking (Salvucci & Taatgen, 2008, 2011). Yet, on the other hand, people keep doing it, sometimes in spite of their awareness of the performance costs (Bardhi, Rohm, & Sultan, 2010). Additionally, the same cognitive architecture is considered to be highly plastic. Recent reviews on the effects of contemporary technologies on human cognition suggest that this plasticity is not always for the better. The constant interactions with technologies may lead to structural changes in the brain (Loh & Kanai, 2016) which could result in better

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[1] I wrote the introduction to reflect the topic addressed in this thesis from a personal experience and to some extent, to add my responsibility to the project. Thus, the pronoun “I” was used. I used “we” in the following chapters to reflect the collaborative nature of this thesis.

[2] I am really bad at multitasking. Close friends of mine would know this, often asking if I would be alright taking a coffee to go since I would have to interleave between walking and sipping coffee.

functioning in some domains but worse functioning in others (see Bavelier, Green, & Dye, 2010; Loh & Kanai, 2016, for reviews). In a similar vein, habitual media multitasking might promote worse and/or better every day functioning to some extent.

Understanding (Media) Multitasking

The Multitasking Paradox: Costs and Benefits

Our cognitive architecture has been suggested to be poorly equipped for multitasking (Salvucci & Taatgen, 2008). This relates to the idea that multitasking generally involves at least two types of cost. The first type of cost relates to the increase of response times when we attempt to interleave multiple tasks, as opposed to performing them one at a time. In a task-switching paradigm (Kiesel et al., 2010; Monsell, 2003), this cost is observed as a slower response time in alternating between two tasks with different stimulus-response mappings, as compared to when the same task is performed repeatedly. This so-called switch cost does not disappear in conditions in which people are given the opportunity to alternate or repeat between tasks at will (Arrington & Logan, 2004; Arrington, Reiman, & Weaver, 2014), and it has been associated with a fundamental bottleneck in information processing (Kiesel et al., 2010; Monsell, 2003). For instance, one interpretation of this cognitive bottleneck is that of the “problem state,” which suggests that we can only keep one goal active at a time (e.g., Borst, Taatgen, & van Rijn, 2010).

In addition to the performance cost, multitasking appears to create psychological costs as well. In a study in which the researchers monitored both the computer-related activities and heart rates of college students for seven days, Mark, Wang, and Niiya (2014) found that students who switched more frequently between computer tabs reported higher levels of stress in a stress-related questionnaire and showed a lower heart-rate variability on average, which, contrary to intuition, corresponds to a higher level of experienced stress (Mark et al., 2014). Together, these findings indicate that multitasking may be associated with a higher level of experienced stress. In another in situ study in which the researchers monitored the activities and interactions of employees in a workplace, Mark, Iqbal, Czerwinski, and Johns (2015) found that employees who switched more frequently between different computer applications and between different internet tabs reported a lower level of productivity at the end of the working day.

Somewhat ironically, it has been reported that people continue to switch between different tasks in spite of their awareness of the switching costs (Kessler, Shencar, & Meiran, 2009) and the psychological costs (Bardhi et al., 2010; Junco & Cotten, 2011). To better understand why people continue to media multitask, we can look into a number of studies which investigated the potential benefits of media multitasking in addition to its costs. Bardhi et al. (2010) interviewed a group of undergraduate students to probe their motives for media multitasking. The results of this interview captured the paradoxical nature of multitasking. On the one hand, media multitasking was harmful: frequent multitaskers experienced a higher level of inefficiency in processing information from the media, a higher level of disorder (e.g., stemming from the number of information streams to be managed), and a higher level of dependency to various forms of media. In line with these results, Hwang, Kim, and Jeong (2014) also found that perceived efficiency predicted the general level of media multitasking. On the other hand, media multitasking was beneficial: people who frequently media multitask perceived a higher level of control over their interaction with the media devices, a higher level of efficiency due to performing multiple things at once, a higher level of engagement to the media consumption process, and a higher level of connectedness to others (e.g., since most of these activities involved forms of communication).

Another benefit of media multitasking might be the ability to modulate one's performance in multitasking situation. Kononova, Joo, and Yuan (2016) found that one's ability to recognize facts from a reading material in a multitasking condition was modulated by one's preference for media multitasking. In their study, memory for an online article was compared between conditions in which participants were required to check their Facebook account (forced multitasking), or in which they could freely check their Facebook account at will (voluntary multitasking), or in a control condition in which they were only asked to read the article. Additionally, Kononova et al. also measured participants' level of media multitasking using a polychronicity index; i.e., an index of how much they preferred to multitask (König & Waller, 2010). They found a main effect of multitasking: Participants recognize fewer facts in the two multitasking conditions compared to the control condition. However, they also found an interaction between conditions and media-multitasking preference: Participants with a higher preference for multitasking were equally accurate in recognizing information in the multitasking conditions as in the control condition. This indicates that people who prefer to multitask may be more efficient in switching between reading an online material and checking Facebook.

Lastly, media multitasking might allow a third party to communicate their message more effectively (see Jeong & Hwang, 2016 for a meta-analysis). Voorveld (2011) found that simultaneous exposure to both online and radio advertising of a product, compared to an individual exposure of each, was associated with a more positive attitude towards the product and a higher intention to buy the product, and it was also associated with better product recognition. Similarly, Chinchanachokchai, Duff, and Sar (2015) found that presenting an advertisement while participants were doing one or two additional tasks, namely reporting letters and dots that appeared on a screen, was associated with a more positive evaluation of the advertisement and a higher task-enjoyment. Somewhat ironically, however, these positive effects of media multitasking might have stemmed from users having a depleted cognitive capacity due to concurrent multitasking, thus leaving less resources available for a thorough evaluation of the advertisements (Jeong & Hwang, 2016). Therefore, there appears to be more about media multitasking than the typical performance costs reported in laboratory studies of task-switching.

Transfer of Training in (Media) Multitasking?

Reports, especially in popular media (e.g., Palfrey & Gasser, 2008; Small & Vorgan, 2008) have suggested that the constant exposures to media-saturated environment might alter people's ability to process information. These reports focused on the youths in particular, who are supposedly exposed to many multitasking scenarios in everyday situations more often. The assumption would be that since they multitask almost constantly, they would become expert multitaskers. In other words, the cognitive skills they acquire from multitasking using media should generalize to other multitasking scenarios as well. There are several problems with this notion. First, there is only limited evidence that multitasking training in one context results in better multitasking ability in another (Lee et al., 2012; Liepelt, Strobach, Frensch, & Schubert, 2011; Strobach, Frensch, Soutschek, & Schubert, 2012). Second and perhaps more importantly, this so-called transfer of training notion would predict that everyday multitasking using media would lead to better or more efficient information processing. As we will witness in the following chapters, this is not always the case.

Consequences of Media Multitasking

The transfer of training account would predict better multitasking, yet, multiple studies reported (negative) consequences of media multitasking. To address this contradiction, I think that an important distinction needs to be made. In general, studies that have demonstrated the negative consequences of media multitasking can be distinguished into two types. The first type pertains to studies in which participants were asked to access media devices while doing a primary task such as driving or studying. The results of these studies on multitasking in inappropriate contexts were rather tautological (i.e., being distracted is distracting), since the decrease in performance can simply be attributed to the additional tasks which have to be performed simultaneously (Aagaard, 2015). Indeed, interacting with mobile phones while driving, as opposed to not interacting with mobile phones while driving, has been associated with various impairments in driving performance (Horrey & Wickens, 2006; Strayer, Drews, & Johnston, 2003), and media multitasking while studying, as opposed to not media multitasking while studying, has been associated with worse recollection of study content (Fox, Rosen, & Crawford, 2009; Hembrooke & Gay, 2003).

The second type of media multitasking studies, which I mainly addressed in this thesis, pertain to studies which attempted to find the neural, cognitive, and behavioral correlates of media multitasking behavior. In other words, these studies tried to evaluate to what extent the differences in the intensity or frequency of media multitasking were correlated with how we think, act, and feel. Studies investigating these questions have used a cross-sectional design (see Uncapher et al., 2017; Uncapher & Wagner, 2018; van der Schuur, Baumgartner, Sumter, & Valkenburg, 2015 for reviews). Typically, participants with very high and low scores on the media-multitasking questionnaire were assigned to groups of heavy and light media multitaskers (HMMs and LMMs, respectively) and they were asked to perform tasks and/or to fill in a series of self-report questionnaires which pertained to different domains of cognition and behavior. The results of these studies yielded elaborate profiles of media multitaskers, suggesting that certain domains of cognition and behavior might correlate with media multitasking. Importantly, however, a comparison of the results across different studies has shown some inconsistencies in these profiles (see Uncapher et al., 2017; Uncapher & Wagner, 2018; van der Schuur, Baumgartner, Sumter, & Valkenburg, 2015 for reviews). Likewise, a number of studies have indicated that HMMs performed worse in tasks related to different domains of cognition (Cain & Mitroff, 2011; Ophir, Nass, & Wagner, 2009; Uncapher, Thieu, & Wagner, 2016), but these findings were largely confined to small-sample studies.

This Thesis

The projects described in the following chapters in this thesis attempted to answer three questions: What constitutes the media multitasking behavior that is captured by the MMI, which domains of cognition and behavior correlate with media multitasking, and to what extent does the presence of media devices affect one's ability to process information? To answer the first question, I relied on network analysis as a visualization and an analysis tool (Borgatti, Mehra, Brass, & Labianca, 2009). To answer the second, I reassessed the current findings in the literature using meta-analytic approach (Borenstein, Hedges, Higgins, & Rothstein, 2009; Liberati et al., 2009) and replication studies (Brandt et al., 2014; Goodman, Fanelli, & Ioannidis, 2016). This reassessment process provided a more critical look towards the available evidence and better estimations of some of the reported correlates. To answer the last question, I conducted an experiment to evaluate to what extent the presence of media devices, in absence of any interaction with them, influenced task performance (e.g., Thornton, Faires, Robbins, & Rollins, 2014). Wrapping up this thesis, I propose a framework for explaining when and why people may engage media multitasking, and why some people may do this more often than others.

Chapter 2: What Constitutes the Media Multitasking Behavior?

Some people multitask more frequently than others. To estimate one's level of media multitasking, we can ask how many hours people spend using media and during what proportion of this time people also concurrently use another type of media. In a seminal study, Ophir, Nass, and Wagner (2009) asked these questions for all possible combinations of 12 mainstream media types in the Media Use Questionnaire (MUQ) and computed the Media Multitasking Index (MMI). This index supposedly reflects the number of media shared in a typical media-consumption hour. Thus, participants with higher MMI would share more types of media in a typical hour. This index has become the most commonly used metric for measuring media multitasking (Baumgartner, Lemmens, Weeda, & Huizinga, 2017).

The MMI captures an overall level of media multitasking behavior per individual, but to what extent the behavior varies across different media types and populations has not been explored. Understanding the underlying media combinations in MMI is important, since we do not know which combinations of media contributes significantly to the final MMI score. I investigated the underlying media combinations behind the MMI in Chapter 2, which I wrote in collaboration with Susanne Baumgartner[3]. We sought to answer this question by reanalyzing existing MUQ responses and rendering them into networks with media types as network nodes and time-sharing between media as network edges. We found that some media combinations were more likely to occur than others and that these more prevalent combinations were stable over different populations.

Chapters 3 & 4: Minds of Media Multitaskers

In Chapter 3, which I wrote with the help of Mark Nieuwenstein[4], we tested the robustness of the correlates of media multitasking behavior as reported in Ophir et al. (2009) in two sets of experiments. Initially, this study provided us the first mixed findings in the project: out of 14 tests conducted, only five yielded a statistically significant effect in the direction proposed by Ophir et al.: An increased distractibility for people with higher scores on the media-use questionnaire. Importantly, only two of these five effects held in a more conservative Bayesian analysis. To get a more reliable, conservative estimate of the strength of these correlates, we then performed a meta-analysis on a total of 39 effect sizes pertaining to the association between media multitasking and distractibility. The results yielded a weak, but significant association between media multitasking and distractibility that turned nonsignificant after correction for small-study effects.

Additionally, a recent study showed a specific, yet divergent finding from one of the tasks presented in Ophir et al. (2009): The change-detection task. Specifically, Ophir et al. (2009) showed that HMMs retained less relevant information when the number of distrac-

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[3] Susanne has a background in communication science and is one of the most active researchers in media multitasking in The Netherlands. In helping me writing this chapter (and in discussing the topic with me in general), she has helped me realized that multitasking is more than just a problem in processing information.

[4] Mark is a cognitive scientist with particular interests in how we can process stimuli which come in rapid successions (e.g., using the Attentional Blink paradigm) and decision-making. However, it was his experience in meta-analysis which contributes the most in helping me developing and writing this chapter. He also acts as my daily supervisor in this project and is one of the first people who introduced me to experiments in cognitive science (I have a background in social psychology).

tors that was shown together with the to-be-remembered information increased. On the other hand, Uncapher et al. (2016) showed that HMMs retained less relevant information regardless of the number of distractors present in the immediate environment, thus suggesting that HMMs might be affected by internal distractions. In Chapter 4, which I wrote with Marieke van Vugt[5] and Mark Nieuwenstein, we conducted a large-scale replication study to provide a more rigorous test of this internal distraction hypothesis. As a formal evaluation of internal distractions, we included experience sampling probes during the experiment, to probe the extent to which participants could remain focused during the experiment. The results showed that frequent media multitasking was not associated with mind-wandering or with a decrease in performance in the change-detection task, thus dismissing the internal-distraction hypothesis.

Chapter 5: Behaviors of Media Multitaskers

The studies presented in Chapters 3 and 4 suggest that media multitasking is not associated with increased susceptibility to internal or external sources of distraction during task performance. At the same time, a growing number of studies have reported correlates of media multitasking with seemingly unrelated types of daily functioning and mental health-related problems. In the study presented in Chapter 5, Janneke Koerts[6] helped me to categorize these findings into different domains in a series of mini meta-analyses (Goh, Hall, & Rosenthal, 2016). Overall, we found that media multitasking behavior is associated with problems in behavior regulation (e.g., inhibition and increased impulsiveness), problems in metacognition (e.g., meta-awareness and planning), frequency of ADHD symptoms, and sensation seeking. To a certain extent, these findings could be interpreted as evidence that people who are easily distracted in everyday situations might be more inclined to media multitask.

Chapter 6: Media-induced Distractions

Chapters 2-5 investigated the cognitive and behavioral correlates of media multitask-

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[5] Marieke is a cognitive modeler with a particular interest in mind-wandering. Naturally, in this chapter she contributed her expertise in mind-wandering.

[6] Janneke is a Clinical Neuropsychologist. She has an extensive knowledge on different types of self-reports of executive function (e.g., the Behavioral Ratings Index of Executive Function; BRIEF) and self-reports of mental health (particularly ADHD). The knowledge she shared has helped me in categorizing the findings in this mini meta-analysis.

ing, under the assumption that the tendency to use different media at the same time might influence our way of processing information. Yet, there is at least one other way in which media may affect information processing and task performance, namely through the mere-presence effect of media devices (e.g., Thornton et al., 2014). In Chapter 6, which I wrote in collaboration with Sebastiaan Mathôt[7] and Mark Nieuwenstein, we tested to what extent the mere-presence of one's (own) mobile phone might disrupt task performance in an antisaccade experiment, and whether the decrease of task performance could be explained by overt attention towards the phone (Ito & Kawahara, 2017). As partial support for the mere-presence effect and the spatial bias effect, we found that the mere-presence of one's own mobile phone was associated with a small increase of certain types of errors in the task, and indeed, participants showed a slight bias in making eye movements toward their phone. At the same time, however, eye movements in the direction of the phone were not faster and they had a smaller amplitude than eye movements made away from the phone. This suggests that while the mobile phone seemed to attract attention, thus biasing eye movements towards its location, participants also tried to avoid looking directly to it, resulting to slower eye movements with smaller amplitudes.

General Discussion: From Mind to Behavior of Media Multitaskers

Having performed studies on the variability in media multitasking and the correlates of media multitasking with minds and behaviors, I became aware that a theoretical framework is missing for explaining some of the questions I ask at the beginning of this introduction: Why do people continue to multitask in spite of their knowledge of the cost? Which (cognitive) system is likely to demarcate heavy from light media multitaskers?

A high level of everyday multitasking as indicated by a high MMI score might reflect multiple things. It might reflect one's ability to do multiple things simultaneously while keeping the performance costs at minimum. In a driving simulation study, Watson and Strayer, (2010) found that a small subset of their participants did not suffer from the costs commonly associated with multitasking. About 2.5% of their participants performed equally well in a sin-

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[7] Sebastiaan is a cognitive scientist with a particular interest in vision, especially in pupillometry. In this chapter, he helped me analyze the eye-movement data. He is also the programmer of OpenSesame: An open-source, graphical experiment builder which I used a lot in this thesis (and will continue to use in years to come).

gle-task (only driving) and in a dual-task (driving and performing an auditory working memory task) conditions. In other words, these participants did not show divided-attention costs. Later, in a separate fMRI study (Medeiros-Ward, Watson, & Strayer, 2015), it was found that these so-called "supertaskers" showed less activation in the brain regions which are proposed to play important roles in multitasking, namely the Anterior Cingulate Cortex (ACC) and the Prefrontal Cortex (PFC; Botvinick, Cohen, & Carter, 2004), indicating that supertaskers may be more efficient in recruiting crucial brain regions which help them to multitask. It could thus be the case that some people become frequent multitaskers because they are actually good at it. I will refer the first group as "good multitaskers."

A high MMI score might also reflect to what extent people are driven to multitask[8]. This might be related to a certain psychological trait, such as impulsiveness (Dalley, Everitt, & Robbins, 2011) or to a certain mental health condition, such as ADHD. With regard to the former, Minear, Brasher, McCurdy, Lewis, and Younggren (2013) found that indeed, people with higher MMI scores reported a higher level of impulsiveness. With regard to the latter, Magen (2017) found that people with higher MMI scores reported more (severe) symptoms of ADHD. Together, these findings suggest that individuals with behavior-regulation problems are more inclined to multitask in everyday situations (Baumgartner, van der Schuur, Lemmens, & te Poel, 2017; Baumgartner, Weeda, van der Heijden, & Huizinga, 2014; Magen, 2017) and this could occur in spite of the individual's awareness of the multitasking costs (e.g., Bardhi et al., 2010). I will refer this second group as "distracted multitaskers."

Good and distracted multitaskers might develop media multitasking habits for different reasons. For good multitaskers, interleaving multiple tasks might actually help them to complete the tasks more efficiently. For distracted multitaskers, interleaving multiple tasks might occur since they find it difficult to maintain their focus of attention to a single task.

It could be the case that among heavy media multitaskers, there are good and distracted multitaskers, and this decreases the magnitude of the association between media multitasking and distractibility. On the other hand, it could be the case that habitual multitasking behavior is not correlated with cognitive functioning. After all, habitual media multitasking might develop for various reasons, and those who have the habit might still be able to perform

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[8] One can also have a high level of multitasking because one prefers to do so (Poposki & Oswald, 2010). However, in my view, this preference can still be attributable to either the ability to multitask or the lack of behavioral control.

well in different domains of cognition. A framework for explaining the individual differences might help the field to move forward, by shifting the research efforts from a trial-and-error search for correlates, to a more theoretically inspired prediction of how heavy and light media multitaskers might differ from each other.

In the general discussion, which I wrote in consultation with Mark Nieuwenstein and Ritske de Jong[9], I propose that the locus coeruleus-norepinephrine (LC-NE) system (Aston-Jones & Cohen, 2005; Sara & Bouret, 2012) might play an important role not only in regulating switching behavior in media multitasking, but also in demarcating good from distracted multitaskers. Specifically, I propose that 1) the LC-NE system regulates whether and when people switch from an exploitation-related mode of behavior (e.g., consuming information from one media stream) to an exploration-related mode of behavior (e.g., switching from one media stream to another); 2) good multitaskers might balance exploitations and explorations; they might only get involved in multitasking in situations in which it is strategic to do so (Ralph & Smilek, 2016) whereas 3) distracted multitaskers might be biased toward explorations; they are less able to set an optimum balance between exploiting and exploring. Subsequently, I discuss the questions and predictions this proposed framework yields for future studies on media multitasking.

Together, the empirical chapters I present in the following examine the cognitive (Chapters 3 & 4) and behavioral (Chapter 5) domains which might vary as a function of media multitasking behavior, after considering which type of media combinations define the typical media multitasking behavior (Chapter 2). Additionally, I provide some evidence for the mere-presence effect of media devices (Chapter 6) and a potential account on what drives the individual differences in media multitasking behavior and why people seem to persist to multitask in spite of their understanding of the cost (General discussion).

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9 Ritske is a cognitive scientist. It is difficult to pinpoint his main interests since he has contributed in different projects of varying topics. I think his interest in my project relates to the question of individual differences: How much of the variation in everyday multitasking behavior can be attributed by differences in information processing efficiency (e.g., working memory capacity) and how much can be attributed by differences in psychological dispositions (e.g., personality traits)? He is also my main promotor.

Chapter 2

What Constitutes the Media Multitasking Behavior?

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Abstract

Many researchers have used the Media Multitasking Index (MMI) for investigating media multitasking behavior. While useful as a means to compare inter-individual multitasking levels, the MMI disregards the variability in media multitasking choice behavior: certain media combinations are more likely to be selected than others, and these patterns might differ from one population to another. The aim of the present study was to examine media multitasking choices in different populations. For this means, we employed a social network approach to render MMI responses collected in eight different populations into networks. The networks showed that the level of media multitasking as measured by the network densities differed across populations, yet, the pattern of media multitasking behavior was similar. Specifically, media combinations which involved texting/IMing, listening to music, browsing, and social media were prominent in most datasets. Overall the findings indicate that media multitasking behaviors might be confined within a smaller set of media activities. Accordingly, instead of assessing a large number of media combinations, future studies might consider focusing on a more limited set of media types.

Keywords: media multitasking, media use questionnaire, media multitasking index, network analysis

Introduction

Media multitasking, the behavior of consuming multiple media streams simultaneously or consuming one media stream while doing another activity, has become increasingly prevalent over the years (Rideout et al., 2010). It is thus not surprising that researchers have begun to investigate whether engaging in media multitasking frequently is related to potential difficulties in information processing and everyday functioning. With regard to everyday functioning, studies have found that heavy media multitaskers (HMMs) reported more problems related to executive function (Baumgartner et al., 2014; Magen, 2017), and they reported increased levels of attentional lapses and mind-wandering (Ralph, Thomson, Cheyne, & Smilek, 2013) in comparison to light media multitaskers (LMMs). However, with regard to the efficiency of information processing of media multitaskers, the findings have been mixed, with some studies reporting that HMMs performed worse in various performance-based tasks while others found no differences (Cardoso-Leite et al., 2015; Wiradhany & Nieuwenstein, 2017), or even that HMMs performed better (Alzahabi & Becker, 2013; Baumgartner et al., 2014). Reviews have also indicated that the findings have been mixed (Uncapher et al., 2017; van der Schuur et al., 2015), with meta-analyses showing weak associations between media multitasking and difficulties in information processing (Wiradhany & Nieuwenstein, 2017) and everyday functioning (Wiradhany and Koerts, *in prep*.).

While the mixed findings could be the result of statistical, small-study, or publication biases (Button et al., 2013; Ioannidis, 2005; Wiradhany & Nieuwenstein, 2017), it could also be the case that previous studies have been comparing different populations of media multitaskers. Indeed, previous studies have been using the Media Multitasking Index (MMI; Ophir, Nass, & Wagner, 2009; Pea et al., 2012) computed from responses from the Media Use Questionnaire (MUQ) to distinguish HMMs and LMMs. MMI captures a broad range of media multitasking behavior combinations, with the number of combinations varying from 36 (Moisala et al., 2016) to 144 (Ophir et al., 2009; Wiradhany & Nieuwenstein, 2017), and the types of combinations ranging from reading while listening to music to playing games while having a phone conversation. The basic idea underlying the MMI is that the concept of media multitasking is best captured by including all possible combinations of media activities and that on the individual level it does not matter whether someone multitasks frequently by listening to music while reading, or by watching television while gaming.

Given that the MMI has been used as a single overall score of media multitasking, little is known about the combinations of media underlying the score. Specifically, from the many media multitasking combinations assessed in the MMI, we do not know the number of combinations people typically engage in, and which media types are typically used for the primary activity or the secondary activity. Additionally, patterns of media multitasking might vary across populations. For instance, media multitasking behaviors among younger populations might differ from those among older populations, in that younger people use different types of media to multitask. To further shed light on the number and the types of media combinations that typically occur in media multitasking, and to investigate whether these combinations differ across populations, we reanalyzed the responses from several MUQ datasets and rendered the responses into networks. Analyzing the properties of these networks provides important insights into the media multitasking behaviors individuals typically engage in, and about potential differences in these behaviors across populations. This approach therefore provides a more nuanced view on media multitasking across populations. This is particularly important for establishing better measurements for specific populations.

Differences in Media Multitasking Choice

Given the rather broad range of media multitasking combinations assessed in the MUQ[10], it is likely that specific media multitasking pairs are preferred over others. Moreover, it is also likely that from the many media multitasking combinations assessed in the MUQ, individuals only engage in very few media multitasking combinations. Lastly, certain types of media might be more likely to be consumed as a primary, others as a secondary activity. The preference for specific media multitasking combinations over others could stem from at least three possible sources: 1) it could be based on a strategic decision to reduce cognitive load, 2) it could be based on a preference to access emotionally gratifying media, and 3) it could be based on a general preference for specific media types that are used habitually.

With regard to reducing cognitive load, it has been established that the human cognitive architecture is not well-equipped for dealing with multiple things simultaneously (Cour-

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[10] Here, we refer to the type of media use questionnaire used in Ophir et al. (2009; see also Baumgartner, Lemmens, Weeda, & Huizinga, 2017; Pea et al., 2012). We do not refer to other types of media use questionnaire which also exist in the literature (see for a comparison, Rosen, Whaling, Carrier, Cheever, & Rokkum, 2013)

age, Bakhtiar, Fitzpatrick, Kenny, & Brandeau, 2015; Salvucci & Taatgen, 2008). As a result, people develop different strategies to deal with interferences induced by multitasking (see for examples, Adler & Benbunan-Fich, 2012; Salvucci & Bogunovich, 2010). One of such strategies is to select media pairs which induce lower cognitive demands. Specifically, Wang et al. (2015) introduced 11 basic cognitive dimensions of media multitasking behaviors. They showed that the likelihood of media multitasking increases as the cognitive demands created within each dimension decrease. For example, they showed that media multitasking combinations which engage more sensory modalities and those with an overlap of used modalities are less frequently combined. Similarly, in a cross-sectional study, Carrier et al. (2009) found that participants preferred “easy” (e.g., listening to music while eating) compared to “difficult” media multitasking combinations (e.g., reading while playing video games), with “easy” combinations involving fewer modalities compared to “difficult” combinations.

With regard to emotional gratification, it has been discussed that people engage in media multitasking in spite of their awareness of its cognitive cost (Bardhi et al., 2010; Z. Wang & Tchernev, 2012). People media multitask because it creates an illusion of their ability to manage a vast amount of information efficiently (Bardhi et al., 2010; Hwang et al., 2014), and because it provides emotional gratifications (Z. Wang & Tchernev, 2012). For example, when studying for school, young people may choose to simultaneously use social media in order to alleviate boredom experienced form the primary task and receive emotional gratification. This is in line with findings by Hwang et al. (2014) who found that the main motivations for engaging in specific types of media multitasking are enjoyment, and social motives.

Lastly, some media multitasking combinations might occur as a part of habitual media consumption (Bardhi et al., 2010; Hwang et al., 2014). That is, individuals engage most frequently in media multitasking with those media that they most frequently use (Voorveld & Goot, 2013). For instance, Hwang et al. (2014) reported that TV-based multitasking could be predicted by habitual motives. That is, in TV-based multitasking, TV was not actively consumed; it was turned on as a part of a ritualistic behavior. Similarly, in an observation study, Rigby, Brumby, Gould, and Cox (2017) reported that the TV was frequently turned on in the background while participants were performing other activities.

In sum, it is likely that not all possible types of media multitasking are equally frequently selected. More specifically, we assume that media multitasking combinations that require lower cognitive demands (e.g., listening to music while browsing), are emotionally gratifying (e.g., accessing social media while listening to music), or are based on media activities that people frequently engage in (e.g., sending messages while watching TV) are more frequently selected than other media multitasking combinations.

Media multitasking combinations do also differ in terms of which media activity is perceived as primary or secondary activity. As in our description of the habitual TV consumption above, in a typical media multitasking situation one medium may function as the dominant activity on which most attention is focused while another medium is used as a secondary, less prioritized activity (e.g. Foehr, 2006; Wang, Irwin, Cooper, & Srivastava, 2015). This distinction is also made in the MMI in which each media activity is assessed both, as a primary and secondary activity. However, we still know little about which media activities are typically used as primary and which as secondary activities. Foehr et al. (2006) found that particularly computer activities are used as secondary activities. In contrast, watching television and listening to music were frequently reported as primary activities. This is somewhat contradictory with common conceptualizations of TV, and listening to music as typical media background activities (Beentjes, Koolstra, & van der Voort, 1996; Rideout, Vandewater, & Wartella, 2003). The present study therefore aims at understanding in more detail which media activities are used primarily as primary and which as secondary media activities.

Differences in Media Multitasking Across Populations

As argued above, we assume that not all media multitasking pairs are equally frequently selected. However, the specific patterns of media multitasking that individuals engage in might also differ across populations. Studies on the effects of media exposure suggest that media multitasking prevalence differs as the function of audience factors (e.g., socio-economic status) and media factors (e.g., media and technology availabilities; Jeong & Fishbein, 2007; Kononova & Chiang, 2015). Indeed, for the latter, a cross-cultural survey has shown that media availabilities explained differences in media multitasking levels between U.S.A., Kuwait, and Russian nationals (Kononova, Zasorina, Diveeva, Kokoeva, & Chelokyan, 2014). Similarly, in another study, types of media consumed (i.e. traditional, such as print media vs. newer media, such as internet browsing) explained differences in media multitasking levels between U.S. and Western European nationals (Voorveld, Segijn, & Ketelaar, 2014). These results suggest that environmental factors play important roles in explaining differences in media multitasking choices across populations from different countries.

With regard to audience factors, studies have shown an inverse relationship between media multitasking levels and age, likely due to the fact that the adoption rate of media technology is higher in youth (e.g., Bardhi et al., 2010). Voorveld et al. (2014) showed that after controlling for types of media use, younger people media multitasked more often than older people. Similarly, another survey with an U.S. national sample also reported that media multitasking was negatively correlated with age (Duff, Yoon, Wang, & Anghelcev, 2014). Lastly, in a cross-sectional study, Carrier, Cheever, Rosen, Benitez, and Chang (2009) showed that people who were born after 1978 multitasked using media 56% of their media time compared with people who were born between 1965 and 1978, and 1946 and 1964 who only multitasked 49% and 35.1% of the time, respectively. Interestingly, one diary study also reported that while indeed teenagers of 13-16 years old media multitasked more often than other age groups, this group was followed by old adults of 50-65 years old (Voorveld & Goot, 2013), indicating that the relationship between age and the frequency of media multitasking might not be linear.

Together, these findings suggest that not only the frequency of engaging in media multitasking but also the types of media multitasking individuals engage in might differ between one population to another as functions of media and audience factors. Specifically, younger populations and populations with greater access to media may have a higher likelihood to engage in media multitasking. Moreover, as social media are particularly popular among younger media users (e.g., Carrier et al., 2009; Duggan & Brenner, 2013), it is likely that media multitasking with social media is particular prevalent among younger populations. In comparison, older populations might be more likely to multitask with traditional media, such as print media and television (Voorveld & van de Goot, 2013).

One major problem of these potential differences in media multitasking across populations is that if the actual media multitasking behavior differs across populations, findings cannot easily be compared. Thus, even if two populations have similar MMI mean scores, the actual multitasking behavior on which these means are based might be highly different. These differences might partly explain why some studies did find effects while others did not.

The Current Study

The existing literature suggests that the number and the type of media combinations typically occurring in media multitasking might vary across individuals and populations. In this study, we reanalyzed eight datasets from published studies. Out of these we first compiled a large dataset of MUQ responses from Western European (i.e. The Netherlands), Northern American (i.e. USA & Canada), and Asian (i.e. Singapore & Indonesia) countries, then rendered the responses into networks. Analyzing the properties of the networks will provide insights with regards to the profiles of media multitasking behavior, as indicated by the types and priorities of media combinations and whether or not these profiles differ from one population to another.

Methods

Media Use Questionnaire: Structure and Index

The Media Use Questionnaire (Ophir et al., 2009; Pea et al., 2012) is the most used measure of media multitasking to date (Baumgartner, Lemmens, et al., 2017). The original questionnaire asks how often people consume two types of media simultaneously, over a combination of 12 different media using a Likert rating (0="Never", .33="A little of the time", .67="Some of the time", and 1="Most of the time" Ophir et al., 2009). To illustrate, one block of questions with regard to television use would start with the media duration question "How many hours did you spend watching television last week?" followed by several questions about the frequency of media multitasking with the primary medium, such as "While watching television, how often do you also listen to music?" The media duration and media sharing proportion questions are then repeated across all media combinations and summed using the formula below:

$$MMI = \sum_{i=1}^{j} \frac{m_i \times h_i}{h_j}$$

where m is the sum score for media multitasking using primary medium *i*, *h* is the number of hours spent consuming primary medium *i* per week, *j* is the total number of media assessed, and h_{total} is the sum of hours spent consuming any of the 12 media.

Over the years, different versions of the MUQ have been developed to adapt with the current media landscapes (Baumgartner et al., 2014; Loh, Tan, & Lim, 2016; Pea et al., 2012), but while the media types might slightly differ from one type of questionnaire to another, the questionnaire structure remains similar. Thus, each version of the MUQ allows for calculating a MMI. Importantly, however, interpreting the MMI could be problematic since two individuals with a similar MMI score could have highly differing media multitasking behavior profiles (Baumgartner, Lemmens, et al., 2017; Cain, Leonard, Gabrieli, & Finn, 2016; Ralph & Smilek, 2016). For instance, two individuals with a similar MMI score could spend very different amount of times with each media activity (because for calculating the MMI, the proportion of media-sharing time is multiplied by the hours spent for media, and divided by the hours again upon summation). Similarly, someone who engages in a high amounts of non-adaptive media multitasking (e.g., playing games while watching television), and someone who engages solely in more adaptive types of media multitasking (e.g., reading books while listening to music) might end up having similar MMI scores. For these reasons, in our analysis, we used the information about the duration of time spent for using media and the proportion of time spent for media-sharing from the raw scores to construct our networks. This allows us gaining insights into both the absolute time people spent with different types of media, and the proportion of time they spent multitasking with different types of media.

Network Analysis

In recent years, there has been an increased interest in the application of network analyses in social sciences (Borgatti et al., 2009; Scott, 2011; Vera & Schupp, 2006). Typically, network analysis was used for investigating social structures, by mapping such structures into a network of connected actors. Specifically, actors are mapped into individual nodes, and their relationships are mapped into connecting lines (edges). Thus, this method emphasizes on the relationships between actors rather than the properties of the individual actor (Otte & Rousseau, 2002). More importantly, by mapping the connections between actors, network analysis can help answer important questions related to the structure of the network (e.g., what is the level of connectivity among actors in the network), and questions related to the importance of the actors (e.g., which actor is the most connected, which actor serves as a connector between one with another). In social sciences, this method can be applied to reveal similarities, social relations, interactions, and flows of information among members of networks (Borgatti et al., 2009).

In this study, we constructed weighted, directed networks using network analysis to visualize and to analyze the types of media combinations and media use prioritizations in media multitasking using responses from the questionnaires. The networks were constructed by mapping different media types into different nodes, and time spent for consuming different types of media simultaneously into edges.

Network mapping. In this study, we mapped eight MUQ datasets from published studies (Alzahabi & Becker, 2013; Baumgartner et al., 2014; Becker, Alzahabi, & Hopwood, 2013; Loh & Ka nai, 2014; Ralph et al., 2013; Ralph, Thomson, Seli, Carriere, & Smilek, 2015; Uncapher, Thieu, & Wagner, 2015; Wiradhany & Nieuwenstein, 2017) into networks. Table 2.1 shows the characteristics of the datasets.

Table 2.1. Characteristics of different MUQ datasets

Article	Location	Total N	Mean MMI*	Types of media assessed	Note
Baumgartner et al. (2014)	Amsterdam, The Netherlands [Western Europe]	523	1.92	Print media, Television, Video on a computer, Music, Video/computer games, Phone calls, Instant/text messaging, Networking sites, Other computer activities	Adolescent participants, 11-15 year olds
Wiradhany & Nieuwenstein (2017; Exp.2)	Groningen, The Netherlands [Western Europe]	205	4.14	Print media, Television, Video on a computer, Music, Non-musical audio, Video/computer games, Phone calls, Instant messaging, Text messaging, E-mails, Reading web pages/other electronic documents, Other computer applications	General population, mostly university students

Article	Location	Total N	Mean MMI*	Types of media assessed	Note
Alzahabi & Becker (2013);	Michigan, USA [Northern America]	450	4.13	Print media, Television, Video on a computer, Music, Non-musical audio, Video/ computer games, Phone calls, Instant messaging, Text messaging, E-mails, Reading web pages/other electronic documents, Other computer applications	University students
Becker et al. (2013)	Michigan, USA [Northern America]	450	4.13	Print media, Television, Video on a computer, Music, Non-musical audio, Video/ computer games, Phone calls, Instant messaging, Text messaging, E-mails, Reading web pages/other electronic documents, Other computer applications	University students
Ralph et al. (2015; Exps 3-4)	MTurk [Northern America]	499	2.12	Print media, Television, Video on a computer, Music, Video/computer games, Phone calls, Instant/text messaging, Social Networking sites, Doing homework, Talking face-to-face	General population, mostly from USA (96.59%), 18-82 year olds

Article	Location	Total N	Mean MMI*	Types of media assessed	Note
Loh & Kanai (2014)	Singapore [Southeast Asia]	153	3.12	Print media, Television, Video on a computer, Music, Video/computer games, Phone calls, Instant messaging, Text messaging, E-mails, Reading web pages/other electronic documents, Social networking sites, Other computer activities	University students
Uncapher, Thieu, and Wagner (2016)	Stanford, USA [Northern America]	143	3.65	Print media, Television, Video on a computer, Music, Non-musical audio, Video/computer games, Phone calls, Instant messaging, Text messaging, E-mails, Reading web pages/other electronic documents, Other computer applications	University students
Ralph et al. (2013); Ralph et al. (2015; Exps 1-2)	Waterloo, Canada [Northern America]	357	1.71	Print media, Television, Video on a computer, Music, Video/computer games, Phone calls, Instant/text messaging, Social networking sites, Doing homework, Talking face-to-face	University students

Article	Location	Total N	Mean MMI*	Types of media assessed	Note
Wiradhany & Nieuwenstein (2017; Exp.1)	Yogyakarta, Indonesia [Southeast Asia]	148	5.66	Print media, Television, Video on a computer, Music, Non-musical audio, Video/ computer games, Phone calls, Instant messaging, Text messaging, E-mails, Reading web pages/other electronic documents, Other computer applications	University students

* The mean of MMI was calculated from the graph using a method which corresponds to equation 1. We first calculated the hour spent for each media type as indicated by the node size times the proportion of media sharing for each media dyads as indicated by the edge thickness attached to each node, then divide it by the total hour spent for all media types, as indicated by the sum of the node sizes.

Prior to mapping the MUQ responses, we first removed responses from non-media activities (i.e., homework and face-to-face conversations). This decision helped us focus on media multitasking between two media-related activities only. We then mapped the media duration responses from the MUQ into network nodes and the proportion of media multitasking (i.e., the time spent for consuming two types of media simultaneously) into network edges. For the media duration responses, since different versions of the MUQ might use different time scales, we first standardized the responses into the hours spent for using media per day, and mapped the responses into nodes of varying sizes, with larger nodes reflecting a higher number of hours spent for one specific media per day. For the proportion of media multitasking, we calculated the mean of the proportion of media multitasking responses of each media pair for each dataset. Thus, each edge represents one dyad of two media which were simultaneously used. Sometimes, participants did not provide a response to a media frequency question. Thus, to ensure that these non-responses did not contribute to the calculated mean, they were treated as missing responses. Then, we mapped these means into network edges of varying thicknesses (0=”Never” to 1=”Almost always”).

To visualize media prioritizations, we used the information with regards to primary and secondary media (e.g., watching television while listening to music has television as the primary media and music as the secondary media; listening to music while watching television has music as the primary media and television as the secondary media) and plotted directed networks with outgoing arrows indicating a pairing from a primary to a secondary media activity. Similarly, incoming arrows indicate that the specific media activity is used as a secondary activity in that specific pairing. This method allowed us to compare media uses as either a primary or a secondary activity.

Differences in media choice. To explore which types of media were used most frequently for media multitasking, we calculated the strength of each node in the network. The strength of a node is calculated as the sum of the edges connected to the node (Barrat, Barthelemy, Pastor-Satorras, & Vespignani, 2003), which reflected the proportion of time for media sharing. Thus, stronger nodes reflected media types which were shared more often with others. To explore which types of media were used as either primary or secondary multitasking activity, the edge of each node was binned into outgoing and incoming edges, indicating the use of a particular media as primary or secondary activity, respectively.

Differences between populations. To compare the datasets, we first measured the weighted edge density of each network. Network density reflects the general level of connectedness within a network (Otte & Rousseau, 2002). In a weighted network, density is shown as a gradient: a network with thinner, fewer edges is less highly connected while a network with more and thicker edges is highly connected. The weighted edge density is calculated as the ratio between the sum of the edges and the theoretical maximum sum of the edges. The theoretical maximum sum of the edges[11] is calculated as the number of possible edges times the maximum weight [12]of each edge. The weighted edge density scores varied from zero to one, with scores closer to zero indicating that on average, in a typical media-consumption hour, fewer numbers of media are shared and scores closer to one indicating that on average a higher number of media is shared. This measure ensures comparability between networks,

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[11] The number of possible edges varies between different versions of MUQ. In versions with loops (i.e. containing questions such as “While you are watching television, how often do you also watch another television”), the number is defined as the square of total media assessed. In versions without loops, the number is defined as the total of media assessed times the total of media assessed -1.

[12] The maximum weight is defined as the highest possible rating for each frequency of media multitasking response, which is equal to 1

since different datasets have different numbers of featured media. These weighted edge densities were then compared between different datasets. Secondly, to further explore if media choices differ across different datasets, we also compared the three strongest nodes of each network. Lastly, we compare the datasets from the different regions of origin, and the dataset with exclusively adolescent participants to the other datasets, which were collected among university students.

All analyses were conducted in R using RStudio (R Core Team, 2017). Networks were created using the igraph package (Csárdi & Nepusz, 2006). The networks were rendered using the Fruchterman-Reingold algorithm which ensures evenly distributed nodes, uniform edge lengths, and minimal number of steps between nodes (Fruchterman & Reingold, 1991). Other graphs were rendered using the ggplot2 package (Wickham, 2010).

Results

Differences in Media Choice

Figure 2.1 shows the rendered networks from different datasets. This figure provides several insights. First, the distribution of the network's edges is not uniform, indicating that certain types of media had a higher likelihood to be shared with others. Specifically, listening to music had the highest node strength, followed by browsing and texting. This indicates that listening to music is the media activity that is most frequently combined with other media activities (see Figure 2.2 for a comparison of network properties). Second, nodes with larger sizes, indicating the amount of time spent for consuming media are 1) located in the center of the networks and 2) they have on average more edges than others. Indeed, node sizes and node strengths, as indicated by the number of connected edges, were positively correlated , $r(83)=.44$, $p<.001$, indicating that as the time for consuming one type of media increases, the likelihood to multitask with this type of media also increases. Third and lastly, the types of media located at the center of the networks are relatively similar: combinations with music, texting, browsing, and social networking are prominent in the networks. Specifically, music was featured as one of the three largest node in 7/8 datasets and as one of the three nodes with the highest multitasking proportion in 6/8 datasets; browsing was featured as one of the three largest node in 5/8 datasets and as one of the three nodes with the highest multitasking proportion in 3/8 datasets. Texting, if combined with IMing was featured as one of the three largest node in 6/8 datasets and as one of the threenodes with the highest multitasking proportion in 7/8 datasets (see Figure 2.2). This indicates the relative similarity[13] of media multitasking behavior across different populations.

Lastly, the strength of incoming and outgoing edges, was not significantly different, Wilcoxon's V=1819, p=.972, indicating that participants use the different media types as primary or secondary activity interchangeably (see Figure 2.3).

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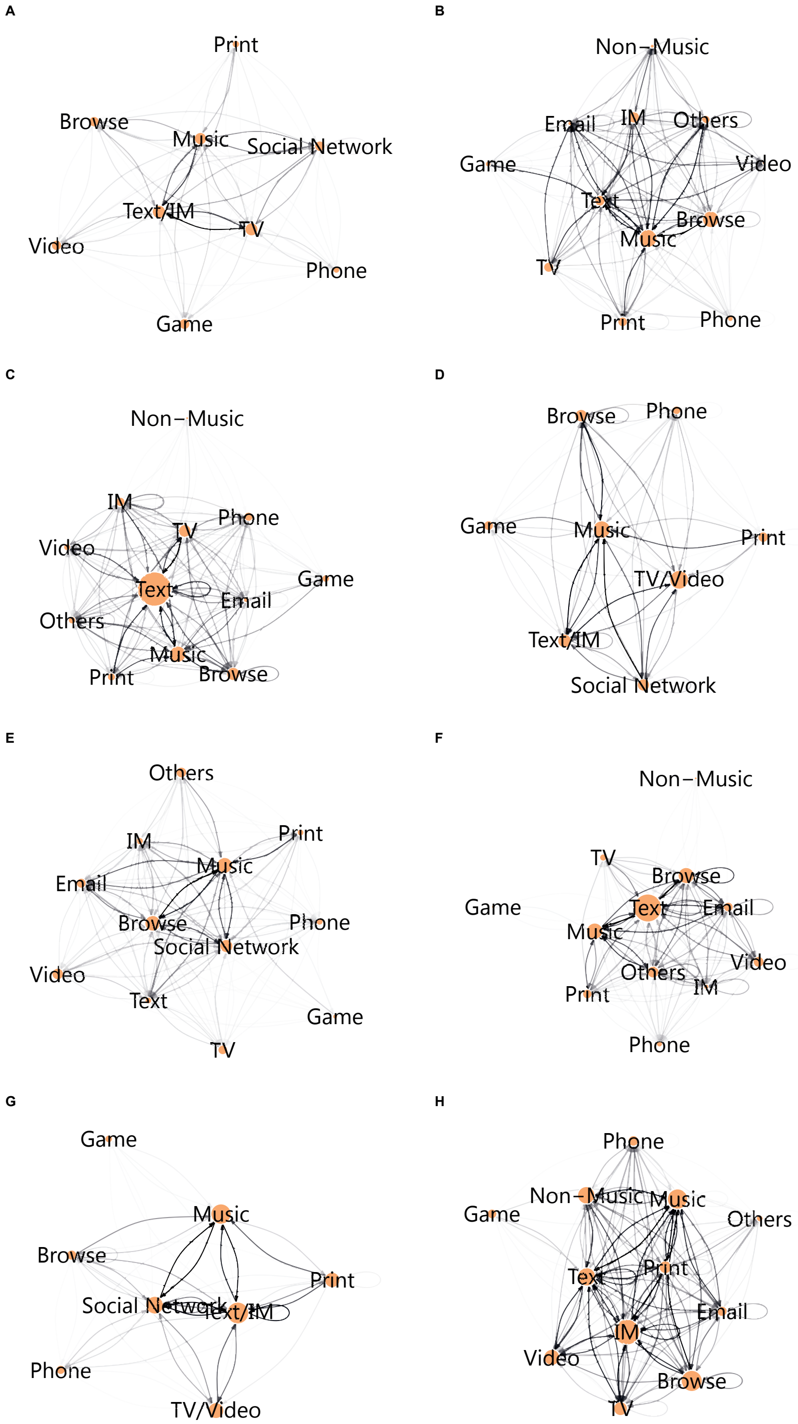
13 Note that different versions of the MUQ might feature slightly different media activities. For instance, in two out of eight datasets, texting and IMing, and watching TV and video were combined into one activity.


A
Print
Browse
Music
Social Network
Text/IM
TV
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Phone
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B
Non−Music
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Others
Game
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Music
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Others
Text
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Figure 2.1. The rendered networks from datasets collected in different locations: A. Amsterdam (the Netherlands), B. Groningen (the Netherlands), C. Michigan (USA), D. MTurk, E. Singapore, F. Stanford (USA), G. Waterloo (USA), and H. Yogyakarta (Indonesia). The node size reflects hours spent per day for different media; the edge thickness reflects frequency pairs of different media

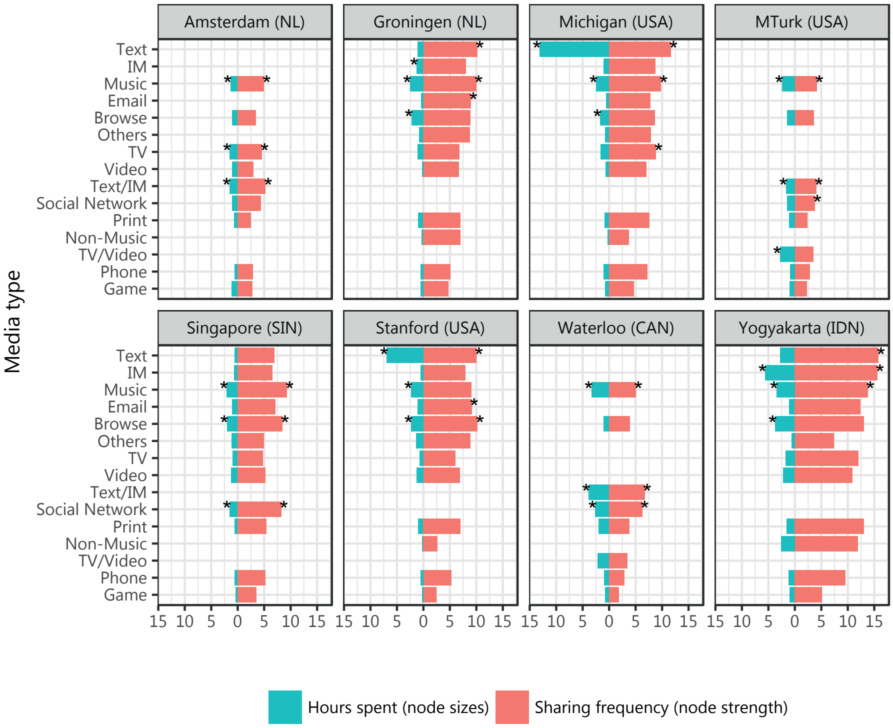

Figure 2.2. Summary of network properties. The blue bars indicate the hours spent for each media type and the red bars indicate the sum of the proportion of media multitasking. The asterisks indicate the three media types with the largest amount of hours spent and the three media types with the highest multitasking proportion in each dataset.

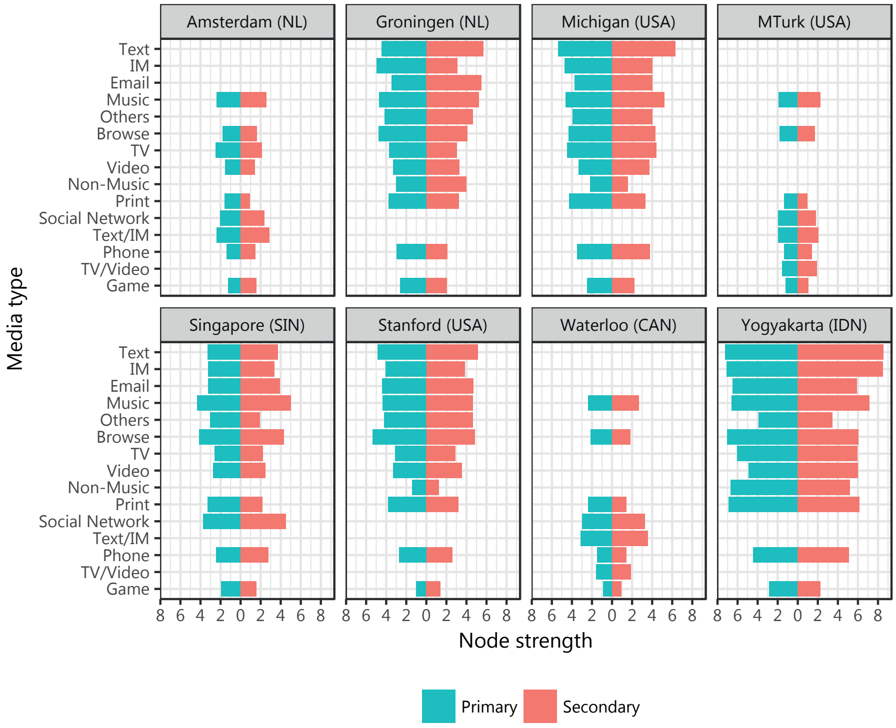

Figure 2.3. Ranked media use by the node importance as indicated by the node strength. Primary media activities (outgoing edges) are plotted in blue; secondary media activities (incoming edges) are plotted in red.

Differences between Populations

Overall, the rendered networks varied in density, with some networks showing an overall higher connectedness (as indicated by the strength of individual nodes and the overall edge density) than others, signifying different levels of media multitasking in different datasets (see Figure 2.4). Specifically, the dataset collected in Yogyakarta (Indonesia) had the highest density score, D=0.97 while the dataset collected using MTurk had the lowest, D=0.41. Since network densities were calculated as the ratio between overall weight of a network and the maximum theoretical weight of the network, these results indicate that media multitasking frequency varies from one population to another.

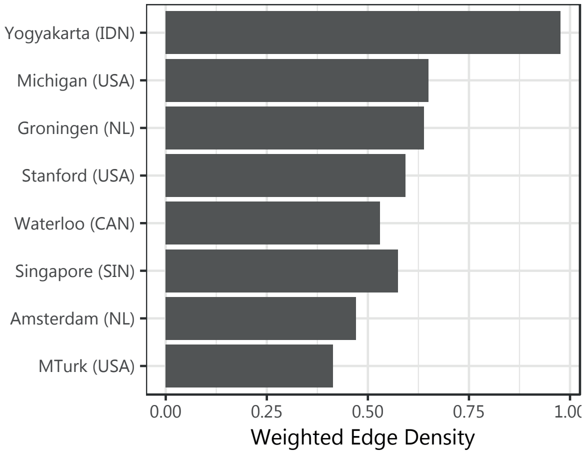

Figure 2.4. Ranked weighted edge density of the datasets.

We further tested if datasets collected within a similar region (i.e. North America, Southeast Asia, and The Netherlands) have similar density scores compared to datasets collected in a different region. We conducted a one-way ANOVA with density scores as the outcome variable and region as the predictor. The results showed that the density scores of datasets from different regions were not significantly different, $F(2,5)=1.58$, $p=.294$. For instance, the datasets collected in the Southeast Asian region had both the highest density score and one of the lowest (i.e., Singapore, $D=0.57$). With regard to age differences the dataset which contains exclusively young participants (i.e., the Amsterdam dataset) had one of the lowest density scores, $D=0.47$, indicating that the level of media multitasking might be lower among younger populations.

Discussion

To measure media multitasking, researchers have frequently used the MMI. As the MMI presents an overall score of media multitasking, the MMI might conceal important differences in the types of media that are used for media multitasking. Thus the types of media that are used might differ from one population to another. In this study, we rendered the media duration and media frequency questions which comprise the MMI from eight different datasets into networks to reveal the underlying media choice patterns. Overall, the rendered networks showed that the proportion of media multitasking, as indicated by the density score of each network, varied from one population to another. At the same time, the analysis suggests that the number and the types of media combinations people typically engage in were relatively similar across populations. This study thus provides initial evidence that the level of media multitasking behavior might vary across different populations, whereas the patterns are relatively similar.

Differences in Media Choices

With regard to media choices in media multitasking, our results suggest that media multitasking activities were not uniformly distributed, with some media activities having a disproportionately higher likelihood to be used for media multitasking. Specifically, across all datasets, listening to music, browsing, and texting/IMing were prominent. Moreover, datasets containing social media activities showed that social media were frequently used for media multitasking. Listening to music, browsing, texting, and accessing social media were also unsurprisingly the nodes with the largest sizes, which indicate that respondents spent most time with these media activities. This finding is consistent with previous reports which showed that time spent with media correlates positively with the likelihood of media multitasking (e.g. Foehr, 2006).

The combinations of media multitasking pairs seem to follow specific patterns, which might be based on cognitive load reduction, instant gratifications, and/or habituation. As a means to reduce cognitive load, we found that media activities which involved high numbers of used and shared modalities were less frequently paired with other activities across all datasets (see also Jeong & Hwang, 2016; Wang, Irwin, Cooper, & Srivastava, 2015). For example, in all datasets, gaming and having a phone conversation were located in the periphery of the networks, indicating a lower frequency of media multitasking. Both activities engage visual, auditory, and motor modalities, and may thus be highly cognitively demanding, particularly when combined. Additionally, media activities which allow for frequent task-switching were more likely to form dyads; in all datasets, texting, listening to music, and browsing had the highest node strength scores. These findings were in line with what has been suggested by Z. Wang et al. (2015) that media combinations occur adaptively, following the rule of “less work.” Indeed, combining media activities which involve different sensory modalities and more control over switching between the tasks would invoke less cognitive demand compared to combinations which involve an overlap in one sensory modality and less control over switching.

With regard to instant gratifications, we found that media activities which involved browsing, social media, and texting/IMing were frequently selected. These activities were characterized by an interaction with others, which could provide a certain socio-emotional gratification, namely to stay connected with one's social network (Bardhi et al., 2010; Hwang et al., 2014; Quan-Haase & Young, 2010) At the same time, several combinations of these activities (e.g., browsing while texting) involve an overlap in the motor modality, and thus could be said to be maladaptive (Z. Wang et al., 2015). Together, it seems to be the case that media users frequently combine browsing, social media, and texting/IMing activities since they provide gratifications and the benefit of these gratifications might outweigh the cost created by the additional cognitive load.

With regard to habituation, our networks showed two important patterns. First, we witnessed that the pairs which involved watching television were no longer frequently selected. This finding is in contrast to earlier reports on media multitasking which indicated that watching TV is a dominant activity among young people, and as such frequently used for media multitasking (see Foehr et al., 2006). Second, pairs which were characterized by a quick, entertaining escape from the daily routine (Quan-Haase & Young, 2010; Z. Wang & Tchernev, 2012), were more frequently selected. Together, these patterns showed a general shift in the trend of media use, namely the increase of "new" media consumption such as internet browsing and mobile phone-related activities and the decrease of "traditional" media consumption such as television viewing and reading (Anderson, 2015; Kononova et al., 2014; Standard Eurobarometer 86, 2016). . One implication would be that the type of media which traditionally consumed as a part of ritualistic behavior without actively consuming it has also changed, namely from watching television to texting, browsing, and social networking. Subsequently, researchers who are interested in studying the potential effects of background media (e.g., Lin, Robertson, and Lee 2009; Pool, Koolstra, and van der Voort 2003) might also want to consider "new" in addition to "traditional" media.

Lastly, the findings show that the different media activities were as likely to be chosen as primary or secondary activity. This was rather surprising, considering that a previous study has shown that specific media types are used primarily as primary or secondary activity (Foehr, 2006). Specifically, in Foehr's (2006) study, watching television and video, and listening to music were reported to be primary activities while in our datasets they were shown to be as likely to be chosen as primary and secondary activity. At the same time, our findings confirmed the findings from a cross-cultural study (Kononova et al., 2014), in which popular media such as television, music, and mobile phones were used interchangeably as primary and secondary activity. One explanation could be that the activities assessed in the MMI were typically entertainment-related activities. Thus, there was no need to establish priorities, for instance for work over entertainment in these types of multitasking (see Adler & Benbunan-Fich, 2012; Yeykelis, Cummings, & Reeves, 2014). Alternatively, it could just be the case that the patterns of media consumption have changed in the past years. The recent developments of smartphones for instance, have allowed individuals to perform multiple unrelated activities with a single device, thus making it unnecessary to distinguish different goals and priorities in multitasking.

Differences between Populations

While the results of our analysis suggest that the types of media multitasking combinations are relatively similar across different datasets, the rendered networks showed different density ratios, indicating that the level of media multitasking differs across populations. There were no clear differences with regard to the pattern of prominent nodes in different datasets. Looking at the overall density ranking, the two datasets with highest density scores were collected in Yogyakarta, Indonesia, and Groningen, the Netherlands while the datasets with the lowest density scores came from Amsterdam, the Netherlands, and MTurk, USA. This is somewhat surprising, considering the possible differences in the level of media ownership and other media-related factors which might influence media multitasking level in different countries (Jeong & Fishbein, 2007; Kononova & Chiang, 2015; Srivastava, Nakazawa, & Chen, 2016). At the same time, these findings confirm findings from a cross-cultural study which showed little qualitative differences in media multitasking patterns among American, Kuwaiti, and Russian respondents (Kononova et al., 2014). While we could not dismiss the possibility that the lack of differences between the datasets might stem from other factors, this result might provide initial evidence that media multitasking has become a global phenomenon, and thus, cognitive and socio-emotional factors might explain media multitasking behaviors better than country-specific indicators.

Looking into regional density rankings, it also became clear that the level of media multitasking as indicated by the density ratio varied within regions. In the Southeast Asia region, the dataset collected in Indonesia showed a higher level of media multitasking compared to the dataset collected in Singapore. This was somewhat surprising, since a recent survey indicates that access to media devices and the internet were better in Singapore compared to Indonesia (Deloitte Southeast Asia, 2017). In addition, previous studies have shown that media ownership positively predicts one's level of media multitasking (Kononova, 2013; Kononova & Chiang, 2015). One explanation could be that the ownership level of mobile media devices such as smartphones, which allows for a more flexible media multitasking activities, was higher in Indonesia compared to Singapore.

In the Northern American region, aside from the dataset collected in MTurk, datasets collected from Michigan, Stanford, and Waterloo showed comparable levels of media multitasking. One explanation why the MTurk sample showed a lower level of media multitasking than others might be that MTurk respondents were typically more heterogeneous with regards to age, level of education, male to female ratio, and occupations (Huff & Tingley, 2015) compared to the non-MTurk samples which consist primarily of university students (Henrich, Heine, & Norenzayan, 2010).

In the Western European region, specifically the datasets from the Netherlands, we again witnessed non-homogeneous density ratios between the datasets collected in Groningen and Amsterdam. Indeed, we found that the dataset with exclusively young participants (aged 12-15) had the second lowest density score, indicating a lower level of media multitasking. In comparison, the Groningen dataset, which primarily consists of University student samples, had higher levels of media multitasking. The difference in level of media multitasking was likely to be explained by differences in age: younger adolescent's media use is still partly restricted by parents and in the school context (R. Wang, Bianchi, & Raley, 2005) while young and older adults, in contrast, can decide more freely on their media choices, and therefore may engage more frequently in media multitasking.

Together, the results suggest that while the levels of media multitasking might differ from one population to another, the combinations of media consumed are nevertheless relatively similar. Thus, overall, these findings indicate that the mixed findings in media multitasking literature can most likely not be explained by different patterns of media multitasking behaviors underlying the MMI. At the same time, our findings indicate that media multitasking has become a global phenomenon which is characterized by frequent switching between “new” media such as browsing, text and instant messaging, and accessing social media. Additionally, the layout of our constructed networks also suggest that media multitasking behavior revolves around a limited set of media combinations, and that people use these media as primary or as secondary activity interchangeably.

Our findings have several theoretical and practical implications. Theoretically, our findings that some prominent media combinations occur in a non-adaptive manner (e.g., texting while browsing; since it involves an overlap in behavioral responses) suggest that in selecting media to combine in multitasking, users take into account other factors, such as the possibility to get instant gratifications, in addition to the possible cognitive demands exerted by the activities (Z. Wang et al., 2015). Future studies should examine these other factors in more detail to fully understand why people engage in media multitasking so frequently. Moreover, future studies may want to examine in which situations people tend to choose multitasking combinations in an adaptive or non-adaptive manner.

From a practical point of view, media multitasking behavior seems to be limited to a small set of media combinations, and media users do not seem to differentiate primary from secondary activities. Consequently, future studies might consider focusing on the cognitive and socio-emotional characteristics associated with specific media pairs instead of assessing a large number of media combinations. Future studies might be able to refrain from assessing each activity as both primary and secondary activity to alleviate the burden for respondents.

The current study has a limitation since our network comparison was done post-hoc, from data collected in previous studies. This means that we could not control over the type of questions asked in the questionnaire and the demographics of the samples. Therefore, it is difficult to attribute the similarities or differences between two networks to specific characteristics of these samples, because the datasets might vary in multiple aspects. For instance, the Yogyakarta and Amsterdam datasets varied with respects to the region, the average age of the samples, and the questions asked in the questionnaire. Ideally, future studies would use a questionnaire with a similar set of questions and would inquire the responses more systematically, i.e., from populations that differ in one instead of several characteristics. This, in turn, would allow for a more direct comparison between the networks and better attributions of the differences across cultures and populations.

Conclusion

In an exploration study, we rendered large sets of media use questionnaire datasets into networks. The networks provided several insights with regard to the pattern of media multitasking combinations. Specifically, we found media combinations which involved texting/IMing, listening to music, browsing, and social media to be the most prominent ones in most datasets. This indicates that media multitasking behaviors might be confined within a smaller set of media activities. We also found several differences in media multitasking behavior across populations, most importantly that the frequency of media multitasking behavior differed across populations. Future studies could benefit from further investigating the specific characteristics of the populations that might explain these differences in media multitasking frequency (e.g., age, education, cultural differences).

Chapter 3

Minds of Media Multitaskers (I)

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Abstract

Ophir, Nass, and Wagner (2009) found that people with high scores on the media-use questionnaire – a questionnaire that measures the proportion of media-usage time during which one uses more than one medium at the same time – show impaired performance on various tests of distractor filtering. Subsequent studies, however, did not all show this association between media multitasking and distractibility, thus casting doubt on the reliability of the initial findings. Here, we report the results of two replication studies and a meta-analysis that included the results from all published studies into the relationship between distractor filtering and media multitasking. Our replication studies included a total of 14 tests that had an average replication power of 0.81. Of these 14 tests, only 5 yielded a statistically significant effect in the direction of increased distractibility for people with higher scores on the media use questionnaire, and only two of these effects held in a more conservative Bayesian analysis. Supplementing these outcomes, our meta-analysis on a total of 39 effect sizes yielded a weak but significant association between media multitasking and distractibility that turned non-significant after correction for small-study effects. Taken together, these findings lead us to question the existence of an association between media multitasking and distractibility in laboratory tasks of information processing.

Keywords: media multitasking, distractibility, selective attention, working memory, task-switching

Introduction

Over the last two decades, the amount of information that is available online through the world wide web has increased exponentially (Palfrey & Gasser, 2008) and the accessibility of this information has likewise increased with the introduction of various modern multimedia devices (e.g., Lenhart, 2015). Taken together, these developments have led to two major changes in individual behavior. First, people spend many hours per day being online, as indicated by a recent survey from Pew research center which showed that 24% of teens in the U.S. report being online "almost constantly" (Lenhart, 2015). Second, people tend to engage in media multitasking (e.g., Brasel & Gips, 2011; Judd & Kennedy, 2011): Instead of being focused on a single task or stream of information, they try to monitor and interact with multiple streams of information simultaneously.

The fact that many people nowadays spend large portions of their waking lives in a media-rich environment raises the interesting question as to whether this experience might be of influence on the information processing mechanisms of the mind and brain. That is, could the frequent engagement in media multitasking have benefits for our ability to deal with multiple streams of information? In a recent study, Ophir, Nass, and Wagner, (2009) addressed this question, and their results produced a surprising conclusion. In the study, Ophir and colleagues introduced the media use questionnaire as a measure of the proportion of media-usage time during which people consume more than one type of media and they used the resulting Media Multitasking Index (MMI) to conduct a quasi-experimental study in which the performance of participants with a high and low MMI was compared for several widely used measures of information processing.

Specifically, as can be seen in Table 3.1, the participants in Ophir et al.'s study completed two task switching experiments, a change detection task with and without distractors, an N-back task with two levels of memory load (2-back and 3-back), an AX-continuous performance task (AX-CPT) with and without distractors, a Stroop task, and a Stop-signal task. Surprisingly, the results showed that people with high scores on the media use questionnaire were impaired when the task required some form of filtering out irrelevant, distracting information, such that HMMs – but not LMMs – were negatively affected by the presence of distractors in the change detection and AX-CPT tasks. In addition, the results showed that HMMs made more false alarms in the N-back task, and they showed slower response times and larger switch costs in the task-switching experiment. In interpreting these findings, Ophir et al. argued that HMMs had difficulty in suppressing the memory representations of earlier encountered targets in the N-back task, and that they had difficulty in inhibiting a previously used task-set in the task-switching experiment. Accordingly, Ophir et al. concluded that heavy media multitaskers are more susceptible to interference from irrelevant environmental stimuli and from irrelevant representations in memory" (p. 15583).

Table 3.1. Tasks, analyses, and effects reported by Ophir et al. (2009). LMM: Light Media Multitaskers. HMM: Heavy Media Multitaskers. d: Effect size in Cohen's d for the effects reported by Ophir et al. P(rep): Acquired replication power for our replication tests with α = .05.

Task	**Conditions Included**	**Findings and effect sizes in Ophir et al. (2009)**	$P_{(rep)}$ **Exp. 1**	$P_{(rep)}$ **Exp. 2**
Change detection	Memory set of 2 with 0, 2, 4, or 6 distractors	Interaction of Group (LMM vs. HMM) and number of distractors for memory set size 2 condition (*f*=.34; *d*=.68): HMMs showed a decline in performance with increasing numbers of distractors, LMMs did not.	.95	.97
	Memory set of 4 with 0, 2, or 4 distractors	No analyses reported.		
	Memory set of 6, with 0 or 2 distractors	No analyses reported.		
	Memory set of 8 with 0 distractors	No significant difference in memory capacity of HMMs and LMMs		

Task	Conditions Included	Findings and effect sizes in Ophir et al. (2009)	$P_{(rep)}$ Exp. 1	$P_{(rep)}$ Exp. 2
AX-CPT	With vs. without distractors	Significant interaction of Group (LMM vs. HMM) and Distractors (present vs. absent) for response times: HMMs slower to respond to target (*d*=1.19) and non-target (*d*=1.19) probes only in the condition with distractors.	.86 .86	.76 .76
N-back task	2-back vs. 3-back	Interaction of Group (LMM vs. HMM) × Condition (2 vs. 3-back) for false alarm rate, with HMMs showing a stronger increase in false alarms as memory load increased from 2 to 3 back (*f*=.42; *d*=.84).	.95	.92
Task switching: Number-Letter	Task-repeat and task-switch trials.	HMMs showed significantly slower response times for both switch (*d*=0.97) and repeat (*d*=0.83) trials and a larger switch cost (*d*=0.96).	.72 .60 .71	.80 .69 .79
Stop signal task	Not specified	No analyses reported, but Ophir et al. did mention there was no significant difference between LMMs and HMMs.		
Stroop task	Not specified	No analyses reported.		
Task switching	Not specified	No analyses reported.		

Results of Follow-up Studies to Ophir et al.'s (2009) Pioneering Work

Following Ophir et al.'s (2009) pioneering study, several reports were published that followed-up on this pioneering work by examining the association between questionnaire measures of media-multitasking and various measures of information processing capacity, distractibility, brain functioning, personality, and daily-life functioning. The results of these studies present a large and mixed set of results.

On the one hand, some studies found correlates of the MMI with lower working memory capacity (Cain et al., 2016; Sanbonmatsu, Strayer, Medeiros-Ward, & Watson, 2013), limited top-down control over visual selective attention (Cain & Mitroff, 2011), lower gray matter density in the anterior cingulate cortex (Loh & Kanai, 2014), lower scores on measures of fluid intelligence (Minear et al., 2013), an improved ability for dividing spatial attention (Yap & Lim, 2013) an improved ability to integrate visual and auditory information (Lui & Wong, 2012), more frequent self-reports of depression and social anxiety symptoms (Becker et al., 2013), higher scores on certain subscales of self-report measures of impulsivity (Minear et al., 2013; Sanbonmatsu et al., 2013), increased self-reports of attentional lapses and mind-wandering in daily life (Ralph et al., 2013), lower academic achievement (Cain et al., 2016), and with lower self-reports for executive functioning in daily life (Baumgartner et al., 2014). At the same time, however, these studies also reported non-significant associations for various other outcome measures, and the results of studies that examined the association between MMI and outcome measures similar to those used by Ophir et al. generally failed to replicate the original effects. For instance, Baumgartner et al. (2014) found that participants with higher scores for media multitasking were less – not more – susceptible to distraction in Eriksen Flanker Task, and Ophir et al.'s original finding of an association with increased susceptibility to distraction in a change detection task was also not replicated in several other studies (Cardoso-Leite et al., 2015; Gorman & Green, 2016; Uncapher et al., 2016). Likewise, Ophir et al.'s finding of increased switch costs in HMMs was not replicated in four subsequent studies (Baumgartner et al., 2014; Cardoso-Leite et al., 2015; Gorman & Green, 2016; Minear et al., 2013), with one study showing that HMMs had less – not more – difficulty in switching tasks than LMMs (Alzahabi & Becker, 2013).

The Current Study

Taken together, it can be concluded that while the follow-up studies to Ophir et al.'s (2009) pioneering study reported evidence suggestive of various correlates of media multitasking, the original findings by Ophir et al. (2009) were not always replicated. Thus, it can be said that the currently available evidence regarding a relationship between media multitasking and distractibility is mixed, and in need of further scrutiny. To shed further light on the possible existence of this relationship, we conducted two replication studies that included all experiments that showed a deficit in HMMs in the original study by Ophir et al. and we conducted a meta-analysis that included the results of all studies probing the existence of a relationship between media multitasking and distractibility in laboratory tasks of information processing. While the replication studies were done to afford insight into the replicability of Ophir et al.'s specific findings, the meta-analysis was conducted to provide a test of the strength of the relationship media multitasking and distractibility across all studies done to date.

Justification of Methods and Approach to Statistical Inference

In this section, we will describe and motivate our approach in testing the existence of a relationship between media multitasking and distractibility. As alluded to above, this approach involved the use of replication tests for the specific findings of Ophir et al. (2009; see Table 3.1) and it involved the use of a meta-analysis to quantify the strength of the MMI – distractibility link across all studies that have probed this relationship, including the two replication studies reported here. While the outcomes of our replication studies shed light on the replicability of the specific effects found by Ophir et al., the meta-analysis can provide an answer to the more central question of whether there exists an association between media multitasking and distractibility in general, and for certain types of tasks in particular. Our choice for relying on the meta-analysis for an answer to the main question of whether there exists an association between media multitasking and distractibility was motivated by the fact that this association has been examined in several other studies, and that, therefore, the most powerful, reliable answer to this question can be gained from considering the evidence that all of these studies provide together.

For the replication studies, we adhered to the recommendations provided for replication research (e.g., Brandt et al., 2014; Open Science Collaboration, 2015). To start, we carefully identified the main findings of interest reported by Ophir et al. (2009), and we selected these findings as our targets for the replication tests[14]. Secondly, we copied the methods of Ophir et al. as closely as possible so as to ensure that there were no methodological differences that could explain any differences in outcomes. Thirdly, we aimed to include as many participants as possible so as to ensure a reasonable level of power for successful replication of Ophir et al.'s results, if they were real. Fourthly, we adhere to the recommendations provided by the Psychonomic society in that we used a rigorous set of statistical methods to evaluate the outcomes of our replication studies. In the following sections, we will further elaborate on how these four points were implemented in our replication studies.

Selection of outcomes of interest for replication studies. For the replication tests, a first point of consideration was that the study by Ophir et al. (2009) included several tasks that had different conditions and different outcomes (e.g., accuracy and response times for four types of trials in the AX-CPT), which were in some cases examined in several different analyses. To avoid the risk of inflation of null-hypothesis rejection rates with multiple testing, a first step in our replication efforts was to select the main findings of interest from Ophir et al. In doing so, we closely examined the report of Ophir et al. to determine which findings were used as the basis for their conclusion that there exists an association between media multitasking and increased distractibility. Our analysis of this matter identified 7 key findings (see Table 3.1), and these findings thus became our outcomes of interest in examining the replicability of Ophir et al.'s findings. Specifically, for the change detection task, Ophir et al. reported a significant group by distractor set size interaction for the condition with 2 targets. For the AX-CPT, the main finding of interest was that HMMs showed slower responses in the condition with distractors, but only on trials in which the probe required participants to refer to the cue they had to maintain in memory during the presentation of the distractors separating the cue and the probe (AX and BX trials). For the N-back task, this was the finding of an interaction between group and working-memory load for false alarms, such that HMMs showed a stronger increase in false alarms as load increased across the 2 and 3 back conditions. Lastly,

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[14] The results of these replication tests are presented in the main text, and our analyses for other outcome measures and conditions are reported in a supplementary document.

for the task-switching experiment, Ophir et al. found that HMMs were slower on both switch and non-switch trials, and they also showed a larger switch cost (i.e., a larger difference in response times for switch and non-switch trials). In discussing these three results, Ophir et al. took each to reflect evidence for increased distractibility (cf. description of results on p. 15585 in Ophir et al.), and, accordingly, we selected each of these three outcomes of the task-switching experiment as targets for our replication attempt.

Methods used in the replication studies. For our replication studies, we aimed to replicate the methods of Ophir et al. (2009) as closely as possible. Specifically, we first asked as many participants as possible to fill in the same media use questionnaire that was also used by Ophir et al., and we then assigned participants with scores in the first quartile of the distribution of media multitasking scores to the LMM group whereas participants with scores in the fourth quartile were assigned to the HMM group. These participants were invited to take part in a lab study. In using the same group of participants for all experiments in the lab study, our procedure differed from that of Ophir et al. because Ophir et al. used different groups of participants for different tasks. In addition, our procedure differed from that of Ophir et al. because we used quartiles as the criteria for the assignment of participants to the LMM and HMM groups, whereas Ophir et al. assigned participants to these groups on the basis of their scores being one standard deviation below or above the group mean. Our choice for using quartiles, as opposed to using Ophir et al.'s standard-deviation based criterion, was motivated by practical and empirical considerations as the use of quartiles would result in larger groups of participants in the LMM and HMM groups, and, furthermore, some previous studies have been successful in identifying differences between LMMs and HMMs using the quartile-based approach (Cain & Mitroff, 2011; Yap & Lim, 2013).

To ensure that the methods we used for the experiments in the lab study were identical to those used by Ophir et al. (2009), we requested and received the original experiment programs used by Ophir et al. This allowed us to copy the exact methods of Ophir et al. for our replication studies. However, there was one task for which we did not copy Ophir et al.'s methods exactly. This concerned the AX-CPT, for which we chose not to include a condition without distractors since Ophir et al. found that HMMs only performed worse than LMMs when this task was done in the presence of distractors. Except for the omission of this condition without distractors, the AX-CPT was identical to the task used by Ophir et al., and the other tasks – change detection, N-back, and task-switching – were all identical to those used by Ophir et al. as well.

Data analysis for the replication studies. In analyzing the results of our replication attempts, we complied with the statistical guidelines of the Psychonomic Society (Psychonomic Society, 2012). As stated in these guidelines, the conventional approach of null-hypothesis significance testing (NHST) has several vulnerabilities and researchers should therefore be encouraged to supplement the results of NHSTs with other metrics and analyses, such as power analyses, effect sizes and confidence intervals, and Bayesian analyses. In implementing this recommendation, we first computed our acquired replication power so as to determine the likelihood that we would be able to replicate the effects of interest, given our sample size. As detailed below, these power analyses showed that our sample sizes were sufficiently large to yield an average replication power of 0.81, which is generally considered to be an acceptable level of power (J. Cohen, 1992). To determine whether our replication attempts were successful, we conducted NHSTs to determine whether the effects of interest reached significance at $\alpha = .05$, and, in doing so, we used one-sided tests for directional predictions that could be tested using a t-test. For hypotheses involving more than 2 condition means, we reported the regular F-statistics, as these are one-sided by definition. In interpreting the results of these NHSTs, we refrained from interpreting non-significant results with $p<.1$ as trends, as it has been demonstrated that such non-significant results should not be taken to reflect a trend in the direction of statistical significance because the inclusion of additional data will not necessarily result in a lower *p*-value (J. Wood, Freemantle, King, & Nazareth, 2014). In addition to conducting the NHSTs, we also calculated effect sizes and their confidence intervals to gain further insight into the strength of both significant and non-significant effects. Lastly, we also conducted a Bayes Factors analysis. As detailed below, this type of analysis is an important supplement to NHST because it provides a more conservative estimate of the extent to which the data support the presence of an effect, and because it also allows one to determine the extent to which a non-significant result provides evidence in favor of the null hypothesis.

Bayes Factors analyses. As alluded to above, a Bayes Factors analysis allows one to quantify the extent to which the acquired data support the existence (H_1) or absence (H_0) of an effect, with a continuous measure that expresses the ratio of the likelihood of the data under these respective hypotheses (Jarosz & Wiley, 2014; Rouder, Morey, Speckman, & Province, 2012; Rouder, Speckman, Sun, Morey, & Iverson, 2009; Wagenmakers, 2007). This measure has advantages over the traditional approach of significance testing because it allows for an assessment of the evidence for both H1 and H0, instead of only allowing the rejection of H0 if the observed data is unlikely under the null hypothesis (i.e. less than α). Furthermore, it has been shown that, compared to significance tests, Bayes factors provide a more robust test of the acquired evidence because significance tests tend to overestimate the evidence against H0. Specifically, when adopting a $BF_{10}>3$ as the criterion for the presence of an effect, it has been found that 70% of 855 effects that reached significance with *p*-value between 0.01 and 0.05 did not not reach this threshold of $BF_{10}>3$ (Wetzels et al., 2011). Thus, a Bayes factors analysis not only supplements the NHST in allowing for a quantification of evidence in favor the null hypothesis, but it can also be said to provide a more conservative test for the presence of an effect than that provided by NHST.

In calculating Bayes factors, we assumed the default prior values included in BayesFactor package in R (Morey, Rouder, & Jamil, 2015), and we expressed the evidence in terms of BF01 (ratio of likelihood of data given H_0 : likelihood of data given H_1) in case our significance test yielded a non-significant effect, and in terms of BF_{10} (ratio of likelihood of data given H_1:likelihood of data given H_0) in case the significance test yielded a statistically significant effect. For all BF's, values greater than 1 signified evidence in favor of one hypothesis over the other, with greater values signifying greater evidence. In characterizing the resulting BF's we followed the nomenclature of Jeffreys (1961), which considers BF's of 1-3 as anecdotal evidence; 3-10 as moderate evidence; 10-30 as strong evidence and 30-100 as very strong evidence.

Experiment 1

Method

Participants. A total of 154 undergraduate students from the Faculty of Psychology, Universitas Gadjah Mada, Indonesia were invited to fill in the Media Use questionnaire in an online study. Of these 154 participants, 148 participants completed the questionnaire. The MMI scores were normally distributed, as indicated by a Kolmogorov-Smirnov test, $z=0.70$, $p=.49$, with an average score of 6.80 and a standard deviation of 1.98. Using the lower and upper quartiles of the distribution of MMI scores as criteria, we classified 23 participants as LMMs and 24 as HMMs. These participants were invited for a lab study for which they would receive a monetary compensation of 50.000 rupiah (~3.5 €). In total, 10 HMMs (M_{MMI}=9.74, *SD*=.66) and 13 LMMs (M_{MMI}=4.09, *SD*=1.12) responded to our invitation for the lab study.

Materials and general procedure. The materials used for the replication studies included the same media use questionnaire as that used by Ophir et al (2009) and four experiments (change detection, N-back, AX-CPT, and task switching) which showed the main effects of interest (see Table 3.1). As in Ophir et al. (2009), the questionnaire was set out in an online study. The data for the four experiments were collected in an open computer lab equipped with multiple Intel I3 desktop computers which had a 2.6 GHz CPU and 2 GB of RAM. Stimuli were presented on a 20-inch LCD monitor, and the presentation of stimuli and collection of responses were controlled using software written in PsychoPy version 1.8.2. (Peirce, 2007). The responses were recorded using a QWERTY keyboard. Each of the four tasks took approximately 15 minutes to be completed and the order of the tasks was randomized across participants.

The media use questionnaire. To assess media multitasking, we used the same questionnaire as the one introduced by Ophir et al. (2009). This questionnaire consists of 144 items which each ask the participant: When using [one of 12 possible media], how often do you also use [the same media or one of the other 11 media]? The types of media covered by the questionnaire include printed media, email, television, video, music, non-music audio, phone, text messaging, instant messaging (e.g., chat), browsing, video games, internet browser, and other media. To answer the items, the participant is asked to choose between “never”, “sometimes”, “often”, and “almost always”. By combining all 12 types of media, thus including the possibility of using the same medium twice, this yields a total of 144 combinations for which responses are weighted with a value of 0 (never), .33 (sometimes), .67 (often) or 1 (almost always). To compute the media multitasking index (MMI), the scores for the 144 items are subsequently entered into the following equation:

$$MMI = \sum_{i=1}^{j} \frac{m_i \times h_i}{h_j}$$

In which m_{i} is the sum score for media multitasking using primary medium *i*, h_{i} is the number of hours spent consuming primary medium *i* per week, and h_{total} is the sum of hours spent consuming any of the 12 media. The MMI thus indicates the percentage of media-usage time during which a participant uses two media at the same time. Note that by implication, the MMI is insensitive to the actual amount of time people spent using different media at the same time, as the calculation of the MMI entails that one hour of media multitasking per day produces the same MMI as 16 hours of media multitasking. This aspect of the MMI has been pointed out in previous studies (Cain et al., 2016; Moisala et al., 2016), and we return to its implications in the general discussion.

Materials, design and procedure for change detection. The change detection task we used was identical to the one used by Ophir et al. (2009), who used a task designed by Vogel, McCollough, and Machizawa (2005). As indicated in Figure 3.1, each trial began with the appearance of a fixation cross for 200 ms which was followed by a 100-ms display of a memory array consisting of 2, 4, 6, or 8 red bars that had to be remembered (see Figure 3.1). Except for the memory array with 8 red bars, the other arrays could also include blue bars which served as distractors, with the possible numbers of blue bars being [0, 2, 4, or 6], [0, 2, or 4], and [0 or 2], for memory arrays with 2, 4, and 6 target elements, respectively. Following the appearance of this array, there was a 900-ms retention interval followed in turn by a test array that was shown for 2000 ms. In the test array, one of red bars could have a different orientation compared to the same bar in the memory array and the task for the participants was to press one of two designated keys to indicate whether a red bar had changed its orientation, which was the case on 50% of the trials. Following this response, the test array disappeared and the memory array for the next trial appeared after 200 ms. The task consisted of a total of 200 trials, yielding 10 change and 10 no-change trials for each combination of memory set size and distractor set size.

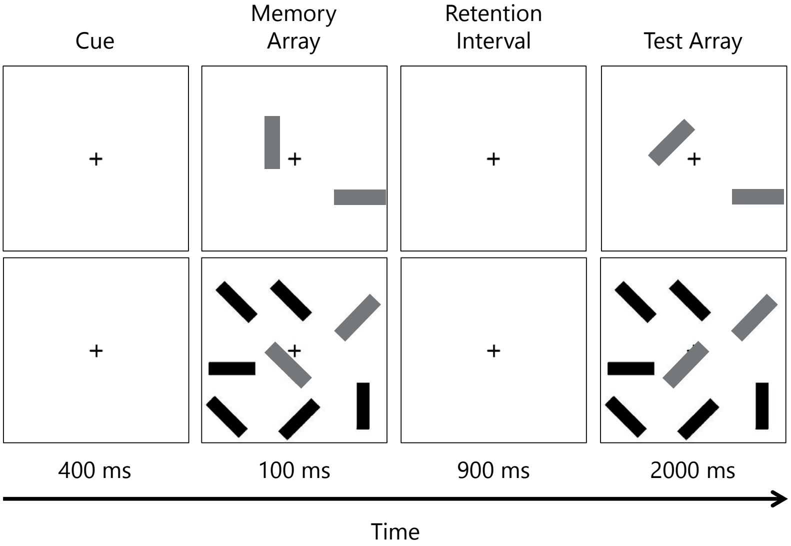

Figure 3.1. Change detection task with 0 distractors (lower quadrants) or with 6 distractors (upper quadrants). The examples shown had a memory set size of 2 items. The grey and black bars were presented in red and blue, respectively.

Materials, design and procedure for AX-CPT. For the AX-CPT, we used the same task as Ophir et al. (2009) used, but we chose to exclude the condition without distractors for the AX-CPT because Ophir et al. found that HMMs only performed worse than LMMs in the condition with distractors. In the task, participants were shown a continuous sequence of letters that each appeared for 300 ms, followed by a blank inter-stimulus interval (ISI) of 1000 ms (see Figure 3.2). The sequence was composed of subsequences of five letters of which the first and last were shown in red and the task for the participant was to respond with one of two keys to each letter, such that they had to press the “4” key of the keyboard when they detected a red “X” that was preceded by a red “A”, whereas they had to press the “5” key for all other letters in the sequence (i.e., any other red or white letter). Thus, the task for the participant was to monitor the stream for the occurrence of a red A followed in time by the appearance of a red X. Across trials, the red letters were selected in such a way that 70% of the subsequences included a red A followed by a red X, whereas the remaining 30% of the subsequences consisted of trials in which a red A was followed by a red letter different than X (hereafter denoted the AY trials), or wherein a red letter different than A was followed by a red

X (hereafter denoted BX trials), or wherein a red letter different than A was followed by a red letter different than X (hereafter denoted BY trials). The experiment consisted of 5 series of 30 subsequences, and participants were allowed to take a short break after each series.

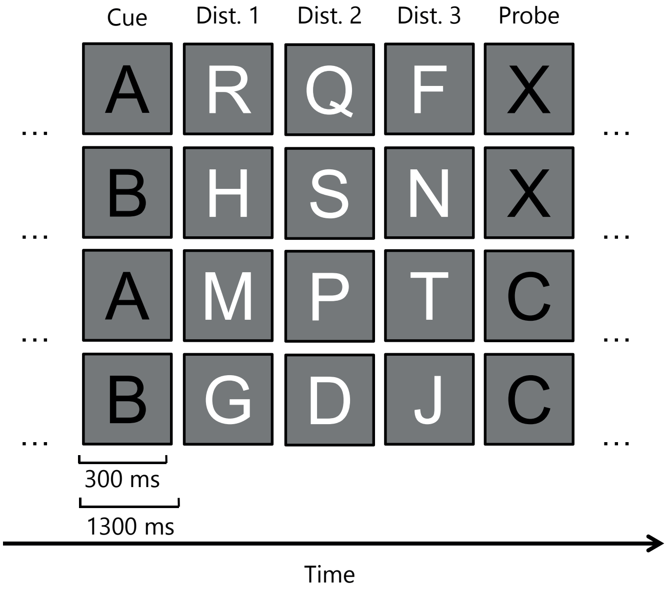

Figure 3.2. AX-CPT with distractors. The figure shows examples of the subsequences of five letters in the AX, BX, AY, and BY conditions. The black letters were presented in red.

Materials, design and procedure for N-back task. The N-back task was also identical to the task used by Ophir et al. (2009). Participants were presented a sequence of black letters on a white screen. Each letter appeared for 500 ms, followed by a blank ISI for 3000 ms (see Figure 3.3). The task for the participant was to determine if a currently shown letter was the same as the one shown two positions earlier (2-back condition), or three positions earlier (3-back condition). To respond to such targets, participants pressed the “4” key of the keyboard whereas they pressed the “5” key in response to all other letters. The two- and three-back conditions each consisted of the presentation of 90 letters, of which 13 were targets. As in the study by Ophir et al., the two-back condition was always done first, followed in time by the three-back condition.

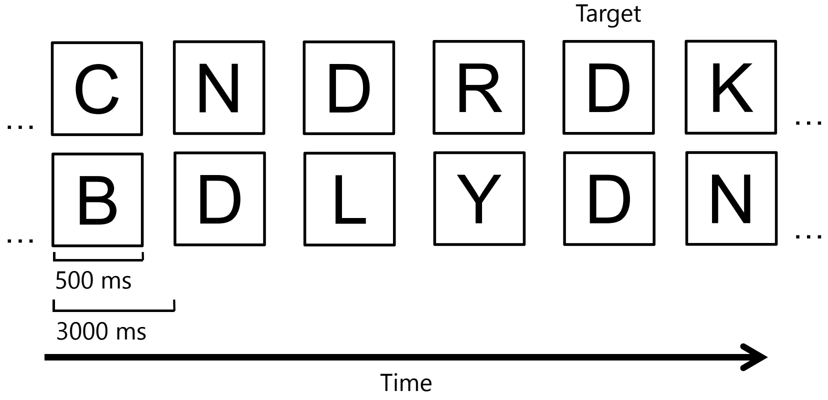

Figure 3.3. Example of a sequence of letters for the two-back (top row) and three-back (bottom row) conditions in the N-back task.

Materials, design and procedure for task-switching. The task switching experiment was also identical to that used by Ophir et al. (2009). In each trial of this task, participants were presented with a fixation cross for 1000 ms followed by a cue for 100 ms that indicated "number" or "letter". After the cue, a number and a letter were shown adjacent to each other (see Figure 3.4). When cued to respond to the number, participants had to indicate whether the number was odd (press "1" on the keyboard) or even (press the "2" key of the keyboard) as quickly as possible. When cued to respond to the letter, participants had to respond as quickly as possible to the letter by pressing "1" if the letter was a vowel and "2" if it was a consonant, with the letter being drawn from the set A, E, I, U, P, K, N, and S. The experiments consisted of 4 blocks of 80 trials, of which 40% were "switch" trials (number cue preceded by letter cue or vice versa) whereas the remaining trials were "repeat" trials. These two types of trials were presented in a random order.

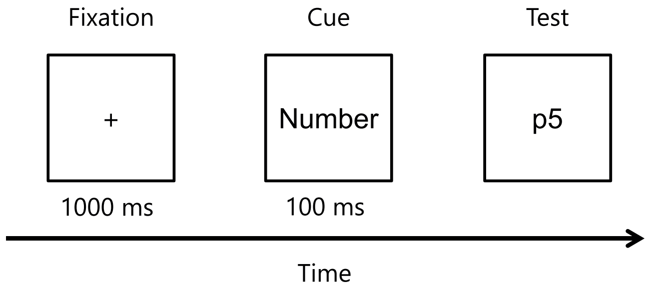

Figure 3.4. Example of a trial sequence in the number-letter task-switching experiment. Switch and repeat trials differ in terms of whether participants are cued to respond to the number (repeat) or the letter (switch) on the next trial.

Data analyses: Outcome measures and criteria for excluding observations. In this section, we describe the criteria we used for the exclusion of participants and trials, and the outcome measures we used for analyses. For all experiments, we excluded participants who performed at chance. This resulted in the exclusion of one participant from the LMM group for the change detection task. For the other experiments, no participants were excluded on the basis of this criterion. Our exclusion criteria for trials differed across experiments, and these criteria are detailed in the sections to follow.

For the change detection task, our analysis included only those trials in which the participant responded in time to the test array, that is, during the 2 seconds for which the test array was presented. This resulted in a loss of 4.02 % of the trials. For the remaining trials we used the hit and false alarm rates to calculate Cowan's K as a measure of working memory capacity (see Cowan, 2000), with $K=S^*(H-F)$, where K is the number of targets retained in working memory, S is the number of elements in the memory set, and H and F are hit and false alarm rates, respectively.

For the AX-CPT, we examined the hit and false alarm rates only for responses to the last red letter in the sequence, which would be a target in case it was an X that was preceded by a red A (AX Trials) or a non-target in all other cases (BX Trials). Since Ophir et al. (2009) only found differences in response times, our analysis of these trial types also focused on response times. For these analyses, we only included those trials in which the participant's response to first and last red letters were correct and we also excluded trials in which the response time to first and last red letters in the sequence were lower than 200 ms. This resulted in the exclusion of 40.6% of the trials[15], thus leaving an average of 89 trials per participant to include in our analysis.

For the N-Back task, we ignored response times and hit rates, and instead focused the false alarm rates because the main finding of interest in Ophir et al.'s (2009) study was an interaction effect of load (2-back vs. 3-back) and group (LMM vs. HMM), on false alarm rates, with HMMs showing a stronger in increase in false alarms with increasing load.

For the analysis of the task-switching experiment we examined the response times for switch and repeat trials, using only those trials in which the response was correct. In addition, we examined the switch cost, which is the difference in response times for switch and repeat trials. Prior to data analysis, we removed trials with response times below 200 ms and we used van Selst and Jolicoeur ‘s (1994) procedure to detect outliers on the upper end of the distribution. This resulted in the exclusion of 4.07% of the trials.

Results

Our report of the results in the main text is restricted to the analyses of the main findings of interest, listed in Table 3.1. We report the results of the analyses of other outcome measures and conditions in a supplementary document. In the following, we describe, per experiment, our achieved replication power for the effects of interest, followed in turn by a report of the results of applying NHST for these effects, along with the outcomes for any auxiliary effects that were tested in the same analysis (e.g., the main effects of group and distractor set size in the change detection task, for which the prediction was a significant interaction without significant main effects; see Table 3.1). In addition, we report the effect sizes and their confidence intervals for all effects, and we report the outcomes of a Bayesian analysis for the 7 effects of interest.

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[15] In deciding to include only trials with correct responses to both the first and the last red letter of the sequence, we may have applied an unusually strict criterion for trial inclusion, as previous studies using the AX-CPT typically included trials irrespective of whether the response to the cue was correct. However, since the correct judgment of the last red letter requires a correct judgment of the first, we felt that it was reasonable to use this more strict inclusion criterion. Notably, however, the results did not change when we used the more lenient inclusion criterion of including all trials with a correct response to the last red letter in the sequence.

Change detection: Achieved replication power. For the change detection task, we had to remove one participant from the LMM group due to chance-level performance. To calculate the achieved power we had for replicating Ophir et al.'s (2009) finding of a significant interaction Group (LMM vs. HMM) and Distractor Set Size (0, 2, 4, or 6), for the condition with a memory set size of 2 items, the final sample size thus consisted of 10 HMMs and 12 LMMs. Since the sample sizes differed per group, we were unable to calculate the exact power we had for our statistical test of the interaction effect, because this would require more detailed insights about the original effects than we could gain from the statistics reported for these effects. To circumvent this matter, we decided to compute a conservative power estimate, by using twice the smallest sample size for our calculations. Thus, our calculation of achieved power was based on a sample size of 2×10=20 for the change detection task. To calculate our achieved replication power, we used the G*Power 3.1. software (Faul, Erdfelder, Lang, & Buchner, 2007), and selected and set the following parameters: F-tests, ANOVA repeated measures, within-between interaction, post hoc, Effect size *f*=.344, α=.05, number of groups=2, number of measurements=4, correlation among repeated measures=.5, and nonsphericity correction ε=1. This calculation showed that a conservative estimate of our replication power for the interaction effect was equal to .95.

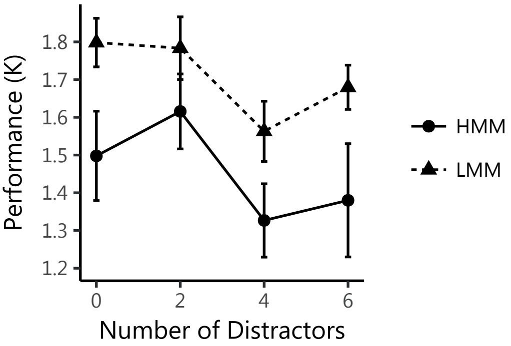

Figure 3.5. Change detection performance for the condition with 2 targets and 0, 2, 4, or 6 distractors in Experiment 1. Error bars represent within-subjects standard errors of the means (Morey, 2008).

Change detection: Results. To determine whether our results replicated Ophir et al.'s (2009) finding of a group X distractor set size interaction, we conducted a repeated measures ANOVA with Group (LMM vs. HMM) as a between-subjects factor and Distractor Set Size (0, 2, 4, or 6) as a within-subjects factor. The analysis yielded a main effect of Group, $F(1, 20)=6.48$, $p=.019$, partial $\eta^2=0.12$, $d=0.74$, and a main effect of distractor set size, $F(3, 60)=2.97$, $p=.039$, partial $\eta^2=0.08$, $d=0.58$. As can be seen in Figure 3.5, the main effect of group reflected the fact that performance was worse overall for HMMs than for LMMs, and the main effect of Distractor Set Size entailed that all participants showed a decrease in performance with increasing numbers of distractors. Most importantly, however, the results did not show a significant Group × Distractor Set Size interaction, $F(3, 60)=0.22$, $p=.880$, partial $\eta^2=0.01$, and our calculation of an effect size for this interaction effect yielded a negative effect because the rate at which performance decreased across increasing distractor set sizes was higher for LMMs than HMMs, $d=-0.21$ (95% *CI*: -1.11; 0.69), thus demonstrating a trend in opposite direction to Ophir et al.'s (2009) finding of increased susceptibility to distraction in HMMs. A Bayes factors analysis for this interaction effect yielded a $BF_{01}=6.83$, thus indicating that our experiment yielded moderate evidence for the absence of this interaction effect.

AX-CPT: Achieved replication power. For the AX-CPT, our primary targets for replication were the reaction times on AX and BX trials (see Table 3.1), for which Ophir et al. (2009) found that HMMs responded more slowly than LMMs. Replication power was calculated by entering our sample size into the G*Power 3.1. software (Faul et al., 2007), with these settings: t-tests, difference between two independent means, post hoc, one-tail, Effect size $d=1.19$ for AX RT and 1.19 for BX RT, $\alpha=.05$, $N_{group1}=10$, $N_{group2}=13$. This analysis showed that our sample size yielded a power of .86 for replicating both of these effects.

AX-CPT: Results. To determine if HMMs responded slower to AX and BX trials, we conducted two independent samples t-tests. These analyses showed that HMMs responded slower than LMMs in BX trials, $t(21)=1.88$, $p=.037$ (one-tailed), $d=0.79$ (95% *CI*: -0.12; 1.70), $BF_{10}=2.42$, but not on AX trials, $t(21)=0.76$, $p=.229$ (one-tailed), $d=0.32$ (95% *CI*: -0.56; 1.20), $BF_{01}=1.43$ (see Figure 3.6). Thus, while the significance tests yielded evidence for a statistically significant difference in response times on BX trials only, the Bayes Factors analysis showed that this effect was based on only anecdotal evidence. Likewise, the Bayes Factors analysis for the non-significant difference in RTs on AX trials also showed that there was only anecdotal evidence in favor of the absence of this difference.

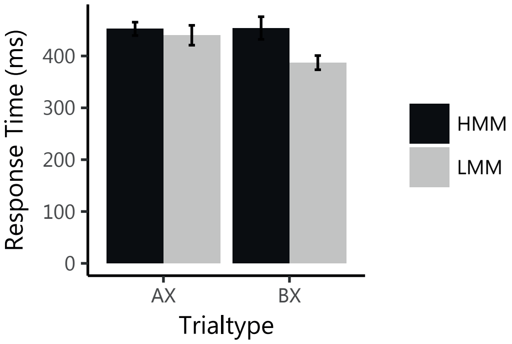

Figure 3.6. Results for the AX-CPT with distractors in Experiment 1. Mean response times (ms) are shown for correct responses to targets (AX) and non-targets (AY, BX, and BY). Error bars represent within-group standard errors of the means (Morey, 2008).

N-back: achieved replication power. For the N-back task, the primary finding of interest in the study by Ophir et al. (2009) was that HMMs showed a significant increase in false alarms as memory load increased across the 2-back and 3-back conditions. Given that our sample sizes for the LMM and HMM groups differed (N = 10 and N = 13 for HMMs and LMMs, respectively), we decided to calculate a conservative power estimate using a sample size of 10 participants per group. The analysis in G*Power 3.1. (Faul et al., 2007) was done with these settings: F-tests, ANOVA repeated measures, within-between interaction, post hoc, Effect size f=0.42, α=.05, number of groups=2, number of measurements=2, correlation among repeated measures=.5, and nonsphericity correction ε=1. This conservative estimate of our replication power had a value of 0.95, thus signifying a more than acceptable level of power for this test (e.g., Cohen, 1992).

N-back task: Results. Figure 3.7 shows the false alarm rates of LMMs and HMMs for the 2 and 3-back conditions. In analyzing these results, we conducted a repeated measures analysis of variance, with group (LMM vs. HMM) as a between-subjects factor and WM Load (2-back vs. 3-back) as a within-subjects factor. The results showed no significant main effect of WM Load, $F(1, 21)=0.97$, $p=.335$, partial $\eta^2=0.04$ and no main effect of Group, $F(1, 21)=0.96$, $p=.338$, partial $\eta^2=0.04$. More importantly, the critical Group × WM Load interaction also failed to reach significance, $F(1, 21)=0.08$, $p=.781$, $\eta^2<.001$, $d=0.13$ (95% *CI*: -0.75; 1.01), $BF_{01}=2.6$.

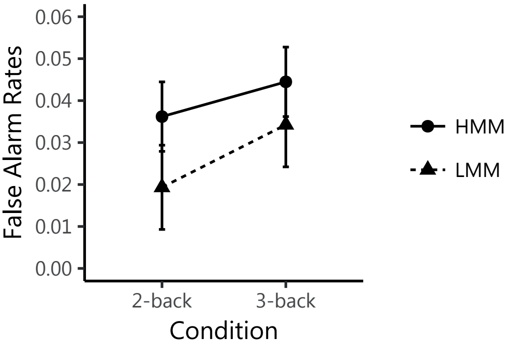

Figure 3.7. Results N-back task. False alarm rates are plotted as a function of WM load (2-back vs. 3-back) and Group (LMM vs. HMM). Error bars represent within-group standard errors of the means (Morey, 2008).

Task-switching: Achieved replication power. For the task-switching experiment, Ophir et al. (2009) found that HMMs were significantly slower to respond on both switch and repeat trials, and that they also showed a significantly larger switch cost, defined in terms of the difference in RT between switch and repeat trials. Replication power for these three effects was computed in G*Power (Faul et al., 2007), with the following settings: settings: t-tests, difference between two independent means, post hoc, one-tail, Effect size *d*=.97 for switch RT, 0.83 for repeat RT and 0.96 for switch cost, α=.05, N_{group1}=10, N_{group2}=13. These analyses showed that our sample size of 10 HMMs and 13 LMMs yielded a power of 0.72, 0.60, and 0.71, respectively, for replicating Ophir et al.'s finding of a difference in switch RT, repeat RT, and switch cost.

Task-switching: Results. The results of our task-switching experiment are shown in Figure 3.8. An analysis of these results showed that, compared to LMMs, HMMs were slower in switch trials, *t*(21)=2.0, *p*=.029 (one-tailed), *d*=0.84 (95% *CI*: -0.07; 1.75), BF_{10}=2.84, and they had a larger switch cost, *t*(12.33, corrected for inequality of variance)=2.97, *p*=.006 (one-tailed), *d*=1.35 (95% *CI*: 0.38; 2.32), BF_{10}=20.1. However, we did not find that HMMs were also slower in the repeat trials, *t*(21)=1.43, *p*=.083 (one-tailed), *d*=0.60 (95% *CI*: -0.29; 1.49), BF_{01}=0.72.

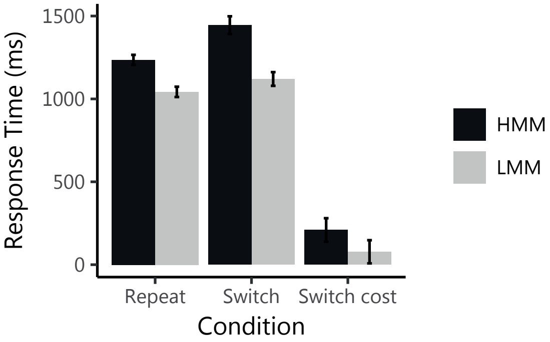

Figure 3.8. Results for the task-switching experiment in Experiment 1. Mean response time (ms) is shown for correct responses on switch and repeat trials, for HMMs and LMMs separately. Error bars represent within-group standard errors of the means.

Discussion

In Experiment 1, we tested the replicability of the 7 findings that we identified as being the key findings that led Ophir et al. (2009) to conclude that heavy media multitasking is associated with increased susceptibility to distraction. In testing the replicability of these findings, we copied the methods used by Ophir et al., we used a sample size that yielded an adequate level of power (Cohen, 1992), and we used the a rigorous approach to statistical analysis, such that we used a combination of power analyses, NHST, effect sizes, and Bayes factors in examining the outcomes of our replication study. By implication, we can assess the success vs. failure of our replication studies in terms of different metrics (see also, Open Science Collaboration, 2015).

To start, one can evaluate the results of our first replication study in terms of the achieved replication power – that is, the likelihood that we would replicate the effects of Ophir et al., given our sample sizes, and assuming that the effects found by Ophir et al. were true – and statistical significance. From this perspective, a first point of consideration is that the results of our power analyses showed that our tests had an average replication power of .81, which is generally considered an acceptable level of power (Cohen, 1992), and which means that one would expect that if the 7 effects reported by Ophir et al. were true, then at least 5 of these 7 effects (i.e. 81% of the 7 effects tested) would be replicated at $\alpha=.05$ in the current replication study. This turned out not to be the case, as only 3 of the 7 effects reached significance in our replication study. Specifically, HMMs were significantly slower than LMMs in responding to BX probes in the AX-CPT, they were significantly slower than LMMs in responding on switch trials in the task-switching experiment, and they showed a larger switch cost than LMMs in the task-switching experiment. On the other hand, we did not find a significant difference in response times on AX trials in the AX-CPT, we did not find a difference in false alarms in the N-back task, we did not find a difference in vulnerability to distraction in the change detection task, and we also did not find a difference in response times on repeat trials in the task-switching experiment.

When evaluating the results of our replication study on the basis of Bayes factors, we find that only one of the three statistically significant effects – the finding of a greater switch cost in HMMs – was based on strong evidence, whereas the effects for response times on BX trials in the AX-CPT, and for switch trials in the task-switching experiment were based on only anecdotal evidence. Importantly, however, the Bayes Factors also showed that only one of the four non-significant effects yielded moderate evidence in favor of the null-hypothesis, and this concerned the absence of an interaction effect of media multitasking and distractor set size in the change detection task. Thus, according to the Bayesian analyses, our replication attempt was largely indecisive, as only two of the 7 effects of interest produced clear evidence for the presence or absence of an effect.

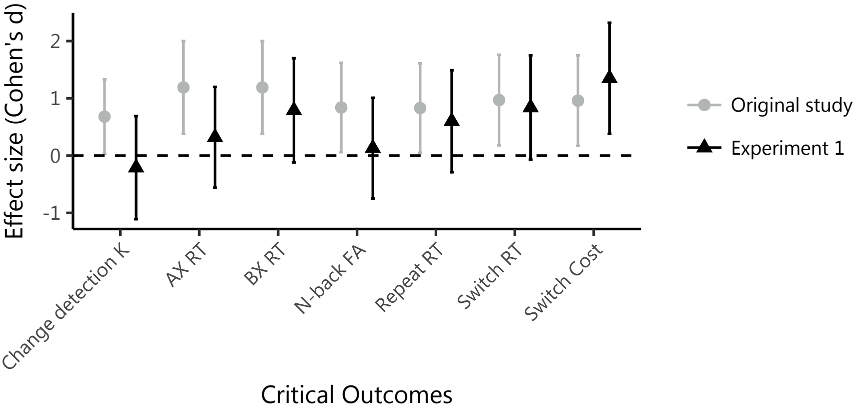

Figure 3.9. Comparison of effect sizes (Cohen's d) and their 95% confidence intervals for the 7 effects of interest in Ophir et al. (Original study) and in our first replication study (Experiment 1).

Moving beyond the binary diagnosis of the presence vs. absence of effects in terms of statistical significance or *BF*>3, we can also evaluate the outcomes of our replication study by considering the corresponding effect sizes and their confidence intervals. This evaluation moves beyond the diagnosis of presence vs. absence of effects, as it sheds light on the strength of these effects. When comparing the effect sizes we obtained in our 7 replication tests to those found by Ophir et al. (see Figure 3.9), we find that the average effect size for the replication tests was markedly lower than the average size of these effects in Ophir et al., M=0.55 and SD=0.51 vs. M=0.95 and SD=0.19, respectively. At the same time, however, all of the effects found by Ophir et al. fell within the 95% confidence interval of the replication effect sizes, and, except for the outcome of the change detection task, all other replication tests yielded evidence for an effect in the same direction as the effects found by Ophir et al. Thus, when considering effect size, the results of our first replication study can be said to conform largely to the outcomes of Ophir et al., with the qualification that the effects were smaller in the current replication study.

Experiment 2

Taken together, we can conclude that the results of our first replication study did not produce a successful replication in terms of statistical tests aimed at determining the presence of an effect (i.e., power analysis, NHST and Bayes Factors), as these metrics showed that we replicated fewer effects than would be expected if the effects of Ophir et al. were true. At the same time, however, 6 out of 7 replication tests did show an effect in the same direction as the effects found by Ophir et al. (2009), but these effects were markedly smaller than those observed by Ophir et al. In considering the possible reasons for why our first replication study generally produced smaller effects than those found by Ophir et al. (2009), an interesting possibility can be found in the fact that the Indonesian participants in our first replication study generally scored much higher on the media multitasking index (MMI) than the participants in most previous studies that used the MMI, including the study by Ophir et al. Specifically, the average MMI for participants in Ophir et al.'s studies was 4.38 whereas it was 6.80 in our study. Accordingly, one could argue that perhaps our finding of smaller effects might have been due to the fact that our participants in the first replication study had unusually high MMI scores. Since previous work suggests that, compared to participants from Western countries such as Britain and the U.S., Indonesian participants have the tendency to use more extreme answer alternatives in completing surveys (Stening & Everett, 1984), we addressed this possibility by running a second replication study using participants from the University of Groningen, The Netherlands. Aside from providing a second attempt at replication of Ophir et al.'s findings, our second replication study also aimed to shed light on the reliability of the MMI, by including a second administration of the Media Use Questionnaire so as to enable an assessment of the test-retest reliability of this questionnaire.

Methods

Participants. A total of 306 students from the University of Groningen, The Netherlands, were asked to complete the Media Multitasking Index questionnaire and 205 of these participants indeed completed the questionnaire. The MMI scores for these 205 participants were normally distributed, Kolmogorov-Smirnov, $z=0.99$, $p=.28$, with a mean of 3.80 and a standard deviation of 1.89. This distribution of scores was comparable to that in the study by Ophir et al. (2009), which had a mean 4.38 and a standard deviation of 1.52. Of our 205 participants, 52 were classified as HMM and 52 were classified as LMM, based on the fact that their scores fell within the lower and upper quartiles of the distribution of scores. Of these 104 participants, 19 HMMs (mean=6.63, *SD*=1.40) and 11 LMMs (mean=1.61, *SD*=.64) responded to our invitation to take part in a lab study in return for monetary compensation or course credits.

Materials, procedures, and data analysis. The second replication study was identical to the first replication in all regards, except for the fact that the experiments for the second study were run in isolated experimental booths, using a program written in E-Prime version 2.0 (MacWhinney, St James, Schunn, Li, & Schneider, 2001), with the stimuli being presented on a 17" CRT monitor that was controlled by an Intel i3, 3.4 GHz CPU with 8 GB of RAM. In addition, the second replication study differed from the first in that participants were asked to fill in the Media Use Questionnaire for a second time at the start of the lab study, thus enabling us to compute the test-retest reliability of the questionnaire. The second administration of the questionnaire in the lab study took place approximately one week after participants had first filled it in. The exclusion of participants and trials was done according to same rules as those used in the first study, and the exclusion of participants and trials is described in detail per experiment in the following sections.

Results

Test-retest reliability of the MMI. To determine the reliability of the MMI, we computed the test-retest correlation for the participants who took part in the lab study. This analysis showed that the correlation between the repeated administrations of the questionnaire was high, with *r*(28)=0.93, *p*<.001.

Change detection task: Achieved replication power. For the change detection task, we had to remove one participant from the HMM group due to chance-level performance, thus yielding a final sample size of 18 HMMs and 11 LMMs. To calculate our power for replicating Ophir et al.'s (2009) finding of an interaction between media multitasking and distractor set size, we entered a sample size of 2×11=22 into G*Power 3.1. (Faul et al., 2007), with the following settings: F-tests, ANOVA repeated measures, within-between interaction, post hoc, Effect size *f*=.344, α=.05, number of groups=2, number of measurements=4, correlation among repeated measures=.5, and nonsphericity correction ε=1. This calculation showed that our sample size for the change detection task yielded a replication power of .97 for finding the group by distractor size interaction effect reported by Ophir et al.

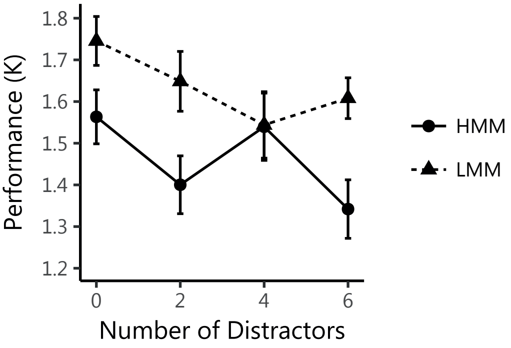

Figure 3.10. Change detection performance for the condition with 2 targets and 0, 2, 4, or 6 distractors in Experiment 2. Error bars represent within-subjects standard errors of the means (Morey, 2008).

Change detection task: Results for 2-target condition. For the condition with a memory set of two items, we examined Cowan's K as a function of Group and Distractor

Set Size (0, 2, 4, or 6; see Figure 3.10). The analysis showed no significant main effect of group, $F(1, 27)=3.29$, $p=.081$, partial $\eta^2=0.06$, $d=0.51$, or of Distractor Set Size, $F(3, 81)=2.08$, $p=.110$, partial $\eta^2=0.03$, $d=0.35$. In addition, the results did not show an interaction of Group and Distractor Set Size, $F(3, 84)=1.29$, $p=.284$, partial $\eta^2=0.02$, $d=0.43$ (95% *CI*: -0.36; 1.22), $BF_{01}=2.69$.

AX-CPT with distractors: Achieved replication power. For the AX-CPT, we had to remove 10 participants due to poor performance. These participants appeared to have failed to understand the task instructions, as they had an accuracy of 0 in one of the conditions. Exclusion of these participants entailed that the subsequently reported analyses of performance in the AX-CPT were conducted with a sample of 14 HMMs ($M_{MMI}=6.48$, $SD=1.29$) and 6 LMMs ($M_{MMI}=1.5$, $SD=0.76$). To calculate our achieved replication power for replicating Ophir et al.'s (2009) finding that HMMs showed increased RTs on AX and BX trials, this sample size was entered into the G*Power 3.1 (Faul et al., 2007) with these settings: t-tests, difference between two independent means, post hoc, one-tail, Effect size $d=1.19$ for AX RT and 1.19 for BX RT, $\alpha=.05$, $N_{group1}=14$, $N_{group2}=6$. These calculations showed even with this small sample of participants, we still had a power of .76 for replicating the results Ophir et al. found in their analyses of RT for AX and BX trials.

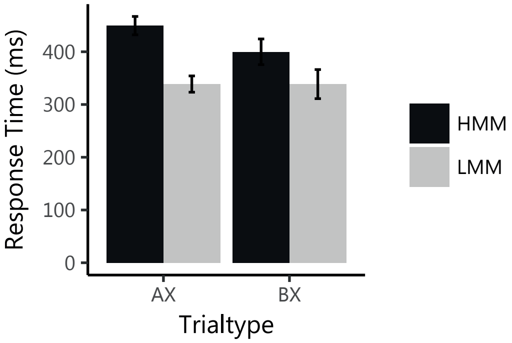

Figure 3.11. Results for the AX-CPT with distractors in Experiment 2. Mean response times (ms) are shown for correct responses to AX and BX trials. Error bars represent within-group standard errors of the means (Morey, 2008).

AX-CPT with distractors: results. To compare the response times of HMMs and LMMS to AX and BX trials in the AX-CPT, we conducted two independent samples t-tests (see Figure 3.11 for the results). These analyses showed that HMMs were slower in AX trials, *t*(18)=2.58, *p*=.009 (one-tailed), *d*=1.26, (95% *CI*: 0.15; 2.37), BF_{10}=6.36, but not in BX trials, *t*(18)=.98, *p*=.169 (one-tailed), *d*=.48, (95% *CI*: -0.56; 1.52), BF_{01}=1.09.

N-back task: Achieved replication power. For the N-back task, we had to remove 2 participants from the HMM group and 2 participants from the LMM group due to poor performance, thus resulting in a final sample size of 17 HMMs and 9 LMMs. The reasons for excluding these participants were that one participant did not respond to any of the trials, two participants did not respond to more than half of the trials, and one participant had a higher false alarm than hit rate. To calculate our power for replicating Ophir et al.'s (2009) finding of an interaction between load (2-back vs. 3-back) and group (HMM vs. LMM) on false alarm rates, we set the sample size to 2×9=18 for obtaining a conservative power estimate. Power calculation was done in G*Power 3.1., with these settings: F-tests, ANOVA repeated measures, within-between interaction, post hoc, Effect size *f*=0.42, α=.05, number of groups=2, number of measurements=2, correlation among repeated measures=.5, and nonsphericity correction ε=1. This calculation showed that our sample of participants entailed that we had a replication power of 0.92 for replicating Ophir et al.'s finding of an interaction of group and memory load on false alarm rates.

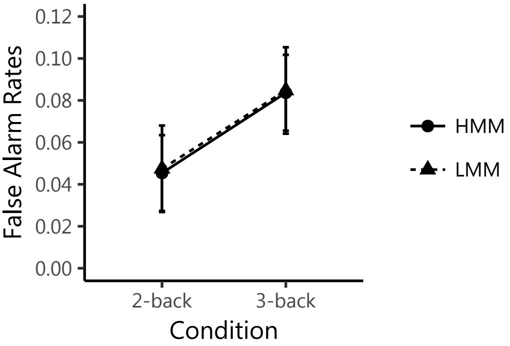

Figure 3.12. Results N-back. False alarm rates are plotted as a function of WM load (2-back vs. 3-back) and Group (LMM vs. HMM). Error bars represent within-group standard errors of the means (Morey, 2008).

N-back task: Results. An analysis of the false alarm rates (see Figure 3.12) as a function of group (HMM vs. LMM) and memory load (2-back vs. 3-back) showed no significant main effect of WM Load, *F*(1, 24)=3.38, *p*=.078, partial η^2=0.12 and no main effect of Group, *F*(1, 24)=.003, *p*=.954, partial η^2<.001. In addition, the interaction of Group × WM Load failed to reach significance, *F*(1, 24)<.001, *p*=.982, partial η^2<.01, *d*<.01, (95% *CI*: -0.85; 0.85), BF_{01}=2.46.

Task-switching: Achieved replication power. To calculate our power for replicating Ophir et al.'s (2009) findings that HMMs showed larger switch costs and higher RTs on repeat and switch trials for the task-switching experiment, we entered our sample size of 19 HMMs and 11 LMMs into G*Power 3.1. (Faul et al., 2007), using these settings: t-tests, difference between two independent means, post hoc, one-tail, Effect size *d*=.97 for switch RT, 0.83 for repeat RT and 0.96 for switch cost, α=.05, N_{group1}=19, N_{group2}=11. These calculations showed that our sample yielded replication powers of 0.80, 0.69, and 0.79, for the effects Ophir et al. found for switch RT, repeat RT, and switch cost, respectively.

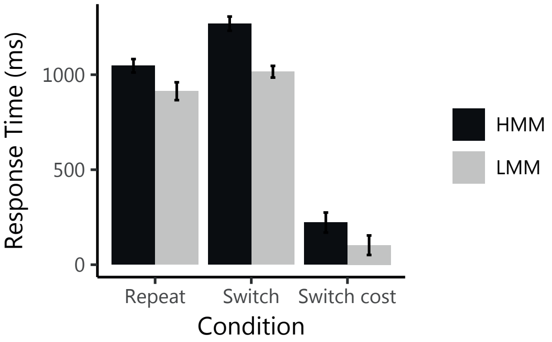

Figure 3.13. Results for the task-switching experiment in Experiment 2. Mean response time (ms) is shown for correct responses on switch and repeat trials, for HMMs and LMMs separately. Error bars represent within-group standard errors of the means.

Task-switching: results. The results for the task-switching experiment are shown in Figure 3.13. The analyses showed that HMMs were significantly slower than LMMs in switch trials, *t*(28)=1.73, *p*=.047 (one-tailed), *d*=0.66 (95% *CI*: -0.14; 1.46), BF_{10}=1.93. The analyses of switch costs and response times on repeat trials showed no statistically significant difference, with $t(28)=1.21$, $p=.117$ (one-tailed), $d=0.46$ (95% *CI*: -0.33; 1.25), $BF_{01}=0.95$, and $t(28)=1.66$, $p=.054$ (one-tailed), $d=0.63$ (95% *CI*: -0.16; 142), $BF_{01}=1.79$.

Discussion

Aside from demonstrating that the MMI has a high test-retest reliability (see also, Baumgartner, Lemmens, Weeda, & Huizinga, 2016), the results from our second replication study largely conform to those obtained in our first replication study. Specifically, our tests of the replicability of Ophir et al.'s (2009) main findings had an average replication power of 0.81, yet only 2 out of 7 findings yielded a statistically significant outcome in the same direction as that found by Ophir et al. Specifically, HMMs were slower in AX trials of the AX-CPT task and they were slower than LMMs on switch trials.

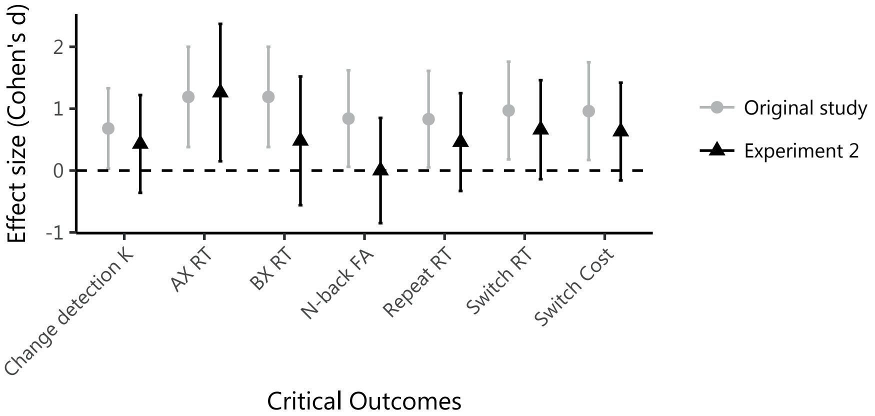

Figure 3.14. Overview of the results of our second replication study. Effect sizes (Cohen's d) and their 95% confidence intervals are shown for the 7 effects of interest in Ophir et al. (original study) and in our second replication study (Experiment 2).

In terms of Bayes Factors, our analyses showed that the difference in AX trials was based on moderately strong evidence, whereas the difference on switch trials was based on only anecdotal evidence. In addition, the BF's showed that all of the non-significant effects involved only anecdotal evidence in favor of the null hypothesis. As for the effect sizes (see Figure 3.14), the results of our second replication study showed that all effects were in the same direction as those found by Ophir et al., with HMMs performing worse than LMMs. However, as in our first replication study, the effects in the second replication study were again smaller than those found by Ophir et al., with *M*=0.56 and *SD*=0.37 vs. *M*=0.95 and *SD*=0.19, respectively. Accordingly, it can be concluded that the results of our second replication generally conform to those of our first replication study in suggesting that while HMMs may indeed perform worse than LMMs on various tests of distractibility, the magnitude of these differences is smaller than the effects found by Ophir et al.

Meta-Analysis

Taken together, the results of our replication studies can be said to provide only partial support for the existence of an MMI-distractibility link, as the majority of our significance tests and Bayes factors analyses did not yield convincing support for the existence of this link, but the outcomes did generally show effects in the same direction as those found by Ophir et al. (2009). As a final step in our examination of the MMI-distractibility link we aimed to arrive at a proper estimate of the strength of the relationship between media multitasking and distractibility in laboratory tests of information processing. To this end, we conducted a meta-analysis that included the results of the current replication studies along with those of all previous studies that have used similar laboratory tasks to investigate the relationship between media multitasking and distractibility, including the seminal study by Ophir et al. (2009). By calculating a weighted mean effect size on the basis of the results of all studies done to date, this analysis can provide the most sensitive and powerful test of the existence and strength of the MMI-distractibility link. In addition, we also made use of moderator analyses to determine whether the MMI-distractibility link differed across certain subsets of tasks or participants, and we used meta-analytical tools to diagnose and correct for the presence of any small-study effects (i.e., the influence of the presence of relatively many small studies that showed large, positive effects, and relatively few, similarly small studies with negative or null effects; Duval & Tweedie, 2000; Egger, Davey Smith, Schneider, & Minder, 1997; Peters, Sutton, Jones, Abrams, & Rushton, 2007; Sterne et al., 2011; Thompson & Sharp, 1999).

Methods

Criteria for study inclusion. We aimed to include all published studies that examined the relationship between media multitasking and distractibility in laboratory tasks such as those used in the original study by Ophir et al. (2009). Accordingly, our inclusion criteria for the meta-analysis were that the study in question should include a statistical test of this relationship, either in the form of a between-group comparison of LMMs and HMMs, or in the form of a correlation between media multitasking and performance on one or more laboratory tests of distractibility in information processing. In determining which tasks can be considered to provide an index of distractibility, we adopted a categorization and definition of distractibility similar to that used by Ophir et al. in their interpretation of their findings. Specifically, we selected tasks in which participants were asked to respond to target stimuli that were presented under conditions in which distraction could either be caused by irrelevant stimuli that were presented simultaneously or before or after the target in a particular trial (environmental distraction), or by irrelevant stimuli held in memory (memory-based distraction), or by an irrelevant, previously used task-set (task-set distraction). Accordingly, any task that involved the sequential or simultaneous presentation of one or more targets and one or more distractors would be considered an index for vulnerability to environmental distraction, whereas any task that involved the possibility of distraction from previously memorized stimuli would be considered an index of vulnerability to memory-based distraction, and any task that involved a comparison of performance with or without a task-switch would be considered as an index of distraction caused by a previously used task-set.

Literature search and studies included. The search for studies on the relationship between media multitasking and distractibility was done using the PsycInfo, ERIC, Medline, and CMMC databases, with a combination of the following keywords: media multitasking* AND (cognitive control* OR working memory* OR attention*). This search yielded a total of 40 published articles of which 12 included one or more experiments that met our selection criteria (Alzahabi & Becker, 2013; Baumgartner et al., 2014; Cain et al., 2016; Cain & Mitroff, 2011; Cardoso-Leite et al., 2015; Gorman & Green, 2016; Minear et al., 2013; Moisala et al., 2016; Ophir et al., 2009; Ralph & Smilek, 2016; Ralph et al., 2015; Uncapher et al., 2016). Aside from these published studies, we also included the effect sizes from Experiments 1 and 2 of the current study. These studies are listed in Table 3.2, along with the type of task that was used in the study, the type of distraction that was involved in this task, and the distractibility effect that was used for computing the effect size.

Table 3.2. Studies and effects included in the meta-analysis. Distraction Type = Type of distraction involved in the study. NHMM = Sample size HMM group. NLMM = Sample size LMM group. Ntot. = Total sample size. Outcome = Dependent variable. Predictor = Effect tested in study.

Distraction Type	Study (year, Experiment)	N_{HMM}	N_{LMM}	N_{total}	Task	Outcome ~ predictor
Environmental	Cardoso-Leite et al. (2015)	12	20	32	Change detection	K ~ Ndist*MMI
	Gorman & Green (2016)	22	20	42	Change detection	d' ~ Ndist*MMI
	Ophir et al. (2009, Exp.1)	19	22	42	Change detection	K ~ Ndist*MMI
	Uncapher et al. (2015)	36	36	72	Change detection	K ~ Ndist*MMI
	Uncapher et al. (2015)	36	36	72	Change detection	K ~ Ndist*MMI
	Wiradhany & Nieuwenstein, Exp.1	10	12	22	Change detection	K ~ Ndist*MMI
	Wiradhany & Nieuwenstein, Exp.2	18	11	29	Change detection	K ~ Ndist*MMI
	Cardoso-Leite et al. (2015)	12	20	32	AX-CPT	Avg. RT ~ MMI
	Ophir et al. (2009, Exp.3)	15	15	30	AX-CPT	AX-RT ~ MMI
	Wiradhany & Nieuwenstein, Exp.1	10	13	23	AX-CPT	AX-RT ~ MMI

Distraction Type	Study (year, Experiment)	N_{HMM}	N_{LMM}	N_{total}	Task	Outcome ~ predictor
Environmental	Wiradhany & Nieuwenstein, Exp.2	14	6	20	AX-CPT	AX-RT ~ MMI
	Baumgartner et al. (2014)	-	-	523	Eriksen flanker	Flanker Congruency ~ MMI
	Gorman & Green (2016)	22	20	42	Eriksen flanker	Flanker Congruency ~ MMI
	Minear et al. (2013, Exp.3)	27	26	53	Eriksen flanker	Flanker Congruency ~ MMI
	Ralph et al. (2015, Exp.1)			76	SART	RT ~ MMI
	Ralph et al. (2015, Exp.2)			143	SART	RT ~ MMI
	Ralph et al. (2015, Exp.3)			109	Inverted SART	RT ~ MMI
	Cain & Mitroff (2011)	17	17	34	Visual search	RT ~ MMI
	Cain et al. (2016)			69	WM Filtering: Count span	Accuracy ~ MMI
	Cain et al. (2016)			58	WM Filtering: Recall	Accuracy ~ Ndist*MMI
	Gorman & Green (2016)	22	20	42	Test of Variables of Attention	RT ~ MMI
	Moisala et al. (2016)	-	-	149	Cross-modal filtering	Accuracy ~ MMI

Distraction Type	Study (year, Experiment)	N_{HMM}	N_{LMM}	N_{total}	Task	Outcome ~ predictor
Memory-based	Cain et al. (2016)			58	N-back	3-back FA ~MMI
	Cardoso-Leite et al. (2015)	12	20	32	N-back	3-back FA ~MMI
	Ophir et al. (2009, Exp.2)	15	15	30	N-back	FA ~ WM Load *MMI
	Ralph et al. (2016)			265	N-back	3-back FA ~MMI
	Ralph et al. (2016)			265	N-back	3-back FA ~MMI
	Wiradhany & Nieuwenstein, Exp.1	10	13	23	N-back	FA ~ WM Load *MMI
	Wiradhany & Nieuwenstein, Exp.2	17	9	26	N-back	FA ~ WM Load *MMI
Task-set	Alzahabi & Becker (2013, Exp.1)	-	-	80	Task-switching	Switch cost ~ MMI
	Alzahabi & Becker (2013, Exp.2)	-	-	49	Task-switching	Switch cost ~ MMI
	Baumgartner et al. (2014)	-	-	523	Task-switching	Switch cost ~ MMI
	Cardoso-Leite et al. (2015)	12	20	32	Task-switching	Switch cost ~ MMI
	Gorman & Green (2016)	22	20	42	Task-switching	Switch cost ~ MMI
	Minear et al. (2013, Exp.3)	27	26	53	Task-switching	Switch cost ~ MMI

Distraction Type	Study (year, Experiment)	N_{HMM}	N_{LMM}	N_{total}	Task	Outcome ~ predictor
Task-set	Minear et al. (2013, Exp.1)	33	36	69	Task-switching	Switch cost ~ MMI
	Ophir et al. (2009, Exp.3)	15	15	30	Task-switching	Switch cost ~ MMI
	Wiradhany & Nieuwenstein, Exp.1	10	13	23	Task-switching	Switch cost ~ MMI
	Wiradhany & Nieuwenstein, Exp.2	18	12	30	Task-switching	Switch cost ~ MMI

Selection of outcome variables. In selecting the outcomes for inclusion in our meta-analysis, we chose to avoid the intricacies involved in modeling multi-level dependencies that would exist due to the varying strengths of correlations between outcomes obtained from different trial types in the same task (i.e., RTs for AX and BX trials, switch costs and RTs for switch and repeat trials in a task-switching experiment) and between outcomes obtained on different tasks for the same sample of participants (e.g., distractibility in the N-back task and distractibility in the change detection task). To this end, we chose to select one outcome per task and we used a procedure for robust variance estimation to correct for variance-inflation stemming from the inclusion of correlated observations for different tasks done by the same participants (Hedges, Tipton, & Johnson, 2010; Scammacca, Roberts, & Stuebing, 2013).

Specifically, for the AX-CPT, we chose to include the response times for AX trials, as this type of trial can be considered a more reliable index of performance because it occurs more frequently in the task than the BX trials[16]. For studies on task-switching, we reasoned that, compared to RTs on switch and repeat trials, the switch cost constitutes the most straightforward index of interference caused by a previously used task-set, and hence we chose to only

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[16] For the study by Cardoso-Leite et al. (2016), we could not include the effect for AX-RT, because these authors only reported an analysis for the average RT on AX and BX trials. Since both types of trials can be assumed to measure the same kind of distractibility effect (cf. Ophir et al., 2009), we included Cardoso-Leite et al.'s effect for average RT in our analysis.

the switch cost, and not the average RTs on switch or repeat trials.

For studies using different tasks than those used by Ophir et al. (2009), we selected the outcome measure which best reflected the participant's performance in the presence of environmental, memory-based, or task-set based distraction. Specifically, for the SART (Ralph et al., 2015) and TOVA (Gorman & Green, 2016) we used response times to targets that were shown in a sequence of distractors. Likewise, for studies using the Eriksen Flanker task (Bauimgartner et al., 2014; Gorman & Green, 2016; Minear et al., 2013), we chose to use the flanker congruency effect for response times to the target, which reflects the difference in RTs when targets are flanked by congruent or incongruent distractors, with larger congruency effects being indicative of greater vulnerability to distraction. For the cross-modal filtering task used by Moisala et al. (2016), we used the correlation between the MMI and accuracy in conditions in which distractors were presented in different sensory modality than the targets. For the count-span and working-memory filtering tasks of Cain et al. (2016), we used recall performance for conditions in which the to-be-remembered targets were shown together with distractors. Lastly, for the visual search task used by Cain and Mitroff (2011), we included the results for a test of an interaction effect of the presence vs. absence of a singleton distractor and group (HMM vs. LMM).

Effect size calculation. Effect sizes were calculated in term of Cohen's d (J. Cohen, 1988, 1992), with positive values denoting evidence for greater vulnerability to distraction in HMMs and negative values denoting an effect in opposite direction. In case of comparisons involving a within-group factor, such as the change detection task with different numbers of distractors, we first calculated partial η2 using the equation below (J. Cohen, 1988; Lakens, 2013):

$$\eta_P^2 = \frac{F \times df_{effect}}{F \times df_{effect} + df_{error}}$$

Assuming a minimum variability in the repeated measures, the partial η^2 was then transformed into a standardized mean difference using the equation (see Cohen, 1988):

$$d = \sqrt{\frac{\eta_P^2}{1 - \eta_P^2} \times 2\,k}$$

with k denoting the number of between-group levels.

Meta-analysis: Testing the MMI – distractibility link. To determine the effect size for the association between media multitasking and distractibility, we used a random-effects model in which the overall effect size is computed from effect sizes weighted by the inverse of their variance (Borenstein, Hedges, Higgins, & Rothstein, 2009). This model was calculated in R using the Metafor package (Viechtbauer, 2010). Calculation of a random-effects model increases statistical power by reducing the standard error of the weighted average effect size (Cohn & Becker, 2003). Using this method, one obtains a weighted average effect size and one can assess the statistical significance of this effect.

Moderator analyses. Aside from examining the strength and significance of the association between media multitasking and distractibility across all studies included in the meta-analysis, we also examined whether the strength of this link was different for studies employing tasks with different types of distraction, for studies using different populations of participants, and for studies employing different statistical methods in assessing the association between media multitasking and distractibility. Specifically, we conducted three moderator analyses. In the first, we examined whether the results were different for tasks involving environmental, memory-based, or task-set distraction. In the second, we examined if the results were different depending on whether the study participants were adolescents, university students, or people from the general population. In the third, we examined if the results were different for studies in which the MMI-distractibility link was tested using either a correlational approach (i.e., resulting in a correlation coefficient that expresses the relationship between distractibility and the participants' scores on a questionnaire measure of media multitasking), or an extreme-groups comparison based on cut-offs determined by either quartile scores or a criterion based on the standard deviation.

Tests and corrections for small-study effects. Lastly, we also examined whether the outcomes of the meta-analysis were influenced by small-study effects (Carter & McCullough, 2014; Duval & Tweedie, 2000; Egger et al., 1997; Peters et al., 2007; Sterne et al., 2011; Thompson & Sharp, 1999). Such effects are said to be present when the outcome of a meta-analysis is influenced by the inclusion of relatively many small-sample studies showing large, positive effects, and relatively few small-sample studies showing negative or null effects. This state of affairs is typically interpreted as evidence for a reporting bias, such that researchers might refrain from attempting to publish small-sample studies showing negative or non-significant outcomes, and journals might likewise refrain from accepting such studies for publication. Alternatively, small-study effects can also arise due to true heterogeneity in case the small-sample studies not only differ from the larger studies in terms of sample size but also in terms of certain methodological aspects (e.g., Sterne, Gavaghan, & Egger, 2000). Accordingly, an interpretation of the presence of small-study effects requires a consideration of whether the studies employing large and small sample sizes differed in terms of certain methodological aspects, and whether the distribution of study effect sizes shows a preponderance of small-sample studies with positive, significant effects, and an absence of similarly small studies showing negative or non-significant effects.

To evaluate the presence of small-study effects, we constructed used a contour-enhanced funnel plot in which effect sizes were plotted against a measure of their precision (i.e., standard error; Egger et al., 1997; Sterne et al., 2011; Sterne & Egger, 2001), and in which areas of statistical significance ($p<.05$) were highlighted (Peters et al., 2007; see also Carter & McCullough, 2014; Nieuwenstein et al., 2015). In such a plot, the presence of small-study effects can be judged by determining whether the effect sizes of smaller studies with lower precision are distributed symmetrically around the estimate of the mean effect size, as would be expected when these effects are sampled from a distribution centered on the estimated mean effect size. Furthermore, by highlighting the areas of statistical significance, one can judge whether the studies that appear to be missing are studies that would have been expected to produce non-significant or null effects, thus allowing for an evaluation of whether the asymmetry might be due to a reporting bias (as opposed to true heterogeneity caused by differences in the design of smaller and larger studies; Peters et al., 2007). In addition to visual inspection, we also performed a regression analysis in which the standard errors of the effect sizes are used as a predictor for the effect size (Egger et al., 1997), thus offering a means to verify the presence of funnel-plot asymmetry in terms of the statistical significance of the association between effect sizes and study precision.

When small-study effects are found that are suggestive of a reporting bias, one should correct the estimated overall effect size for this bias. To this end, one can use the regression analysis to estimate the effect size of a study with maximal precision (i.e., an extrapolation to a study with a standard error of 0; Moreno et al., 2009), or one can apply the so-called trim-and-fill procedure to fill in any effects that appear to missing in the asymmetrical funnel plot (Duval & Tweedie, 2000). While there is ongoing debate about whether these procedures lead to a proper overall estimate of effect size, there is consensus that these procedures can be used as sensitivity tests to determine the extent to which the outcome of a meta-analysis is dependent on the presence of small-study effects. Accordingly, we planned to conduct these corrective procedures in case an asymmetry suggestive of reporting bias was present, thus allowing for a further evaluation of the existence and strength of the association between media multitasking and distractibility.

Results

Forest plot and results random-effect model. Figure 3.15 shows a forest plot with the effect sizes that were included in the meta-analysis. The effect sizes are grouped by the type of distraction that was involved in the task (environmental, memory-based, or task-set), and the effects that were found by Ophir et al. (2009) are listed first for each type of distraction. This visualization of effects shows that the majority of studies investigating the association between media multitasking and distractibility link yielded non-significant results, as the confidence intervals for the majority of effects included 0. To estimate the mean effect size, we conducted a meta-analysis using a random-effect model. The results of this analysis showed a small but significant, positive association between media multitasking and distractibility, with $d=0.17$, (95% *CI*: .165, .173), $p=.007$, one-tailed. At the same time, however, the analysis also made clear that there was significant heterogeneity amongst the effects in the analysis, $I^2=57.02\%$, $p<.001$.

Moderator analyses. To determine if the heterogeneity of the effects of different studies can be explained in terms of differences between studies examining different types of distractibility, populations of participants, or methods of analyses, we conducted three moderator analyses. These analyses revealed that there were no differences between studies examining different types of distractibility, participants from different populations, or different methods of analysis, with $F(2, 36)=1.11$, $p=.342$, $F(2, 36)=0.29$, $p=.745$, and $F(2, 36)=2.81$, $p=.074$, respectively.

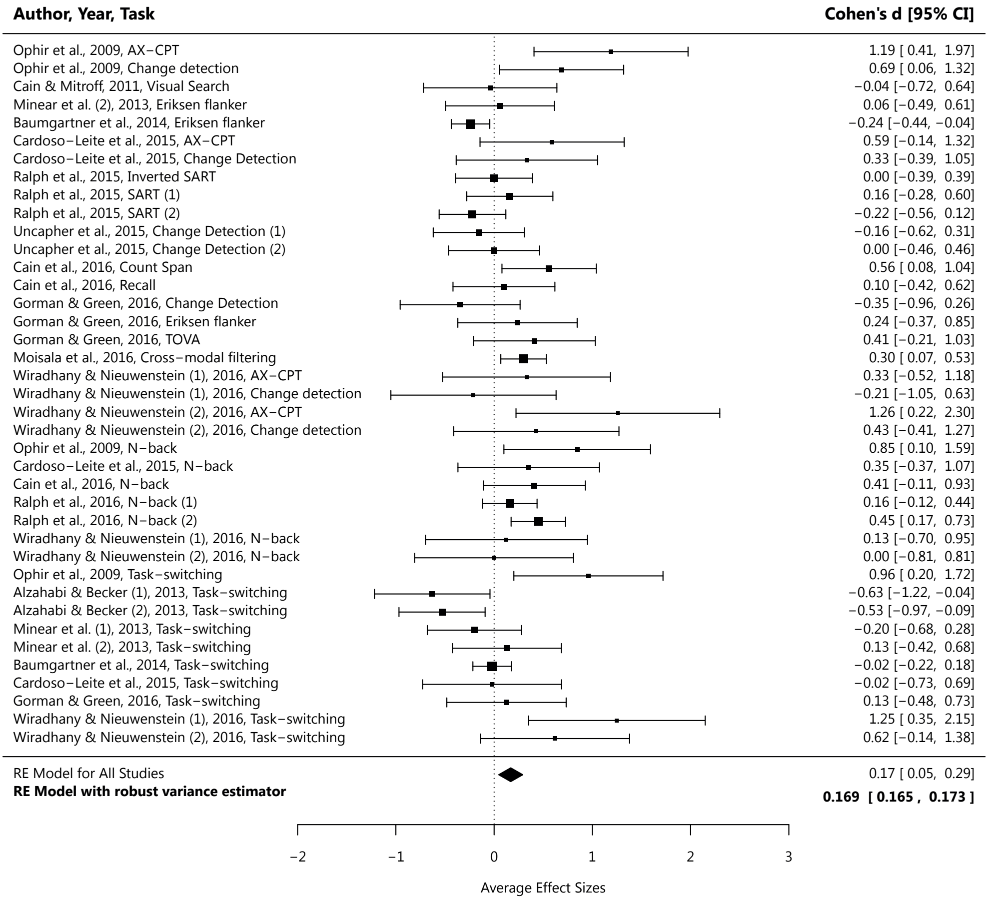

Figure 3.15. Forest plot of the effect sizes (Cohen's d) for studies included in the meta-analysis. The studies are grouped according to the type of distraction that was involved in the task. Error bars represent 95% confidence interval of the effect size. RT: Response times, FA: False alarm rate, CPT: Continuous performance task, TOVA: Test of Variables of Attention.

Funnel plot and small-study effects. Next, we examined whether the dataset showed evidence for small-study effects. To this end, we constructed a funnel plot in which effect sizes are plotted as a function of their standard error, and in which the areas of statistical significance (*p*<.05) were highlighted. In the absence of small-study effects, this plot should form a symmetrical funnel distribution of effect sizes around the mean effect size. As can be seen in Figure 3.16a, however, the distribution is clearly asymmetrical, with a preponderance of small sample (large SE) studies showing large, positive effects, and a relative lack of similarly imprecise studies showing effects on the other side of the mean effect size. As a formal verification of this impression, we conducted Egger's test (Egger et al., 1997) to examine the relationship between effect sizes and standard errors. This test showed that this relationship was significant, z=2.83, p=.005, thus underscoring the presence of funnel plot asymmetry.

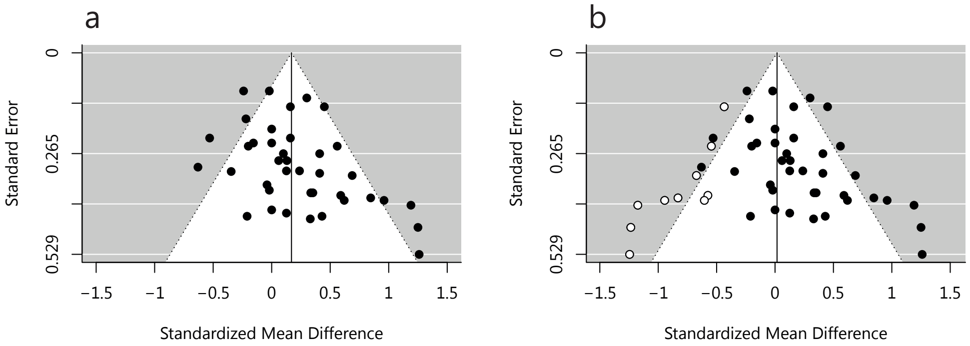

Figure 3.16a. Funnel plot showing the relationship between the effect sizes and standard errors of previous studies into the relationship between media multitasking and distractibility. Effect sizes are plotted along the X-axis and standard errors along the Y-axis, and the grey areas denote the areas in which effects were statistically significant. The vertical dashed line indicates the estimated mean effect size. b. Funnel plot including the effects that were imputed using the trim and fill method.

In interpreting the asymmetrical distribution of small-sample studies, it is important to note that the studies that appear to be missing on the lower left side of the funnel are studies that would be expected to have yielded either non-significant or negative results. This observation is indicative of reporting bias, as the asymmetry appears to be associated with the direction and significance of outcomes (Carter & McCullough, 2014; Peters et al., 2007). Furthermore, it also seems unlikely that the asymmetry can be explained in terms of true heterogeneity between studies, as our moderator analyses made clear that this heterogeneity could not be explained in terms of differences between tasks, study populations, or methods of analysis. Accordingly, it seems possible that the reason for the asymmetrical distribution of small studies could be reporting bias, thus warranting further corrective procedures to determine what the estimated effect size would be when this bias is corrected for. To do so, we performed two corrective procedures. First, we used the trim and fill procedure to impute the ostensibly missing effects on the left side of the funnel, and to recalculate the overall effect size (Duval & Tweedie, 2000). This analysis showed that the association between media multitasking and distractibility turned non-significant after correction, with Cohen's d=0.07, and p=.81 (see Figure 3.16b). Secondly, we used a regression-based method that has been deemed more suitable for datasets with relatively high heterogeneity, as is true for the current dataset (Moreno et al., 2009). With this method, we estimated the expected effect size for a study with a standard error of 0. The results of this analysis corroborated the outcome of the trim and fill procedure in that it yielded an effect size of Cohen's d=.001. Taken together, these results make clear that the earlier estimated effect size was strongly influenced by the presence of small-study effects, such that the small but significant association turned non-significant after correction for these effects[17].

General Discussion

In a pioneering study, Ophir and colleagues (2009) found that people with higher scores on a questionnaire measure of media multitasking show an increased susceptibility to distraction in various laboratory tasks of information processing. While subsequent studies did show associations between media multitasking and various outcome measures other than those used by Ophir et al., they generally failed to replicate the original findings, thus casting doubt on the existence of an association between media multitasking and distractibility. In the current study, we conducted two replication studies to determine the replicability of the original findings by Ophir et al., and we conducted a meta-analysis to assess the existence and strength of the association between media multitasking and distractibility across all studies that compared the performance of HMMs and LMMs on laboratory tests of distractibility in information processing. The results of our replication studies showed only weak and partial support for the findings of Ophir et al., such that only five of our fourteen tests yielded a successful replication according NHST, whereas a Bayesian analysis indicated that only two of these effects were based on convincing evidence for an association between media multitasking and distractibility. Furthermore, the results of our meta-analysis showed that the

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[17] It is worth mentioning that we also conducted a meta-analysis using Bayes Factors (Rouder & Morey, 2011). This analysis is report in the supplementary document and it yielded an effect size estimate of .03, with strong evidence in favor of the null hypothesis.

association between media multitasking and distractibility is weak and strongly influenced by small-study effects; such that the application of two corrective procedures for small-study effects changed the estimate of the overall effect size from a significant Cohen's d of .17 to a non-significant effect of .01-.07.

Taken together, the results of our work present reason to question the existence of an association between media-multitasking, as defined by the MMI or other questionnaire measures, and distractibility in laboratory tasks of information processing. This reason is that our meta-analysis shows that the association between media multitasking and distractibility approximates an effect size of 0 after correction for small-study effects. What remains to be explained then is why some studies did show evidence of such an association, including some of the current replication tests. As a case in point, consider the results of the current replication studies. Although the outcomes of these tests generally failed to replicate the effects of Ophir et al. in terms of statistical significance and Bayes Factors, the outcomes did consistently show non-significant effects in the direction of HMMs being more vulnerable to distraction then LMMs. Accordingly, one may ask how it is possible that so many tests consistently showed a difference in one particular direction, given that this difference does not exist according to the meta-analysis. Importantly, however, this state of affairs might be less telling or mysterious as it seems. To start, it is important to note that our replication attempts were implemented as two independent studies using a between-group comparison in which HMMs and LMMs were compared on 7 indices of distractibility. Given that these indices would be expected to be correlated within the same subjects, especially when they derive from the same task, it becomes clear that any coincidental difference in distractibility between the LMM and HMM groups would translate into a consistent pattern across the 7 indices. Likewise, when considering the broader literature, it is noteworthy that our meta-analysis makes clear that, regardless of statistical significance, there are 11 studies showing greater distractibility in LMMs, 3 studies showing no difference between LMMs and HMMs, and 25 studies showing greater distractibility in HMMs (see Table 3.2). Given that our analysis also suggests the existence of a bias against small-sample studies showing negative and non-significant results, it becomes clear that the distribution of studies showing positive and negative results is not so much different than what would be expected for a set studies that tested the outcomes stemming from a distribution that is centered at an effect size of 0.

An alternative interpretation of the current findings might be that the association between media multitasking and distractibility does exist, but that it is very weak. This conclusion would stem from considering the effect size estimate without any correction for small-study effects. Under this interpretation, an important implication of the current work is that future studies into the relationship between the media multitasking and other outcome measures should take into account the fact that these relationships is likely to be very small and only detectable using extremely large samples of participants. To be precise, to achieve 80% power to detect an effect with an effect size of .17 one would need 428 participants per group for the HMM and LMM groups.

In considering whether or not such large-scale studies would show evidence for an association between media multitasking and distractibility in information processing, a last point of note is that perhaps future studies should also use a different calculation of the MMI (see also, Baumgartner et al., 2014; Cain et al., 2016). To wit, the current calculation yields a measure of the proportion of media-usage time during which someone uses two media at the same time. This means that a person who spends only 1 hour per day using his laptop while watching television can have the same MMI as a person who does this 16 hours per day. Evidently, if there would exist an association between media multitasking in daily life and performance on laboratory measures of information processing, then this association would be more likely to be seen when using a measure of media multitasking that expresses the amount of time someone spends on this activity (see also, Cain et al., 2016; Moisala et al., 2016).

Conclusions and Future Directions

The idea that frequent media multitasking could be associated with differences in information-processing capacity is enticing and timely. However, our experiments and meta-analysis did not provide much support for this idea. Instead, our meta-analysis showed that the association between media multitasking and distractibility is likely to be very small, and therefore unlikely to be detected in studies employing relatively small sample sizes. Accordingly a key implication of the current study is that future studies on the link between media multitasking and cognitive functioning should use relatively large samples of participants to ensure sufficient statistical power.

Supplementary Materials

Experiment 1

Change detection task: Results for 4 and 6-target conditions. In addition to examining the effects of distraction in the condition with a memory set size of 2 items, we also moved beyond the analyses reported by Ophir et al. (2009) in examining the effects of distractors for the conditions with a memory set size of 4 and 6 items. For the condition with a memory set size of 4 items, there were no main effects of Group *F*(1, 20)=0.77, *p*=.395, η^2=0.02 nor of Distractor Set Size (0, 2, or 4), *F*(2, 40)=0.42, *p*=.658, η^2=.006, but we did find a significant interaction of these factors, *F*(2, 40)=3.98, *p*=.027, η^2=0.06. As can be seen in Figure S3.1a, this interaction effect appeared to derive from the effect that LMMs – not HMMs – were more strongly affected by the number of distractors.

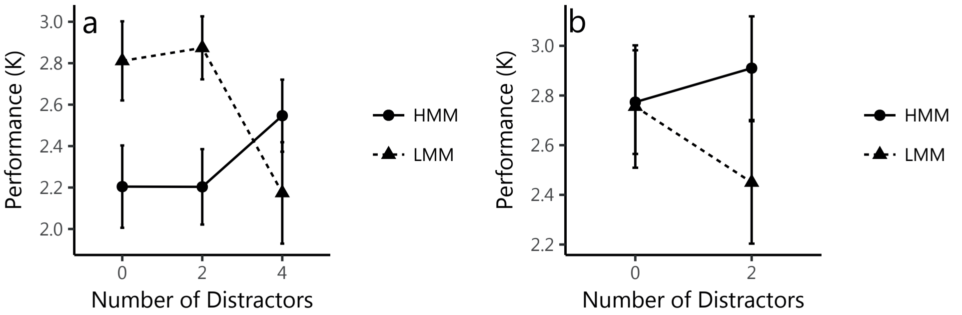

Figure S3.1. Change detection performance for the condition with 4 targets and 0, 2, or 4 distractors (Figure S3.1.a) and the condition with 6 targets and 0 or 2 distractors (Figure S3.1.b) in Experiment 1. Error bars represent within-subjects standard errors of the means (Morey, 2008).

For the condition with a memory set size of 6 items, the analysis showed no main effects of Group *F*(1, 20)=0.27, *p*=.610, η^2=0.01, nor of Distractor Set Size (0 or 2), *F*(1, 20)=0.08, *p*=.771, η^2=.001, and the interaction of these factors also failed to reach significance, *F*(1, 20)=0.59, *p*=.449, η^2=.008 (Figure S3.1b).

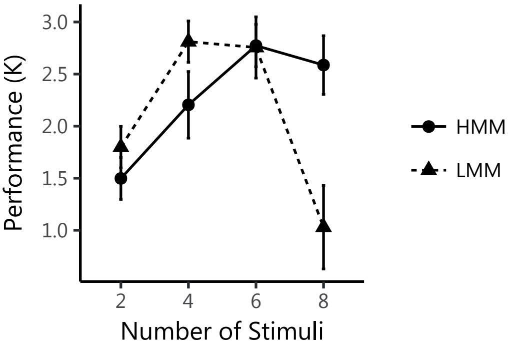

Figure S3.2. Change detection performance for the condition with 2, 4, 6, or 8 targets shown without distractors in Experiment 1. Error bars represent within-subjects standard errors of the means (Morey, 2008).

Change detection task: Results for conditions without distractors. Lastly, we also examined if the change detection task showed any difference in performance between LMMs and HMMs for the conditions without distractors. A repeated measures ANOVA with Group (HMM vs. LMM) and Memory Set Size (2, 4, 6, or 8 items) as factors showed no significant effect of Group, *F*(1, 20)=0.35, *p*=.561, η^2=0.01 but it did show a significant effect of Memory Set Size, *F*(3, 60)=7.59, *p*<.001, η^2=0.18. In addition, the interaction between group and memory set size was significant, *F*(3, 60)=6.04, *p*=.001, η^2=0.15. As can be seen in Figure S3.2, this interaction was driven by an unexpected drop in performance for the LMMs as set size increased from 6 to 8 items. Further scrutiny of the data obtained in the set-size 8 condition did not yield insight into the reasons for this unexpected drop in performance.

AX-CPT with distractors: Results. There were no significant differences in accuracy between LMMs and HMMs in the AX, BX, AY, and BY trials, all *p*'s > .17. Similarly, the analysis showed no overall difference in response times between HMMs and LMMs, *t*(21)=1.68, *p*=.054. Further analyses examining response times for the remaining two types of trials – namely those in which the red letters comprised the pair A-Y or B-Y – showed that HMMs were significantly slower than LMMs to respond to BY trials, *t*(21)=3.12, *p*=.004, but not to AY trials, *t*(21)=0.57, *p*=.58.

N-back task: Results. Unlike the study by Ophir et al., our analysis of *d'* as a function of Group (LMM vs. HMM) and WM Load (2-back vs. 3-back) did show a significant main effect of WM Load, *F*(1, 21)=30.95, *p*<.001, η^2=.361, but no main effect of Group, *F*(1, 21)=0.50, *p*=.486, η^2=.015, *d*=0.25, and no significant Group × WM Load interaction, *F*(1, 21)=0.08, *p*=.783, η^2=.001, *d*=0.06. Furthermore, a general linear model of false alarm in the three-back task with Group and Time on Task as predictors showed no main effect of Group, $\chi^2(1)$=2.4, *p*=.12, no main effect of Time on Task, $\chi^2(1)$=0.03, *p*=.86, and no Group × Time on Task interaction, $\chi^2(1)$=1.9, *p*=.17.

Task-switching: Results. There was no significant difference in accuracy between groups on switch or repeat trials, both *p*'s > .116.

Experiment 2

Change detection task: results for 4 and 6-target conditions. For the condition with a memory set size of 4 items (Figure S3.3a), we found no main effect of Group, *F*(1, 27)=0.12, *p*=.729, η^2=.002 or distractor set size, *F*(2, 54)=1.25, *p*=.293, η^2=0.02, and the Group × Distractor Set Size interaction also failed to reach significance, *F*(2, 54)=1.39, *p*=.256, η^2=0.02. For the condition with a memory set size of 6 items (Figure S3.3b), we also found no main effect of Group, *F*(1, 27)<.001, *p*=.983, η^2<.001 or Distractor Set Size, *F*(1, 27)=3.35, *p*=.078, η^2=0.03, and the Group × Distractor Set Size interaction also failed to reach significance, *F*(1, 27)=2.67, *p*=.114, η^2=0.02.

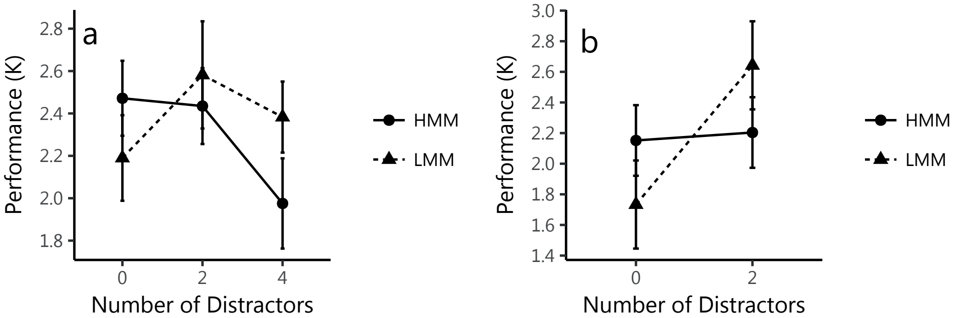

Figure S3.3. Change detection performance for the condition with 4 targets and 0, 2, or 4 distractors (Figure S3.3a) and the condition with 6 targets and 0 or 2 distractors (Figure S3.3b) in Experiment 2. Error bars represent within-subjects standard errors of the means (Morey, 2008).

Change detection task: Results for conditions without distractors. A repeated measures ANOVA with Group (HMM vs. LMM) and Memory Set Size (2, 4, 6, or 8 items, without distractors) as factors yielded no main effect of Group, $F(1, 27)=.002$, $p=.969$, $\eta^2<.001$, no main effect of Memory Set Size, $F(3, 81)=2.49$, $p=.065$, $\eta^2=0.04$, and no Group × Memory Set Size interaction, $F(3, 81)=1.02$, $p=.387$, $\eta^2=0.02$ (Figure S3.4).

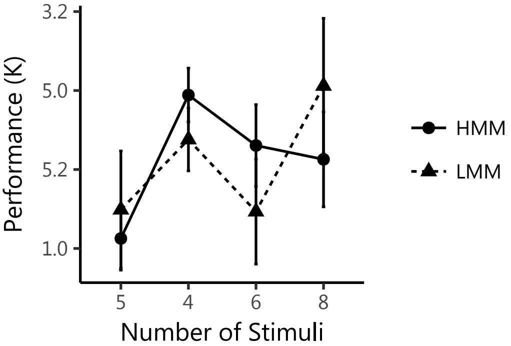

Figure S3.4. Change detection performance for the condition with 2, 4, 6, or 8 targets shown without distractors in Experiment 2. Error bars represent within-subjects standard errors of the means (Morey, 2008).

AX-CPT with distractors: results. HMMs were more accurate than LMMs in AY trials, $t(18)=2.07$, $p=.05$ and LMMs were more accurate than HMMs in BX trials, $t(18)=- 2.48$, $p=.02$. There were no significant differences between the HMM and LMM groups in accuracy for AX and BY trials, *p*’s>.219. Response times also did not differ between groups for the AY, $t(18)=-1.27$, $p=.221$, $d=-0.62$, and BY $t(18)=1.35$, $p=.192$, $d=0.66$ trials, respectively.

N-back task: Results. Our analysis of d’ as function of Group (LMM vs. HMM) and WM Load (2-back vs. 3-back) showed a significant main effect of WM Load, $F(1, 24)=13.88$, $p<.01$, $\eta^2=.124$, $d=0.75$ but no main effect of Group, $F(1, 24)=0.07$, $p=.799$, $\eta^2=.002$, $d=0.09$, and no significant Group × WM Load interaction, $F(1, 24)=.004$, $p=.948$, $\eta^2<.001$, $d<.01$. Our general linear model of false alarm in the three-back task with Group and Time on Task as predictors showed no main effect of Group, $\chi^2(1)=1.4$, $p=.24$, no main effect of Time on Task, $\chi^2(1)=0.04$, $p=.84$, and no Group × Time on Task interaction, $\chi^2(1)=1.6$, $p=.2$.

Task-switching: Results. There is no difference in accuracy between HMMs and LMMs for repeat and switch trials, all *p*'s>.340.

Meta-analytic Bayes Factor

In a meta-analytic Bayes Factor, we assumed a true effect size δ which is constant across experiments and a varying variance (Rouder & Morey, 2011). If the null hypothesis is true, the posterior distribution of effect sizes would be peaked closer to zero. On the other hand, if the alternative hypothesis is true, the posterior distribution of effect sizes would be peaked further away from 0. Under these assumptions, a Bayes Factor was calculated using the meta.ttestBF function of the BayesFactor package in R. The prior distribution of the effect size was set to √2/2 (default) and one-sided analysis was conducted assuming that HMMs performed worse than LMMs in all cases. In cases of effect sizes which were not computed from t-tests, the t values were estimated using the formula below (Borenstein et al., 2009)

$$t = \frac{d\sqrt{(n_1 + n_2 - 2)\,(n_1 n_2)}}{n_1 + n_2}$$

Where d is the estimated Cohen's d from the previous calculation and n1 and n2 are the sample size of HMMs and LMMs, respectively.

Figure S3.5 shows the posterior effect size of the overall experiment. The density distribution peaked at an effect size δ=0.03, indicating that the most probable effect size estimation lies around 0.03. This effect size has a Bayes Factor of 8.50 in favor of the null hypothesis, indicating that it is approximately 8 times more likely that there is no association between media multitasking and increased distractibility.

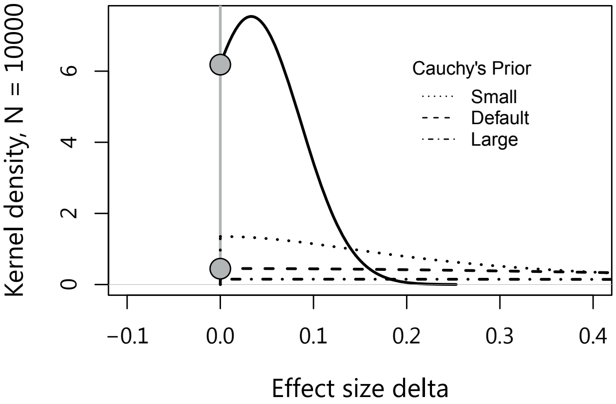

Figure S3.5. Density simulation of effect size δ of the association between media multitasking and increased distractibility with N = 10000 iterations. The dotted, dashed, and dash-dot lines show skeptical, default, and optimistic Cauchy priors, respectively.

To explore if this finding was not due to our selection of the prior distribution, we performed a sensitivity analysis (Kass & Raftery, 1995). That is, we evaluate Bayes Factor over a range of prior possibilities. In this case, the priors were varied from small (1/3 of the default prior) to large (3 × the default prior). The small prior peaked closer to 0, indicating a skeptical prior while the large prior has a wider distribution on the negative effect size, indicating an optimistic prior (see Figure S3.5). In both cases, the data support the null hypothesis, with BF_{01}=2.88 and BF_{01}=25.45 for the small and large priors, respectively, meaning that it is 3 to 25 times more likely that there is no association between media multitasking and increased distractibility.

Chapter 4

Minds of Media Multitaskers (II)

Note: This chapter has been revised and resubmitted for publication in *Attention, Perception, & Psychophysics* as: Wiradhany, W., Vugt, M.K., & Nieuwenstein, M.R.(*in prep.*). Media multitasking, mind-wandering, and distractibility: A large-scale study.

All research material used in this article is available at the Open Science Framework: https://osf.io/nkdw5/.

Abstract

Previous studies suggest that frequent media multitasking – the simultaneous use of different media at the same time – may be associated with increased susceptibility to internal and external sources of distraction. At the same time, other studies found no evidence for such associations. In the current study, we report the results of a large-scale study (N=261) in which we measured media multitasking using a short media-use questionnaire and asked participants to perform a change-detection task that included different numbers of distractors. To determine whether internally-generated distraction affected performance, we deployed experience-sampling probes. The results showed that participants with higher media-multitasking scores did not perform worse as distractor set size increased, they did not perform worse in general, and their responses on the experience-sampling probes made clear that they also did not experience more lapses of attention during the task. Critically, these results were robust across different methods of analysis (i.e., Linear Mixed Modeling, Bayes Factors, and extreme-groups comparison). At the same time, our use of the short version of the media use questionnaire might limit the generalizability of our findings. In light of our results we suggest that future studies should ensure an adequate level of statistical power and implement a more precise measure for media multitasking.

Keywords: media multitasking, cognitive control, working memory, change detection, mind-wandering

Introduction

Media multitasking, the act of consuming multiple media streams simultaneously, has become increasingly prevalent, with a recent report indicating that U.S. adolescents consumed 10.5 hours of media content in 7.5 hours per day by multitasking (Rideout et al., 2010). In light of this development, researchers have begun to examine how the frequency of media multitasking relates to various indices of personality, mental health, and cognition (see Carrier, Rosen, Cheever, & Lim, 2015; Courage, Bakhtiar, Fitzpatrick, Kenny, & Brandeau, 2015; Uncapher et al., 2017; Van Der Schuur, Baumgartner, Sumter, & Valkenburg, 2015 for reviews). On the one hand, several studies showed evidence for a weak association of media multitasking with questionnaire measures of impulsivity and sensation-seeking (e.g., Minear, Brasher, McCurdy, Lewis, & Younggren, 2013; Sanbonmatsu, Strayer, Medeiros-Ward, & Watson, 2013) and ADHD-related symptoms (Baumgartner, van der Schuur, et al., 2017; Magen, 2017; Uncapher et al., 2016). On the other hand, however, studies exploring the correlates of media multitasking in laboratory measures of selective attention, working memory, and executive control have thus far produced less compelling results. Specifically, while some studies in this domain suggest that media multitasking might be associated with increased vulnerability to distractors (e.g., Ophir, Nass, & Wagner, 2009), others suggest that habitual media multitaskers may perform worse across various cognitive tasks, regardless of the presence of distractors (e.g., Uncapher, Thieu, & Wagner, 2016). Importantly, however, not all studies have found evidence for an association between media multitasking and distractibility (e.g., Wiradhany & Nieuwenstein, 2017). In the following sections, we will analyze these findings in further detail.

The External Distraction Hypothesis

The first subset of studies suggest that people who frequently engage in media multitasking behavior may have problems in filtering out distracting information from their immediate environment. We refer to this as the external distraction hypothesis.

Evidence for the external distraction hypothesis. To start, Ophir et al. (2009) showed that heavy, compared to light media multitaskers (HMMs and LMMs, respectively) performed worse in a change detection task with varying numbers of distractors. Specifically, in this study, participants had to memorize two target objects that could be shown together with zero, two, four, or six distractor objects. The results showed that HMMs, but not LMMs, performed worse as the number of distractor objects increased. In addition, HMMs responded slower in an AX-CPT task when the targets appeared amongst distractors, but not when the targets were shown without distractors, thereby suggesting that media multitasking may be associated with increased susceptibility to distraction from task-irrelevant stimuli in the environment. Supporting this idea, Moisala et al. (2016) found that HMMs made more mistakes than LMMs when they were instructed to attend to stimuli in one modality (e.g., visual) while ignoring stimuli from another modality (e.g., auditory).

One possible explanation for these previously observed associations is that HMMs experience increased susceptibility to distraction due to the development of a breadth-biased cognitive control style (Lin, 2009). Specifically, since the media environment is saturated with information and one piece of seemingly irrelevant information can prove to be valuable later, HMMs might develop the tendency to distribute their focus of attention more equally across multiple streams of information. As a consequence, they might become less sensitive in distinguishing relevant from irrelevant pieces of information. Indeed, supporting this idea, HMMs were reported to be better in a sensory-integration task in which a task-irrelevant auditory stimulus could help guide attention towards a target in a dynamic visual-search task if the tone was presented simultaneously with the blinking of the target in the search display (Lui & Wong, 2012; see also Van der Burg, Olivers, Bronkhorst, & Theeuwes, 2008). In other words, this study could be interpreted to suggest that a breadth-biased focus of attention caused the HMMs to be more sensitive to the task-irrelevant information that was in this case beneficial for task performance.

Another possible explanation for increased distractibility in HMMs is that HMMs have a reduced ability to exert top-down control over attentional selection (Cain & Mitroff, 2011). This account derives from the results of a visual search task in which participants had to respond to a target that appeared within one of several shapes that were all shown in the same color. On some trials, a shape with an oddball color was present, and the researchers examined whether HMMs and LMMs differed in their ability to ignore this oddball distractor depending on the likelihood that this oddball could contain the target. Specifically, in the never block, participants were validly instructed that the target would never appear in the oddball distractor color while in the sometimes block, the target could appear in the the oddball color on some percentage of the trials. The results showed that LMMs were less affected by the presence of the oddball distractor in the never block than in the sometimes block, indicating that they used the instruction to modulate their visual attention to filter out the oddball distractor while HMMs showed comparable RTs in the never and sometimes blocks, indicating that they did not use the instructions to modulate their attention. Taken together, the above-described findings suggest that media multitasking may be associated with increased susceptibility to distraction from task-irrelevant stimuli in the environment, and this may arise from a breadth-biased focus of attention and/or a reduced ability to exert top-down control over attentional selection.

Evidence against the external distraction hypothesis. While studies have suggested multiple lines of evidence in favor of the external distraction hypothesis, evidence against the hypothesis has also been accumulating. Specifically, the external distraction hypothesis appears to be at odds with the fact that various studies did not find that HMMs perform worse in the presence of distractors, for example in a Change-detection task (Cardoso-Leite et al., 2015; Gorman & Green, 2016; Uncapher et al., 2016; Wiradhany & Nieuwenstein, 2017) and in an AX-CPT task (Cardoso-Leite et al., 2015). Moreover, our recent meta-analysis (Wiradhany & Nieuwenstein, 2017) showed that out of 39 tests of the external distraction hypothesis, only 10 showed significantly stronger distractibility in HMMs, whereas 3 showed significantly stronger distractibility in LMMs, and the remaining 26 showed no significant difference. The pooled effect size for the association between media multitasking and external distractibility was weak (Cohen's d=0.17) and this association turned non-significant after we corrected for the presence of small-study bias.

The Internal Distraction Hypothesis

A second hypothesis about the relationship between media multitasking and performance on cognitive tasks proposes that media multitasking is associated with worse task performance overall, and this might be due to participants being distracted by something unrelated to the task (e.g., Uncapher et al., 2016). We refer to this as the internal distraction hypothesis.

Evidence for the internal distraction hypothesis. In a change-detection task with two targets and varying numbers of distractors, Uncapher et al. (2016) found that heavy media multitasking was associated with worse performance regardless of the presence of distractors (see also Wiradhany & Nieuwenstein, Exp.1). This was true regardless of whether participants tried to detect changes of orientations of red and blue rectangles (Exp. 1 in Ophir et al., 2009) or line-drawings of everyday objects (their Exp. 2) and, importantly, regardless of whether only the extreme multitaskers (i.e., HMMs and LMMs) or all participants were considered in the analysis. Further, they found that HMMs were less able to discriminate previously presented target and distractor objects in the change detection task from novel objects in a subsequent long-term memory recognition test.

In interpreting these results, Uncapher et al. (2016) proposed that HMMs might experience “continual distraction by information not under experimental control” (p. 7) and further suggested that this might be due to a wider attentional scope during encoding and retrieval, thus resulting in lower performance. Here, taking insight from Uncapher et al.’s proposal that the distraction might not be under experimental control, we suggest that such continual distraction may be related to a difficulty in suppressing task-unrelated thoughts. Indeed, there has also been evidence to suggest that HMMs may experience mind-wandering—the presence of task-unrelated thoughts—more frequently in daily life (Ralph et al., 2013) and while trying to memorize a video-recorded lecture (Loh et al., 2016), thus offering support for the notion that HMMs might have difficulty in performing cognitive tasks due to problems in suppressing task-irrelevant thoughts.

This so-called internal distraction hypothesis may provide a possible account for other findings showing a general deficit of task performance in HMMs. This account may explain why HMMs perform worse in the Raven’s Progress Matrices (Minear et al., 2013) because instead of deliberating sufficiently on the correct responses, they are distracted by task-unrelated thought and go with a less-deliberate response. Similarly, this hypothesis may provide an explanation for data showing that HMMs performed worse than LMMs in the OSPAN task (Sanbonmatsu et al., 2013), the count span task (Cain et al., 2016), and the N-back task (Cain et al., 2016; Ophir et al., 2009; Ralph & Smilek, 2016) due to task-unrelated thought (see also Daamen, van Vugt, & Taatgen, 2016 for direct evidence of task-unrelated thinking during a complex working memory task).

Evidence against the internal distraction hypothesis. Although several studies have reported overall worse task performance of HMMs compared to LMMs, others have found that performance of HMMs and LMMs did not differ in tasks such as a change-detection task (Cardoso-Leite et al., 2015; Gorman & Green, 2016; Wiradhany & Nieuwenstein, 2017, Exp. 2), an N-back task (Edwards & Shin, 2017; Wiradhany & Nieuwenstein, 2017), a Digit span task (Baumgartner et al., 2014), sustained-attention tasks (Ralph et al., 2015), a task-switching paradigm (Alzahabi, Becker, & Hambrick, 2017; Baumgartner et al., 2014; Minear et al., 2013), an Eriksen Flanker task (K. Murphy, McLauchlan, & Lee, 2017), and a Go/noGo task (K. Murphy et al., 2017; Ophir et al., 2009). In addition, one study found that HMMs performed better than LMMs. Specifically, in two experiments, Alzahabi and Becker (2013) found that HMMs performed better in a task-switching task. Lastly, some studies also failed to provide support for the idea that HMMs perform worse overall due to task-unrelated thoughts. Specifically, Ralph et al. (2015) reported that HMMs did not experience more frequent task-unrelated thought while performing a sustained-attention task. Collectively, these findings suggest that either the internal distraction hypothesis is incorrect, or that the internal distraction in HMMs only occurs during specific types of tasks.

The Current Study

Taken together, it can be concluded that the results of previous studies on the association between media multitasking and performance on cognitive tasks are mixed. Some studies suggest that media multitasking may be associated with increased susceptibility to distraction by task-irrelevant stimuli (i.e., the external distraction hypothesis), whereas others suggest that media multitasking may be associated with worse performance overall, due to internally generated distraction (i.e., the internal distraction hypothesis), and yet others show no evidence for either of these associations.

In the current study, we collected data from a large sample of participants (N=261) to determine the respective roles of external and internal distraction in modulating task performance of media multitaskers. Participants completed a questionnaire for media multitasking and a visual change-detection task to assess their vulnerability to internal and external distraction. The change-detection task was similar to the task that was used in previous studies that provided evidence for the external (Ophir et al., 2009) and internal (Uncapher et al., 2016) distraction hypotheses. It required participants to encode two target items (red rectangles) that could appear together with 0, 2, 4, or 6 distractor items (blue rectangles), thus enabling an assessment of the extent to which the presence of distractors interfered with memory for the target items (see also Vogel, McCollough, & Machizawa, 2005). Additionally, to assess whether HMMs and LMMs differed in terms of internal distraction, we first examined whether HMMs performed worse overall. Subsequently, if performance were worse overall, we would further examine whether this could be explained by an increase of task-unrelated thoughts during the experiment (see Smallwood & Schooler, 2015, for a review) by means of a mediation analysis (Fairchild & MacKinnon, 2009).

We tested these hypotheses using linear mixed effects models which included the factors media multitasking, distractor set size, and mind-wandering across the entire sample of participants. Using linear mixed-effects models has several advantages. It allows for analyzing a nested data structure and unbalanced design (Baayen, Davidson, & Bates, 2008; Bolker et al., 2009), which, as will become clear later, were present in our experiment. Additionally, compared to traditional ANOVAs, this method has also been proven to increase statistical power and lead to fewer false discoveries (Baayen et al., 2008; Bolker et al., 2009), and it allows for testing multiple covariates (Baayen et al., 2008; J. Yang, Zaitlen, Goddard, Visscher, & Price, 2014). Moreover, to examine whether the outcomes provided evidence against these hypotheses (i.e., whether there is evidence for the null hypothesis), we complemented the null-hypothesis significance test statistics with Bayes Factors that can provide such evidence.

Methods

Participants

In total, 275 participants volunteered to take part in the study. Seven participants were excluded from data analysis because they did not complete the study, and another seven were excluded because they failed to respond in time to the task on more than 50% of trials (*M*=89%, range 52.5–100%). The data from the remaining 261 participants were used for the statistical analysis. These 261 participants (159 female) had a mean age of 25.31 years (*SD* = 11.09). The study was approved by the Ethical Committee of the Psychology department, the University of Groningen. All participants provided informed consent prior to participating to this study.

Materials and Apparatus

The questionnaire to assess media multitasking and the change-detection task were implemented in OpenSesame 2.9.7 (Mathôt, Schreij, & Theeuwes, 2012). Data for 107 participants were collected in a lab equipped with 10 computer set-ups that were shielded from view of each other. Data for the remaining 154 participants were collected in variable locations, by 2nd year Psychology students who could use their own computers and laptops to collect data, as part of an assignment for a research practicum course. These students were instructed to perform the experiment in a quiet, non-public location. To test whether the results were different for data collected in the lab versus the data collected by students, we included the setting for data collection as a factor in our analyses. Our analysis showed that there were there were differences in demographics, media multitasking scores, and change-detection performance of the participants who were tested in the lab vs. by students using their own computers (see the supplementary materials of this article). Yet, these analyses also showed there was no difference in results pertaining to the relationship between media multitasking and performance on the change-detection task (see the Supplementary materials of this document).

Media-Use Questionnaire. To measure media multitasking, we used the Short Media-Use Questionnaire (Baumgartner, Lemmens, et al., 2017). This questionnaire is a shortened version of a media-use questionnaire used in Baumgartner et al. (2014) and it is one of the many iterations of the Media-Use Questionnaire which was introduced in Ophir et al (2009). All media use questionnaires ask how often participants consume one type of media while consuming another at the same time across a range of different types of media, and then provide a composite metric of media multitasking, typically the Media Multitasking Index (MMI).

The scale that was introduced in Baumgartner et al. (2014) iterates the media pairing question over nine types of media: Print media, Television, Video on a computer, Music, Video/computer games, Phone calls, Instant/text messaging, Networking sites, and Other computer activities. The short version of this questionnaire, which was introduced in Baumgartner et al. (2017) includes the nine most prevalent media pairs involving four types of media in a large sample of adolescents, namely TV, social network sites, instant messaging, and listening to music (see Baumgartner et al., 2017 for a description of the items). The response options are “never”, “sometimes”, “often”, and “almost always”, and these responses are assigned a score of 1, 2, 3, or 4, respectively. These responses are averaged, creating the Media Multitasking-Short (MMS) index. Importantly, in validating the short questionnaire, Baumgartner et al. (2017) found that the variance captured in the short questionnaire explained a significant amount of variance of the long version of the questionnaire they used in 2014, and this was true regardless of whether they calculated the MMS; $r(523)=0.82$ or the MMI using the formula provided in Ophir et al. (2009); $r(523)=0.84$. Our motivation to use the MMS was supported further with the facts that participants could finish the short version of the questionnaire quickly (Baumgartner, Lemmens, et al., 2017) and that the MMS probes a more up-to-date set of media than the original questionnaire introduced by Ophir et al., which did not include Social Media.

Change-detection Task. The change-detection task we used was comparable to the tasks used in Ophir et al. (2009) and Uncapher et al. (2016; Exp. 1). In Ophir et al., participants were asked to memorize the orientation of two, four, six, or eight target objects which could be shown with zero, two, or four distractor objects, and they were subsequently asked to detect the change of orientation of the targets (by 45°), which occurred on 50% of the trials. Participants completed 200 trials in total. In Uncapher et al., participants were asked to memorize the orientation of two target objects which could be shown with zero, two, or four distractor objects, and they were subsequently asked to detect the change of orientation of the targets which occurred on 50% of the trials. It was unclear how much change in degrees of rotation occurred during this experiment. Exactly like in our study, participants in Uncapher et al. completed 200 trials in total. In our change-detection task, participants were asked to memorize two target objects (red rectangles) that were shown together with 0, 2, 4, or 6 distractor objects (blue rectangles) and to detect whether or not one of targets changed its orientation in a subsequent display (see Figure 4.1). The targets and distractors were randomly distributed in a 4×4 grid of an 800×800 pixels display, and each could have an orientation of 0, 45, 90, or 135° relative to a vertical axis. For data collected by students using their own laptop or computer, the size of display was not adjusted depending on the display resolution, meaning that the size of the display on the monitor could vary for data collected by students.

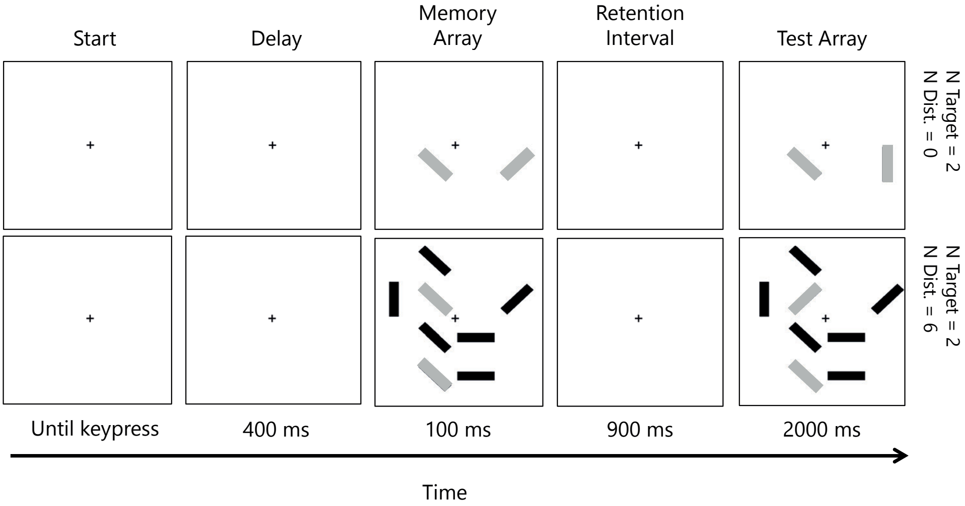

Figure 4.1. Two example trials from the change detection task, with zero and six distractors (upper and lower panels, respectively). Participants had to remember the orientations of two red bars (depicted here as grey), and ignore any blue bars (depicted here as black) in the memory array, and they had to indicate whether one of the two red bars had a different orientation in the test array.

Figure 4.1 shows the order of the stimuli in one trial. Each trial began with a presentation of a fixation cross. Participants started the trial sequence by pressing the spacebar. The fixation cross then remained in viewfor another 400 ms before the memory array display was presented for 100 ms. The memory array consisted of two target objects (red bars, illustrated in grey in Figure 4.1) and 0, 2, 4, or 6 distractor objects (blue bars, illustrated in black in Figure 4.1).

During the memory-array presentation, participants had to memorize the orientations of the targets while ignoring any distractors. Following the memory array, there was a blank retention interval of 900 ms before the test array was presented for 2000 ms. During the presentation of the test array, participants had to indicate whether the orientation of one of the targets had changed by pressing the left (change) or right (no change) arrow key on the keyboard. On 50% of the trials, one of the targets changed its orientation by either 45° or 90° in clockwise or counterclockwise direction. In the remaining 50% of the trials, no change occurred. The different trial types (change or no change, with 0, 2, 4, or 6 distractors) were randomly intermixed in the experiment. In total, the experiment consisted of 200 trials with

25 repetitions of each combination of change (present vs. absent) and distractor set size[18]. The experiment took 15-25 minutes to be completed.

Thought Probes. Typically, the presence of mind wandering during a task is gauged using experience-sampling methods. In these methods, participants are asked to indicate whether mind wandering has occurred at a particular moment (Smallwood & Schooler, 2015).

In the current study, we deployed two types of experience-sampling probes after each block of 16 trials, thus yielding a total of 12 measurements of mind wandering during the change detection task.[19] The first type of probe asked participants to rate whether their focus of attention in the preceeding block was on vs off-task on a 7-point scale; on-task (closer to 7) or off-task (closer to 1), and the second type of probe gauged the participants' ability to notice the fluctuations of their focus of attention (i.e. their meta-awareness; see Christoff, Gordon, Smallwood, Smith, & Schooler, 2009; Schooler et al., 2011) also on a 7-point scale; aware (closer to 7) and unaware (closer to 1). Except for the last block of 8 trials, each block included 16 trials for every combination of change (present vs. absent) and distractor set size. The last block of 8 trials included 2 trials for each of these combinations.

Data Analysis

Following Ophir et al. (2009) and Uncapher et al. (2016), performance on the change detection task was computed in terms of Cowan's K (see Cowan, 2000), with $K=S*(H-F)$, with K denoting the number of targets retained in memory, S denoting the number of targets shown, and H and F denoting the hit and false alarm rates, respectively.

We constructed Linear Mixed-effects Models (LMEs) to test the external and internal distraction hypotheses. In addition to estimating the variabilities in the dataset related to the effects of interest (e.g., distractor set size, MMS), LMEs also allow for estimating variabilities that should be generalized over a larger population (called random effects, e.g., different participants, different stimuli used in the experiment; Baayen, Davidson, & Bates, 2008). To ensure that our findings were not affected by potential confounding variables, we performed

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[18] For comparison, Ophir et al.'s (2009) experiment consisted of 200 trials divided across combinations of 2, 4, 6, and 8 targets and 0, 2, 4, and 6 distractors. Uncapher et al.'s (2016) experiment only included conditions with 2 targets and 0, 2, 4, and 6 distractors and they did not specify the total number of trials.

[19] Note that since the number of trials is 200, the last block only has a set of 8 trials. We did not include thought probes after this last block.

the hypothesis testing for both the external and the internal distraction hypotheses while controlling for Age, Sex, and Testing location variables as additional fixed-effects.

The external distraction hypothesis would predict that HMMs are more affected by the distractors than the LMMs, thus resulting in an interaction of media multitasking and the effect of distractor set size. We tested this hypothesis in a model with MMS and distractor set size as fixed effects, subject as a random intercept effect, and K as the outcome variable. Specifically, we tested whether the addition of an interaction effect between MMS and distractor set size improved the model compared to the model without the interaction, reflecting the idea that HMMs are more affected by the number of distractors than LMMs. In examining the internal distraction hypothesis, we first tested whether the addition of MMS as a fixed effect improved the model, as would be expected if participants with a higher MMS performed worse overall. If MMS indeed predicted K, we planned to perform a mediation analysis by adding the occurrence of task-unrelated thought as a fixed effect. If the internal distraction hypothesis was correct, that is, if any deficit in performance for HMMs could be explained by the increase of task-unrelated thoughts, we should witness 1) a positive correlation between MMS and the occurrence of task-unrelated thoughts and 2) an absence of predictiveness of MMS for K once we control for task-unrelated thoughts.

To evaluate the significance of our effects of interest, we assessed whether the addition of the relevant fixed-effects improved the fit of the model by means of model comparison. Specifically, we used the p-values of the goodness of fit chi-square test of the relevant model comparison as the index of whether our model provided support for the external or internal distraction hypothesis. The chi-square goodness of fit test evaluates whether the model has been improved, with significant χ^2 indicating that a larger amount of variance can be explained by adding the relevant fixed-effects.

To examine whether the data provided evidence for the null hypothesis of no association between media multitasking and internal or external distraction, we used Bayes Factors. Unlike the traditional approach of Null Hypothesis Significance Testing (NHST), in which only the likelihood of the data under the null hypothesis can be calculated (Wagenmakers, 2007), a Bayes Factor analysis allows one to assess the evidence in favor of both H_0 and H_1, given a certain distribution for the prior probability of these hypotheses. Specifically, a BF_{10} expresses the ratio of the likelihood of the data under H_1 over H_0, while BF_{01} expresses the ratio of the likelihood of the data under H_0 over H_1. Thus, the Bayes Factor expresses the extent to which belief in H_0 and H_1 should change in view of the data.

Lastly, since Ophir et al. (2009) performed their analysis only on the extreme groups of multitaskers (i.e., HMMs and LMMs), we also performed an additional analysis using a similar technique, namely categorizing the media multitaskers into HMMs and LMMs and then constructing a repeated-measures ANOVA with K as the outcome variable, Distractor Set Size as a within-group factor, and Group (HMM vs. LMM) as a between-group factor (see also Uncapher et al., 2016). This analysis was preregistered on the Open Science Framework: https://osf.io/nkdw5/. Further elaborations on the method used for classifying HMMs and LMMs can be found in the supplementary materials of this document.

All analyses were conducted using R 3.4.1. in RStudio 1.0.153. The linear mixed-effect models were constructed using the lme4 package (Bates, Mächler, Bolker, & Walker, 2015) and the Bayes Factors were calculated using the BayesFactor package (Morey et al., 2015). Plots were rendered using the ggplot2 package (Wickham, 2010). All significant and non-significant results were reported.

Results

To test the presence of associations between MMS, distractor set size, and performance, we constructed and compared several Linear Mixed Models. Table 4.1 shows the constructed models and effects tested in each model. Note that all models have Subject as a random factor and controlled for Age, Sex, and Testing location as additional fixed-effects.

Table 4.1. Fixed-effects tested in different Linear Mixed-effects models.

Model	**Fixed-effects**
m0	-
m1	Distractor set size
m2	MMS
m3	Distractor set size + MMS
m4	Distractor set size + MMS + (Distractor set size× MMS)

Model	Fixed-effects
m5*	Distractor set size + MMS + (Distractor set size× MMS) + Focus of attention
m6*	Distractor set size + MMS + (Distractor set size× MMS) + Focus of attention + (MMS × Focus of attention)
m7*	Distractor set size + MMS + (Distractor set size× MMS) + Focus of attention + (Distractor set size× MMS × Focus of attention)

*Models m5-m7 were parts of an exploratory analysis, for which we report the results in the supplementary materials.

External Distraction

To test the external distraction hypothesis, we started with analyzing whether performance was modulated by distractor set size. A comparison between models m1 and m0 showed that adding Distractor set size as a fixed effect significantly improved the model, $\chi^2(3)=31.12$, $p<.001$, $BF_{10}=430.27$. Specifically, for each distractor condition, K was significantly lower than for the no-distractor condition, t's<-4.49, indicating that participants performed worse in the presence of distractors.

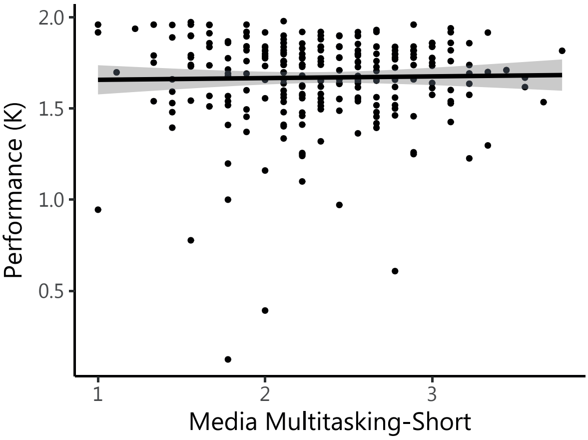

Figure 4.2. A scatterplot showing the association between MMS and the average K with different fits for distractors set size equals zero, two, four, and six. Each dot represents performance of one participant in

one condition. The shaded area represents 95% CI of the mean.

Subsequently, we compared the model that included the interaction between MMS and Distractor set size with the model that did not include this interaction, namely models m4 and m3, respectively. As Figure 4.2 suggests, adding the MMS × Distractor set size interaction did not significantly improve the model, $\chi^2(3)=1.19$, $p=.754$. In fact, the model without this interaction proved to provide a much better fit than the model with the interaction, $BF_{01}=3698.41$.

Taking the same approach as Ophir et al. (2009), we ran an additional analysis using a repeated-measures ANOVA with distractor set size as a within-subject factor, media-multitasking group (HMM; N=35 vs. LMM; N=41) as a between-subject factor, and K as the outcome variable. Consistent with our linear mixed-models analyses, this analysis also showed an effect of Distractor set size, $F(3, 222)=3.23$, $p=.023$, partial $\eta^2=0.04$, but no significant Media multitasking × Distractor set size interaction, $F(3, 222)=0.42$, $p=.741$, partial $\eta^2=.005$, and the Bayes Factor indicated that there was solid evidence for the absence of this interaction, $BF_{01}=24.39$.

Internal Distraction

Effects of MMS. To examine the internal distraction hypothesis, we first tested whether the addition of MMS significantly improved the model with Distractor set size only (m1). Thus, we compared models m3 and m1. This comparison showed that adding MMS as a fixed effect did not significantly improve the model, $\chi^2(1)=2.24$, $p=.121$. Again, there was more support for the model without an effect of MMS than for the model that included this effect, $BF_{01}=2.70$, thus providing evidence against the internal distraction hypothesis. Consistent with the outcomes of the linear mixed-effect models, an extreme-groups comparison also showed no significant difference in K between HMMs and LMMs, $F(1, 74)=0.61$, $p=.440$, partial $\eta^2=.008$, $BF_{01}=2.06$.

Mind-wandering. Our results showed no correlation between media multitasking and overall performance in the change-detection task. Thus, it was not possible to perform the mediation analysis to examine what portion of the amount of variance in the association between media multitasking-overall performance correlation could be attributed to the presence of task-unrelated thought, since there was no variance to explain. Nevertheless, we did conduct an additional exploratory analysis on the relationship between mind-wandering, media multitasking, and performance on the change detection.

To check whether participants meaningfully interpret the thought probes, we assessed the extent of which mind-wandering was correlated with task performance. Specifically, we first examined whether, as in previous studies, a low focus of attention was associated with more errors and faster response times (see Smallwood & Schooler, 2006). This was indeed the case, as responses were less accurate and slower in the blocks in which participants reported a lower focus of attention (see the supplementary materials for the associated statistics).

As the first step of the analysis, we examined the degree of mind-wandering. As can be seen in Figure 4.3, participants were focused on the task in most of the trial blocks: Across 12 blocks, participants reported being off-task (defined as reporting a rating below 4) on 8.63% of the blocks and on-task (reporting a rating above 4) on 83.42% of the blocks. Since the frequency of off-task blocks was low and since the responses for the first (on-task vs. off-task) and second (aware vs. unaware) probes were highly correlated, *r*(259)=0.71, *p*<.001, we did not perform any further analyses for the awareness probes.

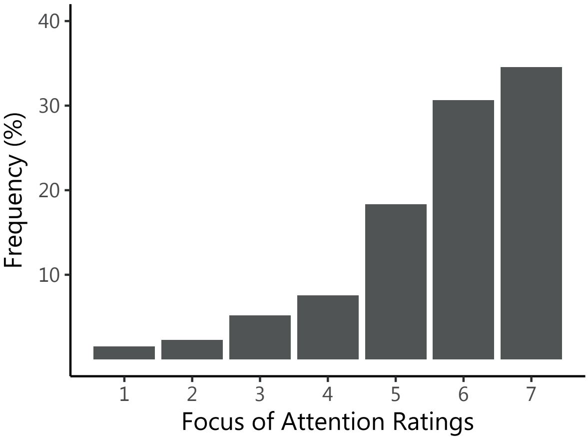

Figure 4.3. Frequency (%) of responses to focus of attention probes. Higher ratings indicate absence of mind wandering and lower ratings indicate presence of mind wandering.

Next, we examined the correlation between MMS and Focus of attention by constructing a linear-mixed-model with Focus of attention as the outcome variable, MMS as fixed-effect, Subject as a random intercept, while controlling for Age, Sex, and Testing location as additional fixed-effects. The results showed that adding MMS as a fixed effect did not significantly improve the model, $\chi^2(1)=1.41$, $p=.236$, $BF_{01}=2.43$, indicating that participants with higher MMS did not mind-wander more frequently during the experiment.

Auxiliary Exploratory Analyses. Lastly, we also conducted a number of auxiliary analyses to examine the influence of a number of methodological details that differed between our change-detection task and the tasks used in previous studies. Specifically, our study differed from previous studies in that our change-detection task was self-paced (i.e., participants initiated each trial by pressing the spacebar), and in that it included a varied, as opposed to a fixed degree of rotation for the target on change trials. In addition, our study differed from previous studies in that we used a sample of participants that not only included university students but also members from the more general population tested by students (see the Supplementary Materials for details on the demographics of these participants). To examine the potential influences of these factors on our results, we conducted a number of auxiliary, exploratory analyses and these analyses showed that none of these factors appeared to be of influence (see Supplementary Materials). Specifically, we found that the results did not depend on how much time participants took to initiate a trial. In addition, they showed that the results did not differ depending on whether the target changed by 45 or 90 degrees on change trials, and they also made clear that the results obtained in the main analyses were consistent when considering different subsets of participants separately. Taken together, these exploratory analyses corroborate the findings we obtained in our main analysis.

General Discussion

Previous studies have reported mixed findings on the association between media multitasking and performance in laboratory tests of attention, working memory, and cognitive control. Specifically, some studies suggest that HMMs are more vulnerable to distractors present in the immediate environment (the external distraction hypothesis), whereas others suggest that HMMs perform worse overall, regardless of the presence of distractors, due to the increased vulnerability to internal distraction (the internal distraction hypothesis), and yet others found no evidence for these associations. In the current study, we tested these possibilities in a large-scale experiment in which we collected data both from university students and members of the general population. In addition, we included thought probes to enable us to determine whether any overall reduction in performance could be ascribed to an increase in task-unrelated thought. In examining the evidence for the internal and external distraction hypotheses, we employed different analysis methods, such that we performed a repeated-measures ANOVA for an extreme-groups comparison as well as a linear-regression analysis across all participants, and we complemented the use of null-hypothesis significance tests with Bayes-factor analyses.

Overall, we found consistent evidence that media multitasking was not associated with increased vulnerability to internal or external sources of distraction. Specifically, while we did find that participants performed worse as distractor set size increased, we did not find that participants with higher media multitasking scores were more strongly affected by the presence of distractors. Thus, in this regard, our findings failed to corroborate the Ophir et al.'s (2009) findings that HMMs perform worse as distractor set size increases and they instead corroborated the results of other studies which also did not report this interaction (see Wiradhany & Nieuwenstein, 2017 for a review). We also found that media multitasking was not associated with worse overall performance in the change-detection task. This result appears to be at odds with the findings of Uncapher et al. (2016; see also Wiradhany & Nieuwenstein, Exp. 1) whereas it corroborates earlier findings showing no association between media multitasking and overall performance in a change-detection task (Cardoso-Leite et al., 2015; Gorman & Green, 2016; Wiradhany & Nieuwenstein, 2017, Exp. 2). Lastly, we found no association between media multitasking and mind-wandering, thereby corroborating an earlier study that also failed to observe this association (Ralph et al., 2015), and thereby providing additional evidence counter to that of two previous studies that did suggest an association between media multitasking and mind wandering (Loh et al., 2016; Ralph et al., 2013).

At present, our findings add to the mixed findings with regard to the association between media multitasking and change-detection performance in particular. Specifically, of the seven studies reported in the literature, one reported an association between media multitasking and increased distractibility (Ophir et al., 2009), three reported an association between media multitasking and worse overall performance (Uncapher et al., 2016, Exps 1 & 2; Wiradhany & Nieuwenstein, 2017, Exp. 1), and four showed neither increased distractibility nor overall worse performance in heavy media multitaskers (Cardoso-Leite et al., 2015; Gorman & Green, 2016; Wiradhany & Nieuwenstein, 2017, Exp. 2). To account for these mixed findings, two points are worth discussing, namely the fact that the current study differed from previous studies in terms of having considerably greater statistical power, and, secondly, that the current study differed from previous studies in using a short as opposed to long questionnaire to measure media multitasking.

With regard to the difference in statistical power, i.e., the likelihood of obtaining a significant test result for an effect of a certain magnitude for a certain sample size (J. Cohen, 1992), it can be said that most previous change-detection task studies have utilized relatively small sample sizes compared to the current sample size of 261 participants[20]. With such small sample sizes, these previous studies could only reliable detect effects with a large effect size (Button et al., 2013), but the current findings and those of our previous meta-analysis (Wiradhany & Nieuwenstein, 2017) make clear the association between questionnaire measures of media multitasking and lab-based measures of distractibility is probably very weak at best. Moreover, the use of small sample sizes is also known to increase the risk of spurious outcomes since the obtained estimates of performance are more likely to deviate from the true level of performance when estimated on the basis of a small sample size (Bakker, van Dijk, & Wicherts, 2012). Accordingly, it follows that the statistically significant associations found in some previous studies might have been driven by spurious effects. Indeed, a similar argument may be made about the only previous study that showed support for an association between media multitasking and overall worse performance for a reasonably large sample of participants (N=139; Uncapher et al., 2016). Specifically, closer scrutiny of the analyses and results of this study makes clear that this association was only found to be significant in an analysis that examined a secondarily-derived measure of performance (*d'* as calculated from a signal-detection analysis), and not for the primary outcome measure of interest (Cowan's *K*). Moreover, this association with *d'* was only found to be significant across the entire sample of participants for one of the two experiments that the participants were asked to do, with the second experiment showing no significant correlations between media multitasking and *d'* or *K*. Therefore, it can be said that the study by Uncapher et al. did not provide consistent, convincing evidence for the association between media multitasking and change-detection

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[20] Out of the eight studies, our study included, only three had a total sample size greater than 100 (Experiments 1 & 2 from Uncapher et al., 2016; the current study) while others had a total sample size lower than 42.

performance for a large sample of participants. Accordingly, one account for the difference between the current findings and the subset of previous studies that did show a significant association with internal or external distractibility could be that these previous findings reflected spurious effects and that the results of our large-scale study are valid in showing that these associations do not exist.

An important alternative explanation for why the findings of the current large-scale study did not show the associations found in some previous studies relates to our use of the short MMS, as opposed to the long MUQ questionnaire (Ophir et al., 2009) used in all previous studies on change-detection performance. Since the short MMS includes only 9 of the 144 media pairs that are included in the long MUQ, it could be that the short MMS does not probe those behaviors that might have driven the association between distractibility and media multitasking found in some previous studies. While this indeed constitutes a logically possible account that awaits an empirical test, there are two reasons for why this account is unlikely to provide a satisfactory explanation for why our findings differed from those of some previous studies. To start, it is important to note that Baumgartner et al. (2017) found that the 9 media pairs included in the MMS produced a score that was highly correlated (r = .84) with a score that was derived from a larger questionnaire that included a total of 72 media pairs. From this finding, one can infer that the MMS would probably also correlate reasonably well with the original MUQ, thus offering a first argument against the possibility that the MMS would lead to markedly different results than the MUQ. Secondly, it is important to note that the studies that did use the original MUQ have also produced highly variable results, with the majority showing null effects and only some showing evidence for a statistically significant association (see also, Wiradhany & Nieuwenstein, 2017). Evidently, this state of affairs is more compatible with the possibility that the true association between media multitasking and distractibility is null, than it is with the possibility that the original MUQ captures variance in some types of media-multitasking behaviors that indeed relates to performance on laboratory tests of distractibility. As said, however, the currently available evidence does not include any empirical test of whether different types of media-multitasking behaviors might relate to distractibility to different degrees, and, therefore, a clear conclusion on this issue will have to await further research.

Taken together, the finding presented in this study provided evidence against both the external and internal distraction hypotheses. Against the external distraction hypothesis, our findings corroborated the results of our recent meta-analysis which suggested that previous evidence for the external distraction hypothesis is weak and driven primarily by studies using relatively small sample sizes (Wiradhany & Nieuwenstein, 2017). By implication, our findings also argue against the breadth-biased (Lin, 2009) and reduced top-down control (Cain & Mitroff, 2011) accounts, which would both predict that participants with higher MMS scores would be more strongly affected by distractor set size than those with lower MMS scores, due to their tendency to absorb as much information as possible or due to a reduced ability to exert top-down control.

Against the internal distraction hypothesis, our finding that media multitasking is not associated with worse overall performance corroborated other studies in the literature which found no association between media multitasking and performance a change-detection task (Cardoso-Leite et al., 2015; Gorman & Green, 2016; Wiradhany & Nieuwenstein, 2017, Exp. 2), an N-back task (Baumgartner et al., 2014; Edwards & Shin, 2017; Wiradhany & Nieuwenstein, 2017), sustained-attention tasks (Ralph et al., 2015), a task-switching paradigm (Alzahabi et al., 2017; Baumgartner et al., 2014; Minear et al., 2013), an Eriksen Flanker task (Baumgartner et al., 2014; K. Murphy et al., 2017), and a Go/noGo task (K. Murphy et al., 2017; Ophir et al., 2009). In addition, our finding that media multitasking is not associated with increase of mind-wandering corroborated other studies which also found no evidence for a media multitasking-mind wandering association (Ralph et al., 2015). Together, this set of findings oppose what has been proposed in a recent review (Uncapher & Wagner, 2018). This review suggests that there was converging evidence in the literature that media multitasking is associated with worse task performance, especially for tasks assessing the encoding and maintenance of information in memory, and this might be due to the higher number of attentional lapses experienced by frequent media multitaskers. Critically, the considered evidence in this review was based on numerical, as opposed to statistical differences in task performance between HMMs and LMMs. Indeed, in cases in which only statistical evidence were considered, there has been a weak support for the attentional lapses account, and furthermore, our current findings provided direct evidence against the notion that 1) HMMs performed worse than LMMs and 2) HMMs experienced increased attentional lapses.

To conclude, the current large-scale study showed that media multitasking, as assessed using the 9 media pairs of the MMS (Baumgartner et al., 2017), is not associated with increased vulnerability to external distraction, or with reduced performance due to the occurrence of internal distraction. Since we assessed media multitasking using only a small subset of all possible media-multitasking behaviors, an important question for future studies will be to examine whether associations between distractibility and media multitasking do exist for other types of media-multitasking behaviors. Furthermore, in conducting these studies it is also important to consider that people tend to underestimate their frequency of switching between media streams (Brasel & Gips, 2011) and that they tend to overestimate the time they spend using media (Deng, Meng, Kononova, & David, 2018). Another recommendation for future studies would therefore be to combine the use of self-report measures with the use of more objective methods such as diaries (Voorveld & Goot, 2013; Z. Wang & Tchernev, 2012), video recordings of behavior (Rigby et al., 2017), or automatic tracking on a participant's devices (Z. Wang & Tchernev, 2012; Yeykelis et al., 2014). By combining these objective measures of media multitasking with self-report measures, and by considering whether different types of media-multitasking behaviors produce different results, we believe that future studies could make an important contribution towards uncovering the existence of any associations between habitual media multitasking and laboratory measures of information processing and distractibility in this exciting and increasingly important scientific field.

Supplementary Materials

Differences between Data Collected in the Lab or by Students

As a first step in examining the results, we compared the demographics, media-multitasking indices, and performance of participants for whom the data was collected in the lab (N=107) or by students using their own computers and laptops (N=154; see Table S4.1). As can be seen in Table S4.1, all measures showed a statistically significant difference between the data collected in the lab and the data collected by students. Specifically, the percentage of female participants was higher for the data collected in the lab, and the participants in the lab were significantly younger, with more variance of age in the data collected by students outside of the lab. In addition, the participants tested in the lab had a higher media-multitasking score, a higher frequency of mind wandering (less focus of attention on task), and worse performance on the change detection task. Importantly, however, our analyses of the relationship between media multitasking, mind wandering, and change detection showed no significant effects of the setting of data collection. Specifically, a linear mixed model with testing location, MMS, and Number of distractors as fixed factors, Subject as a random factor, and K as the outcome variable showed that testing location did not interact with MMS, $\chi^2(2)=5.32$, $p=.070$, $BF_{01}=3.23$, $t=0.77$ or with MMS×Number of distractors, $\chi^2(8)=8.59$, $p=.378$, $BF_{01}=48.68$, all t's<.59, thus indicating that the main findings of interest were consistent across these two subsets of data.

Table S4.1. Results for data collected in the lab vs. by students using their own computers and laptops.

Measure	**Lab (Mean and SD)**	**Own Computer (Mean and SD)**	**Test Statistic**	***p*-value**
Age	20.94 (2.65)*	28.17 (13.36)**	*t*(168.82)=6.47	*p*=.001
% Female	72%	53%	Wilcoxon's *W*=18632	*p*=.002
Media-multitasking-short	1.42 (0.51)	1.27 (0.55)	*t*(259)=2.33	*p*=.021
Focus of attention	4.53 (0.85)	4.79 (1.00)	*t*(259)=2.16	*p*=.032
Awareness of attention	4.52 (0.93)	4.69 (1.09)	*t*(259)=1.35	*p*=.178
Cowan's K	1.63 (0.23)	1.70 (0.25)	*t*(259)=2.16	*p*=.032

* N=99, ** N=152.

Extreme-group Comparisons

For the extreme-groups comparison, to facilitate a more direct comparison for the results of both Ophir, Nass, and Wagner (2009) and Uncapher, Thieu, and Wagner (2016), using both the information of the frequency of consuming one type of media while consuming another and the absolute number of hours spent for consuming one type of media, we first calculated the Media Multitasking Index (MMI; Ophir et al., 2009) which replaces the MMS, using equation 1 below:

$$MMI = \sum_{i=1}^{j} \frac{m_i \times h_i}{h_j}$$

with m_i is the sum of the media multitasking frequency scores using primary medium i, j is the total number of media evaluated, h_i is the number of hours spent consuming primary medium *i*, and h_j is the sum of hours spent consuming all media. The distribution of the MMI had a mean of 1.35 and an *SD* of .54. The scores were normally distributed, W=.99, p=.70 and they were highly correlated with the MMS, r=0.96, p<2.2e -16.

Following Ophir et al. (2009), participants whose MMI lay more than one SD above the mean were categorized as Heavy Media Multitaskers (HMMs) and participants whose MMI lay more than one SD below the mean were categorized as Light Media Multitaskers (LMMs). Using this categorization, we identified 35 HMMs (M=2.35, SD=0.26) and 41 LMMs (M=0.54, SD=0.24).

If instead of MMI, MMS were used as a media multitasking index, we identified 46 HMMs (M=3.24, SD=0.25) and 40 LMMs (M=1.55, SD=0.23) using a similar categorization process as above. In that case, the analysis also revealed an effect of Number of distractors, F(3, 252)=4.9, p=.002, partial η^2=.056, BF_{10}=8.75, but no main effect of Group, F(1,84)=.021, p=.885, partial η^2<.001, BF_{01}=3.05, and no Number of distractors × Group interaction, F(3, 252)=.74, p=.529, partial η^2=.008, BF_{01}=16.13.

Effects of Task-unrelated Thought on Accuracy and Response Times

To verify whether the participants responded seriously to the thought probes, we examined whether performance differed according to the self-reported focus of attention in the thought probes. To this end, we constructed linear mixed-models with subject as a random intercept, focus of attention as a fixed-effect, and accuracy and response times for correct trials as outcome variables. Overall, the results showed that participants were less accurate in blocks in which they reported low focus of attention, $\chi^2(1)$=156.69, p<.001, BF_{10}=3.29e+32, see Supplementary Figure S4.1, but they were not slower or faster $\chi^2(1)$=3.35, p=.067, BF_{10}=0.29.

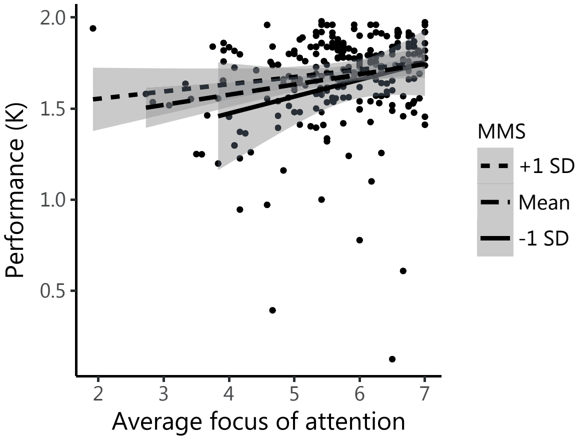

Figure S4.1. A scatterplot showing the association between Focus of Attention and Accuracy of trials following the presentation of the thought probes. Each dot represents performance of one participant in one condition. The shaded area represents 95% CI of the mean.

If we only consider the trials prior to participants responding to the probes, participants were more likely to respond incorrectly in trials in which they reported lower focus of attention, $\chi^2(1)=18.03$, $p<.001$, $BF_{10}=1000.49$ (see Figure S4.1) and they had somewhat slower responses on the preceding trial, $\chi^2(1)=5.56$, $p=.018$, $BF_{10}=0.88$.

Chapter 5

Behaviors of Media Multitaskers

Note: This chapter is currently under revision for publication in *Media Psychology* as: Wiradhany, W. & Koerts, J. (*in prep.*). Cognitive, Mental Health, and Socio-emotional Correlates of Media Multitasking: A Mini Meta-analysis

Abstract

A recent meta-analysis has shown that media multitasking behavior, or consuming multiple streams of media simultaneously, might not be associated with less efficient cognitive processing, as measured with objective tests. Nevertheless, a growing number of studies have reported that media multitasking is correlated with functioning in everyday life and mental health-related functioning. Here, in a series of mini meta-analyses, we show that correlates of media multitasking can be categorized in at least four major themes. Media multitasking behavior is associated with high levels of self-reported problems related with behavior regulation (e.g., inhibition and impulsiveness), high levels of self-reported problems related with metacognition (e.g., meta-awareness and planning), more (severe) symptoms of ADHD, and a higher level of sensation-seeking. At the same time, a high level of media multitasking is also associated with a high level of creativity and social success. However, while findings had low between-studies heterogeneity, the pooled effect sizes were weak, ranging from $z=0.15$ to $z=0.27$. Thus, even though a large proportion of variance of media multitasking behavior is still unaccounted for, increased levels of media multitasking behavior might have implications on different domains of everyday functioning.

Keywords: media multitasking, executive function, impulsiveness, ADHD, mini meta-analysis

Introduction

Multiple studies have demonstrated the negative consequences of media-related multitasking on performance. For instance, phone use (e.g., for texting and having conversations) during driving is associated with increased reaction times for braking responses in driving simulation studies (Strayer et al., 2003; Strayer & Johnston, 2001), and phone and social media uses in classrooms are associated with lower GPAs at the end of an academic semester (Junco, 2012, 2015). Yet, media multitasking behavior, i.e. consuming two or more media streams or activities simultaneously, have become more prevalent (Rideout et al., 2010; Roberts & Foehr, 2008). With the ubiquity of media multitasking behavior and the presumed negative consequences of multitasking in general, it is of no surprise that in recent years, people have started investigating the correlates of media multitaskers using both performance-based and self-reported measures.

Studies focused on the correlates of media multitaskers have presented an interesting contradiction. On the one hand, the group of studies using performance-based measures has shown mixed results. Specifically, some studies showed that heavy, compared to light media multitaskers (HMMs and LMMs, respectively) displayed worse performances in different objective, performance-based measures of cognition (Cain et al., 2016; Ophir et al., 2009; Ralph & Smilek, 2016), while others reported that HMMs performed better on performance-based measures of cognition, compared to LMMs (Alzahabi & Becker, 2013; Baumgartner et al., 2014) or reported inconclusive results (Cardoso-Leite et al., 2015; Gorman & Green, 2016; Minear et al., 2013; K. Murphy et al., 2017; Ralph et al., 2015; Wiradhany & Nieuwenstein, 2017). It is, therefore, not surprising that a recent review (van der Schuur et al., 2015) and a meta-analysis (Wiradhany & Nieuwenstein, 2017) have shown that pooled together, the association between media multitasking and performances on performance-based measures of cognition is weak. Furthermore, the meta-analysis has shown that upon applying meta-analytic correction, the pooled association between media multitasking and performances on performance-based measures of cognition turned out to be null.

On the other hand, there is a growing number of studies showing associations between frequent media multitasking and problems reported on rating scales related to cognitive, social, and mental health issues. Frequent media multitasking has been associated with more self-reported attention lapses and mind-wandering (Ralph et al., 2013), higher levels of impulsiveness (Cain et al., 2016; Magen, 2017; Minear et al., 2013; Sanbonmatsu et al., 2013; Schutten, Stokes, & Arnell, 2017; Uncapher et al., 2016), an increase of social problems (Pea et al., 2012), a higher number of problems with executive functions (Baumgartner et al., 2014; Magen, 2017), more (severe) symptoms of depression and social anxiety (Becker et al., 2013), and more (severe) symptoms of ADHD (Magen, 2017; Uncapher et al., 2016). Together, these findings suggest that media multitasking is not associated with performance on objective measures of cognition, but nevertheless, is associated with different aspects of everyday functioning.

Findings from performance-based and self-reported measures might disagree with one another for several reasons. To start, the two measures arguably estimate one's ability to function on different levels. On the one hand, performance-based measures estimate one's optimal performance: These measures have explicit instructions and are administered under highly standardized conditions. Accordingly, the results of these measures would reflect the efficiency of cognitive processing of an individual (Stanovich, 2009; Toplak, West, & Stanovich, 2013). On the other hand, self-reported measures of the same construct estimate one's typical performance: These measures probe a wide range of everyday behaviors which are related with the construct which is being estimated. Accordingly, the results of these measures would reflect the ability of an individual to execute a task in conditions in which no explicit instructions or goals are given (Stanovich, 2009; Toplak et al., 2013). Critically, it is possible for an individual to score low in one type of measure but high in the other type and vice versa. For instance, individuals with dysexecutive symptoms might perform well in an executive function test, yet they reported frequent problems in everyday situations (Burgess et al., 2006). Somewhat analogously, the International Classification of Functioning, Disability, and Health (ICF), which is developed by the World Health Organization (World Health Organization, 2001), also draws a distinction between functions (i.e., the structural integrity of the body to allow for optimal use; the optimal performance) and activities (i.e., the life areas, tasks, and actions associated with an individual; the typical performance). Similarly, impairments on a functional level do not always necessarily result in impairments on the actively level due to compensation and adaptation. Accordingly, people who frequently media multitask might not perform worse in performance-based measures of cognition, yet report everyday problems associated with cognition due to the fact that laboratory measures might capture some, but not all aspects of cognition or measure cognition on a different level than self-reported measures.

Presently, media multitasking behavior seems to be associated with various reports of cognitive, social, and mental health-related issues. To better understand how and to what extent media multitasking behavior is associated with these heterogeneous issues, we can look into the processes associated with media multitasking behavior which we outline in the sections below.

Media Multitasking

Media use in everyday life. Multimedia is ubiquitous. In 2001 alone, it was estimated that each household in the United States has 2.4 sets of television on average (Roberts & Foehr, 2008). A recent survey from the Pew Research Center surveying 1060 adolescents between 13 and 17 years of age also reported that 73% of the respondents have access to a smartphone, and 91% of the respondents go online from mobile devices (Lenhart, 2015). In addition, data from emerging countries such as Indonesia also showed a widespread access to smartphones: A recent survey of 2000 Indonesian respondents reported that 85% of the respondents used their smartphone to access the internet (Marius & Anggoro, 2014). Multimedia devices do not only get easier to access, but they also provide increased possibilities to stay connected and to consume a vast amount of information easily.

With the ubiquity of multimedia devices, it is not surprising that the duration and frequency of multimedia exposure have been increasing. With regard to the frequency of multimedia use, a recent survey from the Pew Research Center surveying 1060 adolescents between 13 and 17 years of age reported that 92% of them went online daily. This included 24% of adolescents who are online “almost constantly” (Lenhart, 2015). With respect to the duration of multimedia use, another survey from the Kaiser Family Foundation reported that multimedia-use duration increased from 6.5 hours to 7.5 hours per day from 1999 to 2009 (Rideout et al., 2010).

Since there is a fixed amount of time per day to spend and only so much information to consume, perhaps it is not surprising that media multitasking behavior has become the selected strategy for media consumption. Indeed, the Kaiser report estimated that adolescents managed to consume 10.75-hour worth of media content in just 7.5 hours by multitasking (Rideout et al., 2010). In addition, the proportion of hours spent for multitasking has been increasing as well: in 1999, children of 8-18-year old spent about 1 hour to multitask out of 7.5 hours of media consumption per day. In 2004, these numbers grew into about 2 hours out of 8.5 hours of media consumption per day and in 2009, about 3 hours out of 10.8 hours of media consumption per day (Rideout et al., 2010). Similarly, the proportion of younger people who media multitask is higher than that of older people. In a cross-sectional study Carrier, Cheever, Rosen, Benitez, and Chang, (2009) showed that people who were born after 1978 multitasked using multimedia 56% of the time compared with people who were born between 1965 and 1978, and 1946 and 1964 who multitasked 49% and 35.1% of the time, respectively. Together, these findings indicate not only that the amount of information presented in media is increasing, but also people, especially younger ones, try to keep up with media consumption by media multitasking.

What characterizes media multitasking? Media multitasking behavior is mainly characterized by rapid switches of attention between different media streams. An observational study of concurrent television and computer usage showed that, on average, participants switched their attention 120 times within 27.5 minutes (Brasel & Gips, 2011). Similarly, another observational study reported that contemporary office workers spent on average 3 minutes on a task before switching to another (González & Mark, 2004). Switching does not only happen between media devices, but also between different media activities. For instance, Judd (2013) reported from computer session logs that college students switched between different tasks in a computer about 70% of the time and spent on average 2.3 minutes on one task before switching to another.

With the high frequency of switching between different media streams, it is likely for media multitasking behavior to disrupt other ongoing cognitive and behavioral processes. Firstly, media multitasking might disrupt one’s current train of thoughts, which may result in worse task performance. In a study in which participants were asked to study an article about influenza, participants recalled less information about the article in conditions in which they were either forced to check their Facebook account or allowed to check their Facebook account while studying the article (Kononova et al., 2016). Other studies have shown that media-induced interruptions might have no significant impacts on task performance (Fox et al., 2009; Mark, Gudith, & Klocke, 2008), but nevertheless, people who experienced constant interruptions during work reported more stress and frustration at the end of the day (Mark et al., 2008). Secondly, media multitasking behavior might disrupt ongoing social interactions. For instance, individuals who are multitasking might not be able to contribute optimally to a group discussion (Bell, Compeau, & Olivera, 2005). Furthermore, constant multitasking may be associated with a feel of isolation and a fear of missing-out (Carrier et al., 2015; Cheever, Peviani, & Rosen, 2018), and this might have a profound impact on mental health: One study showed that individuals who used 7-11 different social media platforms had higher odds of having depression and social anxiety (Primack et al., 2017; see also Becker et al., 2013). Lastly, media multitasking behavior might disrupt other everyday behavior patterns. For instance, adolescents who reported higher level of media multitasking also reported having fewer hours of sleep per night (Calamaro, Mason, & Ratcliffe, 2009). Similarly, in a longitudinal study, adolescents with a higher level of media multitasking reported more sleeping problems at the time of the data collection, three months, and six months later (van der Schuur, Baumgartner, Sumter, & Valkenburg, 2018).

The Current Study

Media multitasking behavior might interfere with ongoing cognitive, social, and behavioral processes in everyday situations. This behavior might not be correlated with performances on objective measures of cognition (van der Schuur et al., 2015; Wiradhany & Nieuwenstein, 2017), but nevertheless it might have profound impact on everyday functioning, as indicated by self-reported measures of cognition, socio-emotional issues, and mental health-related issues. This article aims to examine and summarize the current body of literature on media multitasking in order to create an overview of the different domains of everyday behavior in which functioning might be affected by media multitasking behavior. The evidence was synthesized in a series of mini meta-analyses which were categorized into different domains of everyday functioning. Additionally, we also examined the risk of bias across the findings and performed a moderator analysis if risk of bias occurred.

Methods

Study Selection

All studies which examined the association between self-report measures of media multitasking and cognitive, social, and mental health issues, as measured with self-report rating scales, were considered for inclusion. Studies were identified in the PsycInfo, ERIC, MEDLINE, SocINDEX, and CMMC databases, as well as the Directory of Open Access Journals (DOAJ) database. A combination of the following keywords was entered in the search terms: media multitask* AND (problem* OR executive* OR impuls* OR attention*)[21]. Together, the search yielded 130 results from the first set of databases and 68 results from the DOAJ database.

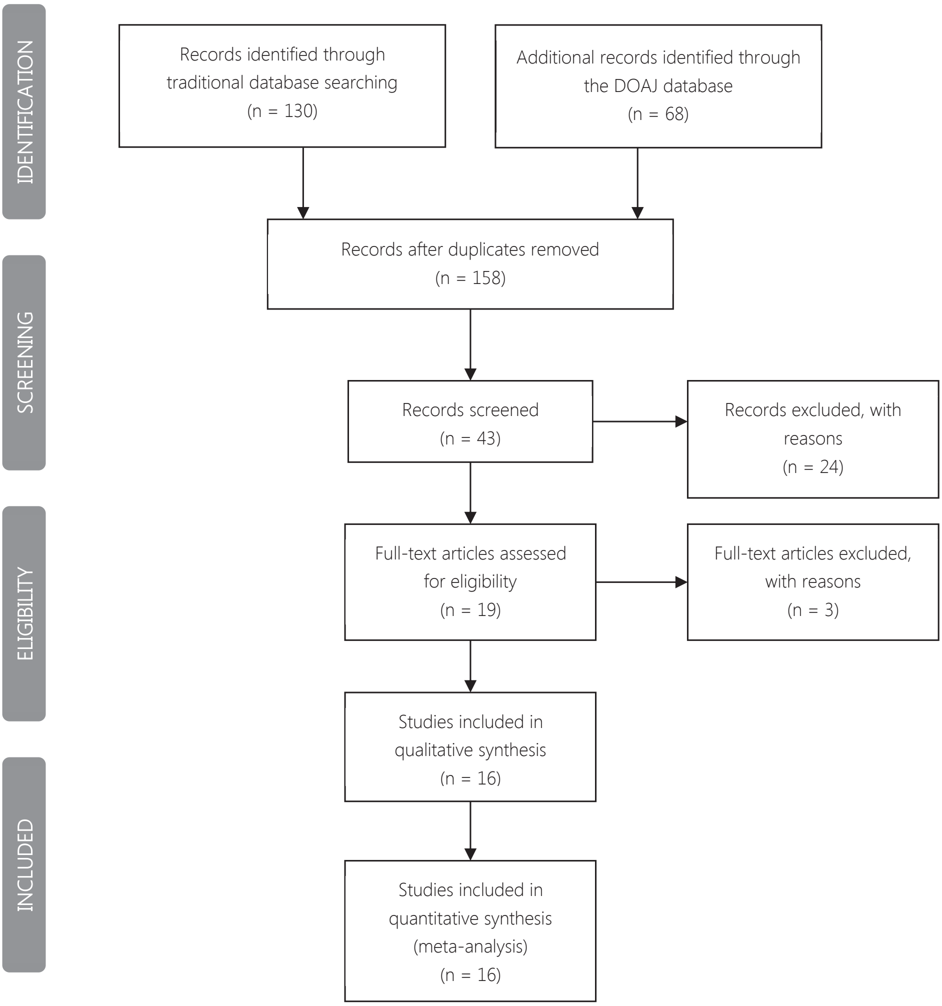

Figure 5.1. A flow diagram showing the selection of study process.

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[21] To ensure that all possible relevant results have been included in the meta-analysis, in addition to these keywords, we performed a search using more general keywords, namely *media multitask** AND (*cognition* OR *emotion* OR *trait*). This search yielded no additional results.

As Figure 5.1 shows, of the 198 studies identified, 40 were duplicates and therefore removed. Of the 158 studies, only 43 pertained to the term “media multitasking” (i.e., not only pertained to “media” or “multitasking” exclusively) and therefore considered for further screening. Of 43 studies screened, we removed studies which did not meet the criteria below.

First, studies must have examined the association between measures of media multitasking and self-report measures of cognitive, socio-emotional, and mental health issues. Therefore, four review articles (Aagaard, 2015; Carrier et al., 2015; Lin, 2009; van der Schuur et al., 2015), two meta-analysis (Jeong & Hwang, 2016; Wiradhany & Nieuwenstein, 2017), one measurement validity article (Baumgartner, Lemmens, et al., 2017), 12 articles which only included laboratory task performance measures (Alzahabi & Becker, 2013; Alzahabi et al., 2017; Cain & Mitroff, 2011; Edwards & Shin, 2017; Gorman & Green, 2016; Lui & Wong, 2012; Moisala et al., 2016; K. Murphy et al., 2017; Ophir et al., 2009; Ralph & Smilek, 2016; Ralph et al., 2015; Yap & Lim, 2013), two articles in which the level of media multitasking was manipulated (Kazakova, Cauberghe, Pandelaere, & De Pelsmacker, 2015; Lin et al., 2009), one article in which only a brain imaging measure was used (Loh & Kanai, 2014) and two articles in which only media multitasking behavior was observed (Loh et al., 2016; Rigby et al., 2017) were excluded from further eligibility assessment.

Second, since this study pertains to media multitasking behavior in general, only studies using a general media multitasking measure were included. Therefore, one article in which only a specific combination of media multitasking was used (Kononova et al., 2014) and one article (Wu, 2017) which measured the perception of media multitasking ability instead of actual media multitasking frequency were removed. Lastly, one article was excluded since the relevant effect sizes could not be extracted from the published article (Shih, 2013)[22]. In all, a total of 16 articles containing 18 independent studies[23] were included for synthesis (Baumgartner, Lemmens, et al., 2017; Baumgartner et al., 2014; Becker et al., 2013; Cain et al., 2016; Cardoso-Leite et al., 2015; Duff et al., 2014; Hadlington & Murphy, 2018; Hatchel, Negriff, & Subrahmanyam, 2018; Magen, 2017; Minear et al., 2013; Pea et al., 2012; Ralph et

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[22] The author was contacted for requesting the relevant zero-order correlations not reported in the article. Unfortunately, due to unforeseen circumstances the original dataset was no longer available. Nevertheless, we are thankful to Dr. Shui-I Shih for her cooperation.

[23] Two of the studies (Baumgartner, van der Schuur, et al., 2017) were longitudinal studies with 3 waves each. All study waves were included (see Table 5.1).

al., 2013; Sanbonmatsu et al., 2013; Schutten et al., 2017; Uncapher et al., 2016; X. Yang & Zhu, 2016). Table 5.1 shows the measures of self-reported functioning included in each study and the number of participants assessed.

Table 5.1. Overview of included studies in meta-analysis, including the number of participants, and the measures of self-reported functioning used in each study

Authors (year)	**N_{total}**	**Measure(s) of self-reported functioning**	**Sample description**
Pea et al. (2012)	3461	Social success, Normalcy feelings	100% females, M_{age}=10.57
Becker et al. (2013)	319	Social Phobia Inventory (SPIN), Patient Health Questionnaire (PHQ)-Depressed Mood	69.6% females, undergraduate students
Minear et al. (2013)	221	Barratt Impulsiveness Scale (BIS)	68.32% females, M_{age}=19.8
Ralph et al. (2013)	202	Mindful Attention Awareness Scale – Lapses Only (MAAS-LO), Attention-related Cognitive Errors Scale (ARCES), Memory Failures Scale (MFS), Mind Wandering-Spontaneous (MW-S), Mind Wandering-Deliberate (MW-D), Attentional Control-Switching (AC-S), Attentional Control-Distractibility (AC-D)	72.28% females, undergraduate students
Sanbonmatsu et al. (2013)	277	Barratt Impulsiveness Scale (BIS), Sensation-seeking Scale (SSS)	56.77% females, *Median*$_{age}$=21
Baumgartner et al. (2014)	523	Behavior Rating Inventory of Executive Functions (BRIEF): Working Memory, Inhibition, and Shifting subscales	48% females, M_{age}=13.09

Authors (year)	N_{total}	Measure(s) of self-reported functioning	Sample description
Duff et al. (2014, Study 1)	308	Cognitive Failures Questionnaire (CFQ), Personal Control Scale (PCS), Brief Sensation-seeking Scale (B-SSS), Creativity, Imagination, Need for Simplicity (NfS)	58.12% females, M_{age}=20.37
Duff et al. (2014, Study 2)	501	Cognitive Failures Questionnaire (CFQ), Personal Control Scale (PCS), Brief Sensation-seeking Scale (B-SSS), Creativity, Imagination, Need for Simplicity (NfS)	51.09% females, M_{age}=34.43
Cardoso-Leite et al. (2015)	60	Cognitive Failure Questionnaire (CFQ), Attention Deficit/Hyperactivity Disorder Self-Report Scale (ADHD-ASRS)	13.33% females, M_{age}=20.68
Uncapher et al. (2015)	139	Barratt Impulsiveness Scale (BIS), Attention Deficit/Hyperactivity Disorder Self-Report Scale (ADHD-ASRS)	58.04% females, M_{age}=22.1
Cain et al. (2016)	70	Domain-specific impulsivity in school-age children (DiSC)	49.31% females, M_{age}=14.4
Yang & Zhu (2016)	310	Barratt Impulsiveness Scale (BIS), Brief Sensation-seeking Scale (B-SSS)	49.35% females, M_{age}=15.3
Baumgartner et al. (2017, Study 1, wave 1)	1241	Inattentiveness scale-based on DSM-V criteria for ADHD	49% females, M_{age}=12.61*
Baumgartner et al. (2017, Study 1, wave 2)	1216	Inattentiveness scale-based on DSM-V criteria for ADHD	49% females, M_{age}=12.61*
Baumgartner et al. (2017, Study 1, wave 3)	1103	Inattentiveness scale-based on DSM-V criteria for ADHD	49% females, M_{age}=12.61*

Authors (year)	N_{total}	Measure(s) of self-reported functioning	Sample description
Baumgartner et al. (2017, Study 2, wave 1)	1083	Inattentiveness scale-based on DSM-V criteria for ADHD	-
Baumgartner et al. (2017, Study 2, wave 2)	939	Inattentiveness scale-based on DSM-V criteria for ADHD	-
Baumgartner et al. (2017, Study 2, wave 3)	439	Inattentiveness scale-based on DSM-V criteria for ADHD	59% females, M_{age}=14.37
Magen et al. (2017)	196	Behavior Rating Inventory of Executive Functions (BRIEF): all subscales, Attention Deficit/Hyperactivity Disorder Self-Report Scale (ADHD-ASRS)	74% females, M_{age}=23.44
Schutten et al. (2017)	303	Barratt Impulsiveness Scale (BIS)	83.23% females, M_{age}=19.63
Hadlington et al. (2018)	144	Risky Cybersecurity Behavior (RcSB), Cognitive Failure Questionnaire (CFQ)	77.77% females, M_{age}=20.63
Hatchel et al. (2018)	263	Social Interaction Anxiety Scale (SAIS), Rosenberg Self-Esteem Scale	49.6% females, M_{age}=20.58

*The sex proportion and Mean of age refers to the combined samples of Study 1 across the three study waves.

Effect Size Selection and Calculation

Effect sizes were selected from reported outcome measures which reflect distinguishable constructs. For instance, a study examining the association between media multitasking and measures of executive function would report measures of attentional shifting, working memory, and inhibition, which are separate constructs. Study findings related to these measures would be regarded as individual effect sizes. In total, 59 unique effect sizes were extracted from the studies listed in Table 5.1. Of the 59 unique effect sizes, we decided to exclude the effect sizes associated with the Need for Simplicity from the studies conducted by Duff et al. (2014) since the study in which this measure was described has been retracted from publication (Liu, Smeesters, & Trampe, 2012) and therefore we deemed using this scale as inappropriate. Therefore, 57 effect sizes were included in the final series of mini meta-analysis.

Effect sizes were calculated in Fisher's z, indicating the normalized correlation coefficients between self-reported measures of media multitasking and self-reported measures of cognitive, socio-emotional, and mental health issues. A positive z indicates that frequent media multitasking is associated with more (severe) issues and a negative z indicates that frequent media multitasking is associated with less (severe) issues. In most cases, the included studies reported Pearson's product-moment correlations (r) as measures of effect sizes. These r's were converted into Fisher's z using formula 1 below (Borenstein et al., 2009):

$$z = 0.5 \times ln\left(\frac{1+r}{1-r}\right)$$

In which *r* is the Pearson's product-moment correlation.

Analysis

Categorization of findings. Since different studies featured in the meta-analysis and the featured rating scales measured different domains of cognitive, social, and mental-health, we grouped the respective effect sizes into different categories based on the similarity and dissimilarity between constructs. To illustrate, the Mindful Attention Awareness Scale (MAAS; Brown & Ryan, 2003) and the self-monitoring subscales of the Behavioral Ratings of Executive Functions (BRIEF; Gioia, Isquith, Guy, & Kenworthy, 2000; Gioia, Isquith, Retzlaff, & Espy, 2002) infer a relatively similar construct related to thought-monitoring, which is relatively dissimilar to the construct related to forming precise information in memory inferred by the Memory Failures Scale (Carriere, Cheyne, & Smilek, 2008).

To guide the categorization process of findings related to cognition, we referred to factors of executive function described in the BRIEF (Gioia, Isquith, Guy, & Kenworthy, 2000; Gioia, Isquith, Retzlaff, & Espy, 2002). Executive function, the group of cognitive processes that involves guiding goal-directed behavior (Burgess et al., 2006; Chan, Shum, Toulopoulou, & Chen, 2008; Diamond, 2013) provides an umbrella concept which encompasses most of the cognitive operations reported in the findings. Our decision to refer to BRIEF was motivated by several reasons. First, the BRIEF is a well-known and regularly used self-report measure of executive function (Baumgartner et al., 2014; Huizinga & Smidts, 2010; Toplak et al., 2013) and was used in many of the included studies. Second, the BRIEF measures a comprehensive range of executive functions from an everyday perspective (Gioia et al., 2000), thus, providing an ideal basis for assessing issues which might be associated with media multitasking.

Based on factor loadings from a large sample of children and adolescents, the BRIEF categorizes executive function into two factors, namely Behavioral Regulation and Metacognition (Gioia et al., 2000, 2002; Huizinga & Smidts, 2010). The behavioral regulation factor has subscales which relate to the regulation of one's impulses (Inhibit), attention (Shift), self-regulation (Self-Monitor), and emotion (Emotional Control). The metacognition factor has subscales which relate to the ability to assess one's current state of the task at hand (Task-Monitor), maintaining an online representation of learned information (Working-Memory), beginning a task or independently generating ideas (Initiate), keeping things in order (Organization of materials), and anticipating future events (Plan/Organize).

Findings which were not directly related to cognition, namely findings from different social and mental-health related rating scales were categorized in a similar way to scales of cognition, with scales with similar constructs categorized in one group. For all categories, the first author performed the categorizations and the second author checked the resulted categories. Disagreements between authors were resolved by consensus.

Using the categorization processes above, we identified four different themes for correlates between media multitasking and self-report measures of cognitive, social, and mental health issues: measures related to behavior regulation, measures related to metacognition, measures related to ADHD, and measures related to sensation-seeking and risk-taking. For each theme, random-effect models and pooled effect sizes were calculated to provide estimates of the magnitude of the correlation in each theme. Measures which did not fit into one of the themes were categorized in "others." Since measures categorized in "others" pertained to highly heterogeneous constructs, a pooled effect size was not calculated for this theme.

Random-effect model. Since the current meta-analysis featured different rating scales and outcome measures, we constructed a random-effect model to estimate the pooled effect size. This model assumes that the different scales had comparable, but not identical effect sizes which are distributed around some mean that reflected the true effect (Borenstein et al., 2009). In our case, we assumed that the different outcomes measured different subsets of functioning. Thus, the effects might vary from one function to another.

The random-effect model was constructed in R (R Core team, 2015) using the Metafor package (Viechtbauer, 2010). To account for variance inflation of the pooled effect size due to the dependency of multiple outcome measures from one study, we calculated the robust variance estimation (RVE; Hedges, Tipton, & Johnson, 2010). RVE works by estimating the correlations between dependent outcome measures and adjusting the standard error of the pooled effect size based on these correlations (Hedges et al., 2010; Scammacca, Roberts, & Stuebing, 2013).

Heterogeneity and risk of bias. When significant between-studies heterogeneity was detected, we performed a moderator analysis and a risk of bias analysis. The moderator analysis assesses whether the between-studies heterogeneity can be explained by shared characteristics of different sub-groups of studies (Hedges & Pigott, 2004).

The risk of bias analysis tested whether the heterogeneity was stemming from bias coming from the level of precision in each study. Under a presence of bias, it is common for studies with smaller sample sizes to show an overestimation of effect sizes due to sampling errors compared with studies with bigger sample sizes, a phenomenon called small-study effect (Sterne et al., 2000). A small-study effect might indicate the presence of publication bias, since other studies with smaller sample sizes showing underestimation of the effect ended up not being published (Ioannidis, 2005; Ioannidis, Munafò, Fusar-Poli, Nosek, & David, 2014). As a formal inspection of small-study effects, we conducted an Egger's test (Egger et al., 1997), in which a simple linear regression with effect sizes as a measure of magnitude of study effect and sample sizes or standard errors as measures of study precision is constructed.

Results

Behavior Regulation

Random-effect model. Figure 5.2 shows a forest plot for a group of scales which measured the association between media multitasking and constructs related to the ability to regulate behavior. Naturally, the BRIEF subscales related to the behavior regulation factor were categorized in this theme: Emotion Regulation (e.g., "Has outburst for little reason," Gioia et al., 2002), Self-monitor (e.g., “Is unaware of how his/her behavior affects or bothers others,”), Shift (e.g., “I get stuck on one topic or activity,” Gioia et al., 2002), and Inhibit (e.g., “I do not think before doing,” Gioia et al., 2002).

In addition to the BRIEF subscales, we categorized other measures which assess the level of behavior regulation in this theme. Specifically, the PPSI-Personal control (e.g., “Sometimes I do not stop and take time to deal with my problems, but just kind of muddle ahead,” Heppner & Petersen, 1982), AC-switching (e.g., “I am slow to switch from one task to another,” Carriere, Seli, & Smilek, 2013), AC-distractibility (e.g., “I have difficulties concentrating when there is music in the room around me”, Carriere et al., 2013), BIS (e.g., “I do things without thinking”, Patton, Stanford, & Barratt, 1995) and DiSC (e.g., “I interrupted other people,” Tsukayama, Duckworth, & Kim, 2013).

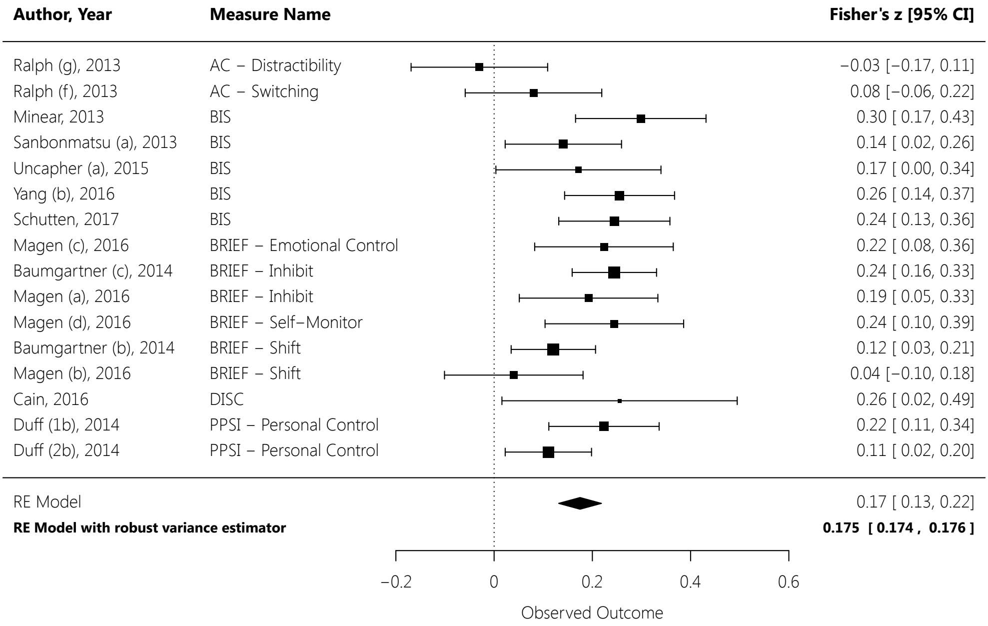


Figure 5.2. Forest plot of the effect sizes (Fisher’s z) for studies measuring the association between media multitasking and behavior regulation. Error bars indicate 95% confidence intervals of the means. AC: Attentional Control; BIS: Barratt Impulsiveness Scale; BRIEF: Behavior Rating Inventory of Executive Function; DISC: Domain-specific Impulsivity in School-age Children; PPSI: Personal Problem-solving Inventory

Overall, the random-effect model revealed a small, but significant positive association between media multitasking and self-reported problems related to behavioral regulation, $z=0.175$, 95% CI [.174, .176], $p<.001$. At the same time, however, a significant heterogeneity between the effect sizes was detected, $I^2=49.82\%$, $Q(15)=29.51$, $p=.014$.

Heterogeneity & risk of bias analysis. To address the heterogeneity in the model, we performed moderator analyses with three moderators. First, we explored whether the between-studies heterogeneity could be explained by different sub-dimensions of behavioral regulation. Following the Behavior Regulation subscale of BRIEF, we further categorized the studies into studies measuring Emotional Regulation, Self-monitor, Inhibit, or Shift subscales of BRIEF. The non-BRIEF scales were categorized as follows: the PPSI-personal control scale and AC-distractibility were categorized together with the Self-monitor subscale, the AC-shifting were categorized together with the Shift subscale, and the BIS and DISC were categorized together with the Inhibit subscale. Second, we added sex, as indicated by the proportion of females in the study samples as a moderator. Third, we added age, as indicated by the mean age of the study samples as a moderator. The three moderators did not contribute to the unexplained variance in the model, $F(3, 12)=1.58$, $p=.244$; $F(1, 14)=0.10$, $p=.755$; $F(1, 11)=1.92$, $p=0.187$, respectively, indicating that the heterogeneity could not be explained by differences in subscales of the BRIEF, sex, and age.

As for the risk of bias, the Egger's test showed no relationship between effect size and study precision, $z=0.08$, $p=.936$. This indicates that under the presence of heterogeneity, effect sizes were stable across different studies with different sample sizes.

Metacognition

Random-effect model. Figure 5.3 shows a forest plot for a group of studies which measured the association between media multitasking and constructs related to metacognition. The BRIEF subscales related to the metacognition factor were categorized in this theme: Initiate, (e.g., “I need to be told to begin a task even when willing”, Gioia et al., 2002), Working Memory, (e.g., “I have trouble remembering things, even for a few minutes,” Gioia et al., 2002), Task-Monitor (e.g., “I make careless errors,” Gioia et al, 2002), Plan/Organize, (e.g., “I become overwhelmed by large assignments” Gioia et al., 2002), and Organization of Materials (e.g., “I cannot find things in room or school desk,” Gioia et al, 2002).

In addition to the BRIEF subscales, we also categorized other measures which assess the level of metacognition in this theme, namely MW-Deliberate and MW-Spontaneous (e.g., "I find my thoughts wandering spontaneously," Carriere et al., 2013), MAAS-Lapses Only (e.g., "I snack without being aware that I'm eating," Carriere, Cheyne, & Smilek, 2008), ARC-ES (e.g.,"I have gone to the fridge to get one thing (e.g., milk) and taken something else (e.g., juice)," Carriere, Cheyne, & Smilek, 2008), and CFQ (e.g., "Do you read something and find you haven't been thinking about it and must read it again?," Broadbent & Cooper, 1982).

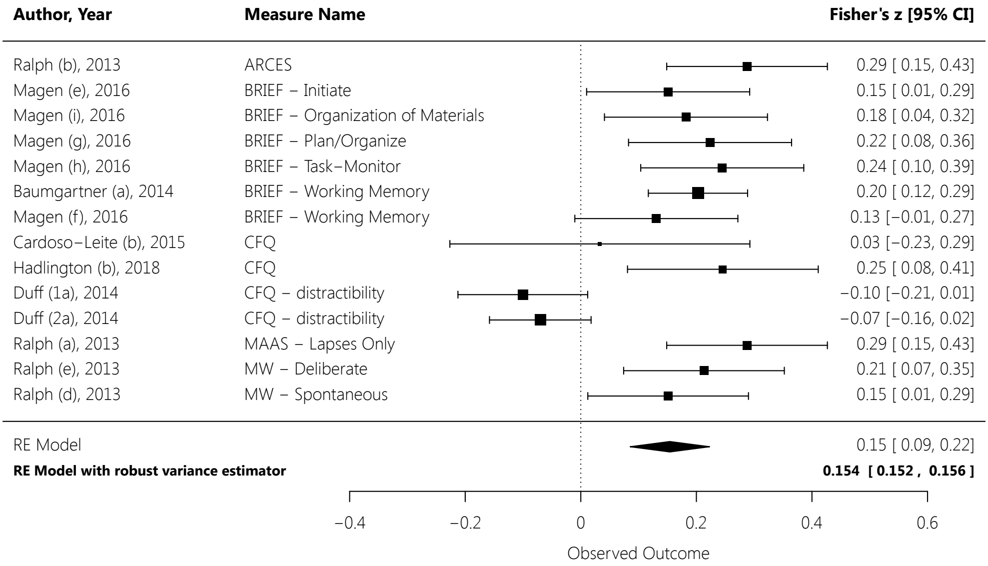


Figure 5.3. Forest plot of the effect sizes (Fisher's z) for studies measuring the association between media multitasking and metacognition. Error bars indicate 95% confidence intervals of the means. ARCES: Attention-Related Cognitive Errors; BRIEF: Behavior Rating Inventory of Executive Function; CFQ: Cognitive Failures Questionnaire; MAAS: Mindful Awareness Attention Scale; MW: Mind-Wandering scale

Overall, the random-effect model revealed a small, but significant positive association between media multitasking and problems with metacognition, *z*=0.15, 95% *CI* [.152, .156], *p*<.001. At the same time, however, a significant heterogeneity between the effect sizes was detected, I^2=73.62%, *Q*(13)=57.39, *p*<.001.

Heterogeneity & risk of bias analysis. To address the heterogeneity in the model, we performed moderator analyses with three moderators as mentioned in the previous sections, namely the subscales of BRIEF, age, and sex. Here, the metacognition subscale of BRIEF was used, namely Initiate, Working Memory, Task-Monitor, Organization of Materials, and Plan/Organize. The non-BRIEF scales were categorized as follows: the MW-Deliberate, MW-Spontaneous, ARCES, MAAS-LO, and CFQ were categorized in the Task-monitor subscale. Both the BRIEF subscales and Age did not contribute to the unexplained variance in the model, *F*(6, 7)=0.17, *p*=.976; *F*(1, 8)=1.95, *p*=.200, respectively, indicating that the heterogeneity could not be explained by differences in subscales of BRIEF and age. However, the Sex moderator turned out to be significant; *F*(1, 12)=4.79, *p*=.048, with studies with higher proportion of females reporting higher correlation estimates.

As for the risk of bias, the Egger's test showed no relationship between effect size and study precision, *z*=0.759, *p*=.44. This indicates that under the presence of heterogeneity, effect sizes were stable across different studies with different sample sizes.

ADHD

Random-effect model. Figure 5.4 shows a forest plot for a group of studies which measured the association between media multitasking and symptoms of ADHD.

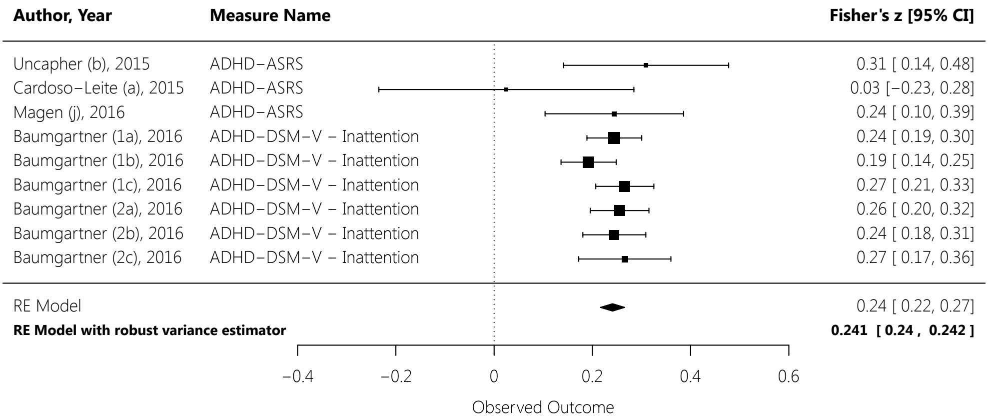


Figure 5.4. Forest plot of the effect sizes (Fisher's z) for studies measuring the association between media multitasking and symptoms of ADHD. Error bars indicate 95% confidence intervals of the means. ASRS: Adult Self-report Scale; DSM-V: Diagnostic and Statistical Manual (of Mental Disorders)-V

The random-effect model showed a small, but significant positive association between media multitasking and symptoms of ADHD, z=0.24, 95% *CI* [.240, .242], p<.001. The between-studies heterogeneity was low, I^2=0%, Q(8)=7.41, p=.49, indicating that the effect was consistent across different studies.

Sensation-seeking and Risk-taking

Random-effect model. Figure 5.5 shows a forest plot for a group of studies which measured the association between media multitasking, sensation-seeking and risk-taking.

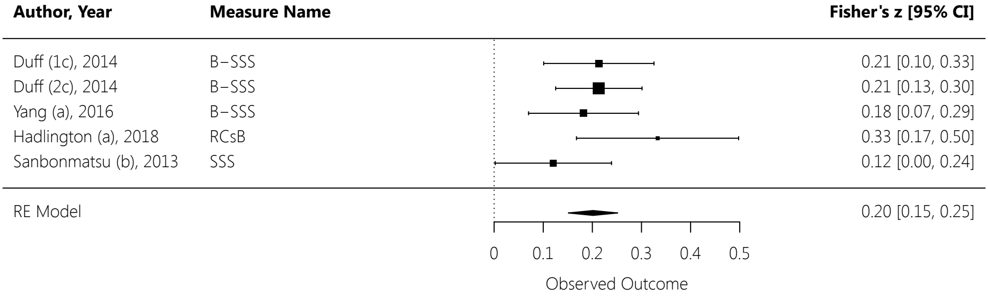
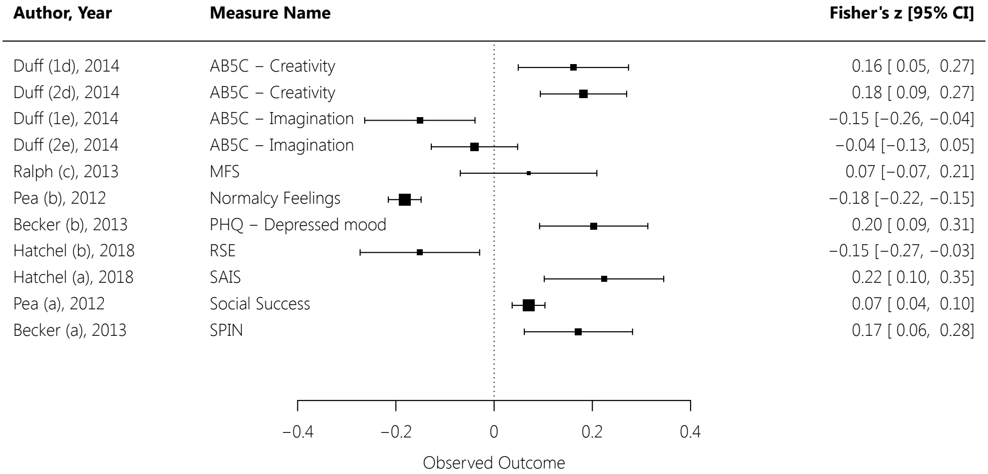


Figure 5.5. Forest plot of the effect sizes (Fisher's z) for studies measuring the association between media multitasking and sensation-seeking. Error bars indicate 95% confidence intervals of the means. SSS: Sensation-seeking Scale; B-SSS: Brief Sensation-seeking Scale; RCsB: Risky Cybersecurity Behavior Scale.

Overall, the random-effect model revealed a small, but significant positive association between media multitasking and sensation-seeking, z=0.20, 95% *CI* [.15, .25], p<.001. The between-studies heterogeneity was low, I^2=0%, Q(4)=4.45, p=.34, indicating that the effect was consistent across different studies.

Others



Author, Year	Measure Name	Fisher's z [95% CI]
Duff (1d), 2014	AB5C – Creativity	0.16 [0.05, 0.27]
Duff (2d), 2014	AB5C – Creativity	0.18 [0.09, 0.27]
Duff (1e), 2014	AB5C – Imagination	−0.15 [−0.26, −0.04]
Duff (2e), 2014	AB5C – Imagination	−0.04 [−0.13, 0.05]
Ralph (c), 2013	MFS	0.07 [−0.07, 0.21]
Pea (b), 2012	Normalcy Feelings	−0.18 [−0.22, −0.15]
Becker (b), 2013	PHQ – Depressed mood	0.20 [0.09, 0.31]
Hatchel (b), 2018	RSE	−0.15 [−0.27, −0.03]
Hatchel (a), 2018	SAIS	0.22 [0.10, 0.35]
Pea (a), 2012	Social Success	0.07 [0.04, 0.10]
Becker (a), 2013	SPIN	0.17 [0.06, 0.28]

Figure 5.6. Forest plot of the effect sizes (Fisher's z) for studies measuring the association between media multitasking and measures which do not fit in any of the categories. Error bars indicate 95% confidence intervals of the means. MFS: Memory Failure Scale; PHQ: Patient Health Questionnaire; SPIN: Social Phobia Inventory; AB5C: Abridged Big-5 Dimensional Circumplex; SAIS: Social Interaction Anxiety Scale; RSE: The Rosenberg Self-Esteem Scale.

Figure 5.6 shows a forest plot for a group of studies which measured the association between media multitasking and constructs which did not fit to any of the previous categories. Media multitasking was positively correlated with social success, symptoms of depression, social phobia, imagination, and creativity, but negatively correlated with normalcy feelings.

General Discussion

Media multitasking behavior is ubiquitous and may disrupt ongoing cognitive, socio-emotional, and behavioral processes in everyday situations. In this article, we examined which domains of everyday functioning might be affected by media multitasking. Specifically, using a series of mini meta-analyses, we synthesized the correlates of media multitasking behavior with measures of cognition, social, and mental health issues as indicated by self-reports found in the literature. The findings were categorized into different themes reflecting different domains of everyday functioning, based on the similarities and dissimilarities between the constructs reflected in the findings. For the measures related to cognition, especially, the categorization process was guided by the latent factors of the BRIEF, which reflect daily-life executive function (Gioia et al., 2000, 2002; Huizinga & Smidts, 2010).

Overall, our findings can be categorized into four distinct themes. Specifically, frequent media multitasking has weak, but stable associations with an increased number of self-reported problems related to behavior regulation (z=0.18), an increased number of self-reported problems related to metacognition (z=0.15), higher scores on questionnaires focused on symptoms of ADHD (z=0.24), and higher levels of sensation-seeking and risk-taking (z=.20). Additionally, frequent media multitasking was correlated with higher scores on questionnaires focused symptoms of depression and social phobia and increased levels of creativity, imagination, and social success.

Regarding the association between media multitasking and behavior regulation, it was found that participants with higher levels of media multitasking reported more difficulties with controlling/monitoring their thoughts, emotions, and behavior, and reported more difficulties with shifting from one task to another. Additionally, participants with higher media multitasking scores reported higher levels of impulsiveness. Somewhat consistently, other studies have also found that participants with higher media multitasking scores were likely to choose smaller, immediate rewards instead of later, larger ones and they endorsed intuitive, but incorrect answers of the Cognitive Reflection Test (Schutten et al., 2017). Together, this set of findings is perhaps unsurprising. As indicated in the introduction, media multitasking is characterized by frequent switches between different streams of information. Thus, media multitaskers experience more frequent switches between different thoughts and activities in everyday situations, perhaps more than they can manage (González & Mark, 2004). Consequently, they may experience more difficulties regulating and shifting between different thoughts, emotions, and behavior, and may report higher levels of impulsiveness.

Media multitasking was also associated with more self-reported difficulties related to metacognition. Specifically, participants with higher levels of media multitasking reported more difficulties with maintaining online representations (working memory), planning, task monitoring, and organizing; and they experienced more frequent mind-wandering in daily life. Consistently, other studies have also found that participants with higher levels of media multitasking reported a lower focus of attention while performing a change-detection task

(Wiradhany, van Vugt, & Nieuwenstein, in prep.; but see Ralph et al., 2015 for no effect) and while memorizing a video-recorded lecture (Loh et al., 2016). With regard to working memory, specifically, we also found that media multitasking is not associated with memory failures as measured by the MFS (*d*=.07, Ralph et al., 2013), which collectively suggests that frequent media multitaskers experience increased problems with maintaining online representations of information in memory, but not with forming memory representations per se. These findings were in contrast with findings from a study which found that heavy media multitaskers experienced difficulties in forming exact representations in memory (Uncapher et al., 2016). The association between media multitasking and increased problems with metacognition may also stem from frequent switches and interruptions which are experienced by media multitaskers. With frequent switches and interruptions, it is difficult to maintain one's current train of thoughts (Altmann, Trafton, & Hambrick, 2014; Katidioti & Taatgen, 2013). Consequently, monitoring different thoughts and emotions becomes more difficult. Additionally, with frequent media multitaskers reporting more instances of mind-wandering, it is interesting to ask what role does mind-wandering play in metacognition. For instance, do people experience more problems with metacognition due to the presence of mind-wandering, or is mind-wandering the consequence of having more problems with metacognition?

Media multitasking was also associated with higher scores on questionnaires focusing on symptoms of ADHD. This is also rather unsurprising, given that in the preceding sections, we discussed findings with regard to the associations between media multitasking and problems with behavioral regulation and metacognition, two components of executive function. Indeed, it has been previously shown that people who have ADHD reported more problems with executive function (Boonstra, Oosterlaan, Sergeant, & Buitelaar, 2005; Mahone et al., 2002; Mcauley, Chen, Goos, Schachar, & Crosbie, 2010; McCandless & O'Laughlin, 2007; Toplak, Bucciarelli, Jain, & Tannock, 2009). Additionally, a meta-analysis also showed that media use in general is positively correlated with ADHD-related behaviors (Nikkelen, Valkenburg, Huizinga, & Bushman, 2014).

Media multitasking was also associated with higher levels of sensation-seeking and risk-taking, traits which are closely related to impulsiveness (Dalley et al., 2011; Whiteside & Lynam, 2001). Individuals with higher levels of sensation-seeking are characterized by a higher stimulation threshold for optimal behavioral performance (Hoyle, Stephenson, Palmgreen, Lorch, & Donohew, 2002; Zuckerman, 2007) and a higher likelihood to act prematurely without foresight, which at times lead to risk-taking behaviors (Dalley et al., 2011; Hoyle et al., 2002; Zuckerman, 2007). Indeed, consuming multiple streams of information has been shown to promote a higher level of engagement (Bardhi et al., 2010; Z. Wang & Tchernev, 2012) and to provide gratifications (Hwang et al., 2014) which together provide stimulations for those who seek them. Accordingly, people with higher level of sensation-seeking and risk-taking might media multitask to seek for additional stimulations.

Lastly, some of the reported findings did not fit in any of the above categories. First, we found a study which reported the association between media multitasking and increased symptoms of depression and social anxiety (Becker et al., 2013). This is somewhat consistent with a recent nation-wide study also showed that individuals who use multiple social media platforms in daily life had higher odds of having increased levels of depression and anxiety (Primack et al., 2017). This leads to question whether increased levels of depression and anxiety are related to media multitasking, or to use of multiple media in general. The second group contains findings related to creativity, imagination, and social success. Specifically, media multitasking is associated with higher self-reported levels of creativity and social success. This set of findings indicates the potential benefits of media multitasking behavior.

To summarize, consuming multiple streams of information in media multitasking is challenging and can be overwhelming. In addition to having to select and to take action on multiple streams of information, media multitaskers might also experience more distractions in everyday situations. Somewhat predictably, our sets of findings suggest that people who reported higher levels of media multitasking also reported higher levels of difficulties in monitoring (i.e., in relation to metacognition) and managing (i.e., in relation to behavior regulation) different thoughts, emotions, and actions. Additionally, they also reported more symptoms of mental health problems (i.e., ADHD, depression, and social anxiety) and higher level of sensation-seeking and risk-taking. At the same time, they also reported higher level of creativity and social success. Together, media multitasking is associated with increased problems on different domains of everyday functioning. Importantly, since most studies reported correlations, the causality direction is still unclear.

Media multitasking behavior might precede, occur as a consequence, or have a reciprocal relationship with cognition, socio-emotional functions, and mental health. Currently, this meta-analysis does not allow for disentangling the causal relationship between media multitasking and everyday functioning. Preceding problems with cognition, socio-emotional functions, and mental health, media multitasking behavior may promote a specific mode of processing information in the environment (Lin 2009). Specifically, heavy media multitaskers might develop a breadth-biased focus of attention, due to constant exposures to media-saturated environments. That is, they prefer to skim a large quantity of information rather than deeply process a small amount of information. Consequently, adopting this mode of information processing might lead media multitaskers to apply cognitive control processes such as thought-monitoring and attention regulation less strictly. This might have a profound consequence. In an fMRI study, Moisala et al. (2016) found that in addition to worse task performance in which participants had to attend to sentences in one modality (e.g., auditory) while ignoring distractor sentences presented in another modality (e.g., visual), heavy media multitaskers also have higher activations in the right superior and medial frontal gyri, and the medial frontal gyrus. Increased activations in these areas have been linked to, among others, increased top-down attentional control. Therefore, heavy media multitaskers might require more effort in filtering distracting information than light media multitaskers. Alternatively, it could also be the case that media multitasking behavior leads to overreliance of exogenous control of attention (i.e. from incoming notifications from media; Ralph et al., 2013). Consequently, heavy media multitaskers train their endogenous control less often and thus, experience more problems related to cognitive control.

Media multitasking behavior might also occur as a consequence of existing problems with cognition, socio-emotional functioning, and mental health. People with ADHD and people with problems with behavior regulation and metacognition are more easily distracted and therefore are more inclined to media multitask. Similarly, people with high levels of sensation-seeking are more inclined to media multitask for stimulation-seeking purposes. Relatedly, indicating that excessive media multitasking behavior might be a result from a preexisting condition, tudies have also shown that individuals with smaller gray matter volumes in the Anterior Cingulate Cortex (ACC) – a brain region which has been shown to be more active during error and conflict detections (Botvinick, Braver, Barch, Carter, & Cohen, 2001; Botvinick et al., 2004) - reported higher levels of media multitasking. Similarly, the increased activations of the brain areas associated with top-down control in heavy media multitaskers

(Moisala et al., 2016) might also indicate that these areas function less efficiently in heavy media multitaskers, compared to light media multitaskers.

Lastly, media multitasking behavior might have a reciprocal relationship with problems with cognition, socio-emotional functioning, and mental health and vice versa. To this end, several longitudinal studies have attempted to examine whether media multitasking behavior and everyday-related problems are reinforcing each other over a longer time period. The results of these studies showed that media multitasking did not appear to have a reciprocal relationship with the occurrence of sleeping (van der Schuur et al., 2018) and attentional problems (Baumgartner, van der Schuur, et al., 2017) three and six months later. Nevertheless, these studies showed that the associations between media multitasking and sleeping and attentional problems were stable over time. That is, the correlation remained significant during the first, second, and third periods of data collection. Together, this might indicate that individuals have a stable level of media multitasking behavior over time and similarly, the occurrence of some everyday-related problems is also stable over time.

Limitation and Future Directions

The findings in our set of mini-meta-analyses are limited in several ways. To start, while the effects found in different groups of findings were somewhat reliable across different studies, critically, the overall pooled effects were weak, with z ranging from .15 to .27. Thus, while media multitasking appears to be associated with interconnected problems of executive function, symptoms of ADHD, anxiety, depression and sensation-seeking most of the variance of the media multitasking behavior is still unaccounted for. At the same time, the magnitude of the pooled effects does not indicate a high prevalence of clinical conditions (e.g., ADHD or depression) and subsequently, these findings do not appear as alarming as some might suggest (see Uncapher et al., 2017). Additionally, we arbitrarily used the factor loadings of the BRIEF (Gioia et al., 2000) to guide our categorization process, which might introduce bias and or contribute to our level of within-theme heterogeneity. For instance, scales related to self-monitoring might arguably fit better in the metacognition domain, however, in the BRIEF, these scales are categorized in the behavior regulation domain.

Furthermore, while the majority of findings indicate problems related to media multitasking in everyday functioning, our mini-meta-analyses also reveal encouraging findings, with media multitasking being associated with increased levels of creativity and social success. Future studies might be interested in further examining the adaptive values of everyday media multitasking behavior, especially given that some studies have shown that media multitasking behavior is stable over a longer period of time (Baumgartner, van der Schuur, et al., 2017; van der Schuur et al., 2018).

In themes related to cognition, we witnessed high level of heterogeneity. Importantly, the heterogeneity could not be explained by different subscales of BRIEF, indicating that the unexplained variance stemmed from another source. Our analysis indicated that studies with a higher proportion of females reported higher correlation between media multitasking and self-reports associated with metacognition. Future studies might need to consider that the association between media multitasking and self-report of functions in everyday domains might be moderated by a third variable.

Lastly, since all findings we synthesized in the meta-analysis were correlational, it is still an open question whether media multitasking behavior leads to, is an effect, or has a reciprocal relationship with the occurrence of cognitive, socio-emotional, and mental health-related issues in everyday situations. Futures studies might be interested in disentangling this association in a more controlled manner.

Conclusion

In a series of mini meta-analyses, we have shown that media multitasking is associated with more (severe) symptoms of ADHD, increased levels of self-reported problems related to behavior regulation and metacognition, and higher levels of sensation-seeking and risk-taking. At the same time, media multitasking is also associated with an increase of creativity and social success. However, the overall small effects were small and a large proportion of variance of media multitasking behavior is still unaccounted for.

Chapter 6

Media-induced Distractions

Note: This chapter is currently under review in *Journal of Cognition* as: Wiradhany, W., Mathôt, S., & Nieuwenstein, M.R. (*in prep.*). Investigating the Mere-presence Effect of Mobile Phones in an Antisaccade Experiment.

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All research material used in this article is available at the Open Science Framework: https://osf.io/4kbnu/.

Abstract

Mobile phones are ubiquitous, and recent studies have shown that their mere presence might be taxing to task performance. We tested the mere-presence effect of mobile phones and its potential underlying mechanism in an antisaccade experiment in which we positioned two objects, one on each side of a computer monitor. The flanking objects could be two 3D-printed phones (Phone absent) or a combination of one 3D-printed phone and the participant's own mobile phone. Thus, participants could make a saccade either toward (Phone present-congruent) or away from (Phone present-incongruent) their own phones. We found a sizeable antisaccade effect: Participants made more saccade errors and started their eye movements later in the antisaccade block. Importantly, participants made more saccade errors in the Phone-present condition, indicating a mere-presence effect. This mere-presence effect occurred regardless of whether participants performed anti- or prosaccades. Participants also made fewer errors in the phone-congruent trials in the prosaccade condition and they made slower saccades in phone-congruent trials. Therefore, our results suggest that while mobile phones attract spatial attention, participants might also have a tendency to avoid looking directly at their phone. Accordingly, we propose that the mere-presence effect of mobile phones might be associated with an interference with task performance, which leads to a performance decrease regardless of task difficulty. In addition, our results show some evidence suggesting that the allocation of spatial attention might be biased toward the location of one's phone.

Keywords: mobile phones, antisaccade, mere-presence, spatial bias, attention

Introduction

Mobile phones are ubiquitous. In the United States alone, about 95% of the population owns a mobile phone, of which around 77% are smartphones (PEW Research Center, 2018). Adolescents and young adults, in particular, are more likely to own a mobile phone compared to other demographic groups (Anderson, 2015; PEW Research Center, 2018). In principle, these affordable, yet powerful devices afford multiple activities that can help us become more productive (Hanson, 2007). At the same time, however, one may ask to what extent media technologies in general and the constant presence of our mobile phone in particular might affect our capabilities in processing information (Bavelier et al., 2010).

Interacting with a mobile phone while doing another task is associated with a performance cost. For instance, in driving simulation studies, interacting with a mobile phone is associated with increased latency of breaking and an increased likelihood of missing important traffic signals (Horrey & Wickens, 2006; Strayer & Johnston, 2001). In an educational setting, interacting with phones interferes with learning (Chen & Yan, 2016; David, Kim, Brickman, Ran, & Curtis, 2014), and interacting with phones while attending lectures is associated with a short- and long-term decrease in academic performance: Students who accessed their phones during lectures retained less lecture content (Wood et al., 2012) and had lower GPA at the end of the academic semester (Junco & Cotten, 2012; Lepp, Barkley, & Karpinski, 2014). These results are perhaps unsurprising for cognitive scientists, since the performance cost can be attributed to the additional task (i.e., interacting with a mobile phone) that has to be done in addition to the primary task (Aagaard, 2015; Chen & Yan, 2016). Yet, for laypersons, these results might be upsetting since people generally tend to overestimate their ability to do two things at once in different settings (Sanbonmatsu, Strayer, Medeiros-Ward, & Watson, 2013; Schlehofer et al., 2010).

Recently, however, studies have also shown that even the mere-presence of a mobile phone might be associated with a performance cost. That is, the presence of a mobile phone might also be detrimental to task performance even if one is not actively using the phone. The studies showing this effect used a between-subject design; they compared task performance of participants in a condition in which a mobile phone was present with performance of another group of participants who were in a condition in which a mobile phone was absent or replaced by another object. Przybylski and Weinstein (2012) found that under the mere presence of a mobile phone, as opposed to a notebook, pairs of participants who had casual (Exp. 1) and meaningful (Exp. 2) conversations reported subjectively lower conversation quality. Specifically, participants reported lower levels of closeness and connection with their conversation partners when a mobile phone was present. Similarly, Thornton, Faires, Robbins, and Rollins (2014) found that the mere-presence of mobile phones in both a dyadic setting (Exp. 1) and a classroom setting (Exp. 2) was associated with reduced performance on a Trail making test and an Additive digit-cancellation task. However, the same participants did not perform worse on an easier version of the Trail making test and a simple digit-cancellation task. It thus appears that the mere-presence of a mobile phone is associated with cognitive processing costs but only in a (more) challenging situation: When the tasks are more difficult (Thornton et al., 2014) and when the conversations are more meaningful.

Two studies have tried to further elucidate the mechanisms underlying the mere-presence effect of mobile phones. Ward, Duke, Gneezy, and Bos (2016) proposed that the mere-presence of a mobile phone might deplete available cognitive resources, particularly those associated with attention. That is, the presence of a personally relevant stimulus (i.e., the mobile phone) could be associated with an increase of activation of a specific goal-directed behavior (e.g., checking the phone). Since participants would therefore allocate a part of their attentional resources to attend to the phone, less resource would be available to deal with the task at hand, thus decreasing task performance. In their first experiment, Ward et al. tested this idea for two domains of cognition which are supposed to suffer from limited attentional resources, namely Working Memory Capacity and Fluid Intelligence (Engle, Tuholski, Laughlin, & Conway, 1999). Specifically, they manipulated the distance between participants and their phone and expected a stronger effect in the condition in which the distance between participants and their phone was closer. Specifically, the phone was either located on the same desk on which the experiments were conducted, it was left in the participant's pocket/bag, or it was placed in another room. Results showed that, indeed, in the high-salience condition (i.e., phone on the desk), participants performed worse on an OSPAN task and on the Raven's matrices task, which measured working memory capacity and fluid intelligence, respectively. To test whether these findings indeed reflected a consequence of a reduced availability of attentional resources, Ward et al. also contrasted performance of participants over two tasks with varying levels of dependence to attentional resources, the OSPAN task (high level) and the Go/No-go task (low level). Indeed, the results showed that in the high-salience condition, participants performed worse in the OSPAN task, but not in the Go/No-go task. Based on these findings, Ward et al. concluded that the mere-presence of one's mobile phone negatively affects task performance due to the depletion of available attentional resources.

In contrast to the findings and conclusions of Ward et al. (2016), Ito and Kawahara (2017) proposed that people perform worse under the mere-presence of mobile phones due to shifts of overt attention towards the phones. That is, the mere-presence of mobile phones was proposed to bias participant's overt attention to a certain location (i.e., where the phone is) and the magnitude of this effect was hypothesized to depend on one's level of internet addiction. Specifically, Ito and Kawahara reasoned that the phone might serve as a spatial cue for attention, thereby facilitating search if the target appears near the phone. To test these hypotheses, Ito and Kawahara asked participants to perform a visual search task in which the target could appear in a location that was either congruent or incongruent with where a mobile phone or notebook was placed relative to the visual search display. They found a mere-presence effect: Participants who performed the task in the presence of a mobile phone were slower in detecting the target than participants who performed the task in the presence of a notepad. They did not find a spatial bias effect: Participants did not detect the target slower or faster when it appeared in a congruent location with the phone. However, the authors did find a trend towards a phone congruence × internet addiction interaction effect on visual search reaction time (RT). Specifically, participants with higher internet-addiction scores had lower RT means in the phone-congruent condition than phone-incongruent condition, which implies that they were faster in detecting targets which appeared in a congruent location with the phone.

While Ito and Kawahara (2017) did not find a phone congruence effect (all *p*'s>.08), the idea was nevertheless compelling, and it would be interesting to test the spatial bias effect more rigorously. To elaborate, mobile phone might facilitate and or reduce task performance. Facilitating task performance, mobile phones might act as a spatial cue which would help detecting targets faster when these targets are presented near the phone. A prime example of this effect can be found in findings from the classical Attention Network Task: in orienting attention, response times for cued targets are faster than that of uncued target (Fan, McCandliss, Sommer, Raz, & Posner, 2002). In contrast, mobile phone might serve as a distractor and therefore reducing task performance in phone-congruent trials. For instance, it has been found that eye movement trajectories deviated away from the location of distractors, even in cases in which the distractors were only expected to occur at a certain location, without actually being presented there (van der Stigchel & Theeuwes, 2006). In two experiments in which participants had to make speeded eye movements toward the location of a target which could appear with a nearby distractor in 80% of the trials, they found that participant's eye movements deviated away from the location of the distractor, even when the distractor was only expected to be presented at that location. In the case of mobile phones, it could thus be that spatial attention is repelled away from the location of the phone, and this may decrease task performance.

Taken together, the current body of evidence suggests that the mere-presence of a mobile phone may be distracting because it is associated with a depletion of central attentional resources, and because it induces a spatial bias of attention towards the location of the phone. To shed light on the mere-presence effect, here we conducted an antisaccade experiment (Everling & Fischer, 1998; Hutton & Ettinger, 2006; Munoz & Everling, 2004) in which we positioned two objects adjacent to a computer monitor. The flanking objects could be two 3D-printed phones (Own-Phone absent); or one of the phones was a 3D-printed phone whereas the other was the participant's own mobile phone (own-phone Present). Thus, participants had to make a speeded eye movement (i.e., a saccade) either toward (own-phone present, congruent) or away (cwn-phone present, incongruent) from their own phone. This allowed us to test the mere-presence effect, i.e., the effect of phone presence regardless of its position as well as the spatial bias effect, i.e., the effect of phone congruence relative to the eye movement.

The antisaccade task was chosen because it provides a metric of volitional control over behavior (Everling & Fischer, 1998; Hutton & Ettinger, 2006; Munoz & Everling, 2004). In the antisaccade task, participants are presented with a visual cue that appears in their peripheral vision. In the prosaccade condition, they are instructed to make saccades toward the cue, whereas in the antisaccade condition, they are instructed to make saccades to the location opposite from the cue. A successful antisaccade reflects two different processes: The inhibition of the reflexive prosaccade and the (voluntary) initiation of eye movement toward the opposite direction (Munoz & Everling, 2004). Importantly, antisaccade executions have been associated with functions which are related to availability of cognitive resources, namely goal activation (Nieuwenhuis, Broerse, Nielen, & de Jong, 2004) and working memory (Unsworth, Schrock, & Engle, 2004).

The demand on volitional, goal-driven processing is greater for antisaccades, and stronger mere-presence effects have been found in more challenging tasks. Therefore, we predicted that, when their phone was present as compared to absent, participants would make more errors and have a higher saccade latency, especially when performing antisaccades. In addition, if mobile phones serve as a spatial cue, the spatial bias hypothesis predicts fewer errors and faster saccades towards the participant's phone, compared to away from it. If mobile phones serve as a distractor, the hypothesis predicts more errors and slower saccades towards the participant's phone. We did not have a clear hypothesis as to whether this spatial bias effect would differ between pro- and antisaccades.

Additionally, in a set of exploratory analyses, we also included questionnaires for measuring the participants' engagement to their phone (Weller, Shackleford, Dieckmann, & Slovic, 2013) and for media multitasking – that is, the tendency to use more than one type of media device at the same time (Baumgartner et al., 2014; Ophir et al., 2009) – to evaluate whether any effect of phone-presence and congruence might relate to the level of attachment to phone and to media multitasking habits. The results of these exploratory analyses are reported in the supplementary materials of this document.

Methods

Participants

Twenty-four undergraduate students (14 females, M_{age}=20.38, SD_{age}=1.61) with normal or corrected vision participated in this study in exchange for course credits. The study was approved by the Ethical Committee of the Psychology department, the University of Groningen. All participants provided informed consent prior to participating to this study.

Materials and Equipment

Mobile phones. We asked participants to bring their own mobile phone for the experiment. To evaluate to what extent a participant's own mobile phone induces a mere-presence effect compared to other objects, we created 3-D printed mobile phones as control objects. These 3D phones were available in black and white to match the color of the participant's phone.

Antisaccade task. The antisaccade task was presented on a 22” LCD monitor screen with a refresh rate of 60 Hz and a resolution of 1600 x 900 pixels. Stimuli were generated and presented using OpenSesame (Mathôt et al., 2012) and eye movements and pupil size were recorded using the EyeLink 1000 camera with a sampling rate of 1000 Hz.

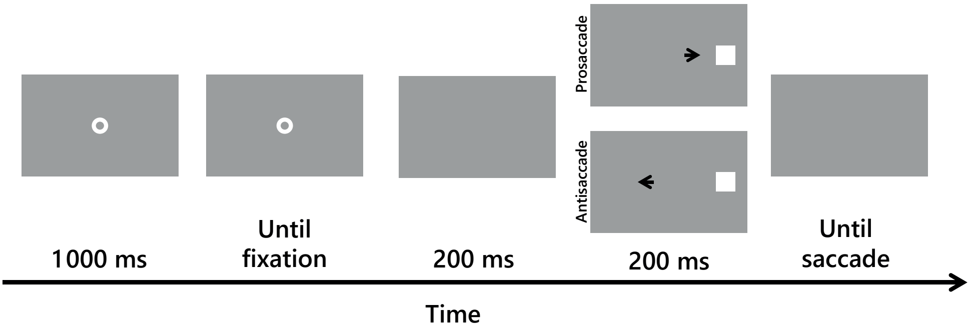

Figure 6.1. The schematic presentation of the trial sequence. The arrows indicate the desired directions of the eye movements and are not visible to the participants.

Figure 6.1 shows the sequence of events in a trial. The trial started with a fixation dot against a grey screen. Upon detecting fixation, the dot remained visible for another 1000 ms, followed by a grey canvas for another 200 ms. Following this display, a white, 64 × 64 pixels square was presented for 400 ms at one of six possible locations along the horizontal axis, positioned 500, 600, or 700 pixels to the left and to the right of the center of the display.

Data-collection setting. Participants were individually tested in a windowless, dimly lit (~15 lx of ambient light) laboratory. They were seated at a desk and were asked to put their heads on the chinrest during the experiment. The chinrest was positioned 70 cm away from the monitor and about 45 cm from the eye tracker that was positioned on the desk. A desk separator was positioned behind the monitor to limit the participant’s view of the rest of the laboratory (see Figure 6.2). The experimenter sat behind the participant during the data collection to record the occurrence of phone notifications.

Mobile-phone attachment questionnaire. The mobile-phone-possession-attachment questionnaire (Weller et al., 2013) consists of five questions which aim to estimate one’s level of attachment to one’s phone. The questions are answered using a 5-point likert scale. The scores are summed, with larger scores showing a higher degree of attachment to one's mobile phone.

Media multitasking questionnaire. Media multitasking was measured using the short version of the Media-Use Questionnaire (Baumgartner, Lemmens, et al., 2017). The questionnaire includes nine questions that ask participants to indicate how often they consume one type of media (e.g., IMing) while using another (e.g., watching television) on a 4-point Likert scale. The resulting scores are averaged, creating the Media Multitasking-Short (MMS) index. A higher index indicates that participants more frequently engage in media multitasking while using media.

Design and Procedure

Upon providing informed consent, participants were instructed to perform an antisaccade task on a computer. The pro- and antisaccade trials were presented in different blocks. In the prosaccade block, participants were instructed to make a saccade toward the location of the white-square cue and in the antisaccade block, participants were instructed to make a saccade toward the opposite, equidistant location from the cue on the horizontal axis. Participants completed 12 practice trials of each pro- and antisaccade block prior to the data collection. Each pro- and antisaccade block consisted of 90 trials.

The presence of participant's own mobile phone was manipulated in three separate blocks. In the Phone-absent block, two 3-D printed phones that matched the color of the participant's phone were positioned on small pedestals flanking the sides of the monitor at eye-level height. During this block, the experimenter put the participant's mobile phone on a desk behind the desk separator, outside of the participant's view. In the Phone-present blocks, the participant's own mobile phone was positioned either to the right or to the left of the monitor while a 3-D printed phone of the same color was positioned at the opposing side (see Figure 6.2). In the analysis, we matched the location of participant's own phone with the saccade-target location to contrast the trials in which the saccade had to be made towards a location congruent or (Phone present-congruent) or incongruent with the location of the participant's own phone (Phone present-incongruent). Together, this yielded a 2 (Pro- and Antisaccade) × 3 (Phone absent, Phone present-congruent, Phone present-incongruent) full factorial, within-subjects design. Participants completed 540 trials in total.

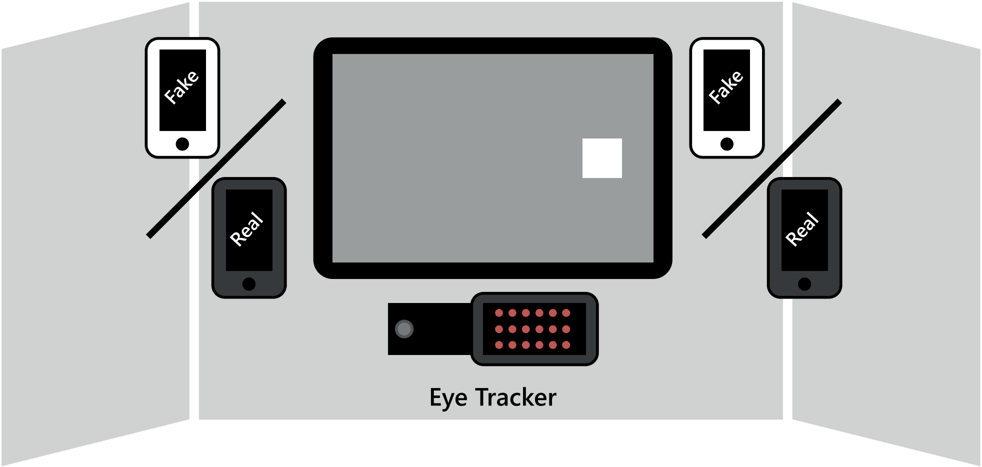

Figure 6.2. The experiment setup. The phones were positioned on top of small pedestals (not shown) and they could be a combination of two 3-D printed phones, the participant's own phone on the left and the 3-D printed phone on the right, or the 3-D printed phone on the left and the participant's own phone on the right.

Participants received no explicit instruction with regard to the status of their phone (e.g., silent, with vibration, with tones). If prompted, the experimenter would instruct the participant to keep their phone status 'as it usually is, during the day.' However, the experimenter took note whenever participants received apparent notifications during the experiment.

Analysis

Preprocessing. The raw eye-movement data was downsampled to 100 Hz and corrected for drifts. A saccade was defined as an eye movement along the x-axis which spanned more than half the distance toward the target location, relative to the center of the display. Accuracy was determined by examining whether a saccade occurred toward or away from the target location, with the former being considered a correct saccade. Saccade latencies were defined as the time point at which the eye movement reached more than halfway toward the target or non-target location, relative to the center point of the monitor.

Eye traces on the horizontal axis were mirrored so that positive values indicated correct eye movements and negative values indicated incorrect eye movements (see Figure 6.3A-D and Figure 6.4A-D).

Hypothesis testing. We tested our hypotheses by constructing Linear Mixed Models using the lme4 package (Bates et al., 2015) in R 3.5.0 (R Core Team, 2017). Significant effects were determined by the p-values, which were computed using the lmerTest package (Kuznetsova, Brockhoff, & Bojesen, 2018). To test the mere-presence and spatial bias hypotheses separately, we made a planned comparison in lmer in which we calculated the differences in saccade accuracy and latency for the pro minus antisaccade blocks, for phone present minus phone absent, and for phone congruent minus phone incongruent. The advantage of using a planned comparison compared to a traditional regression analysis is that it allows for testing nested effects; that is, it allowed us to compare phone-absent with phone-present trials (while collapsing over congruent and incongruent trials), as well as congruent with incongruent trials (while ignoring phone-absent trials). We set a significance criterion threshold of .05. All significant and non-significant effects are reported.

Results

Data Preprocessing

Trials in which participants did not make a saccade, or in which saccade latency was less than 50 ms, or in which participants received a notification were removed (8.6% of trials; .2% due to incoming notifications). No participants were removed from the final analysis. For saccade latencies we analyzed correct trials only.

Tests of the Difference between Pro- and Antisaccade Conditions

To evaluate whether performance differed between the pro- and antisaccade blocks, we constructed two linear mixed models to examine effects of Saccade type on Saccade errors and Saccade latencies separately. In these models, the difference between pro and antisaccade trials was tested as a fixed effect, and we included Saccade type × Subjects as a random slope, and Target position as a random intercept. Overall, we replicated the classic antisaccade effects. Participants were more likely to make erroneous saccades in the antisaccade condition than in the prosaccade condition, z=10.57, p<.001. In addition, saccade latencies were slower in the antisaccade blocks, t=-17.98, p<.001. Erroneous saccades had faster latencies than correct saccades regardless of the saccade types, t=-17.92, p<.001.

Test of Mere-Presence Effects

To test whether participants made more saccade errors and slower saccades when their phone was present, we constructed two models: one with only main effects of Saccade Type and Phone presence, and one that also included the Saccade type × Phone presence interaction. These models had Saccade type × Subjects as a random slope, Target location (at different eccentricities) as a random intercept, and Saccade errors and Saccade latencies as the outcome variables. To determine whether the Saccade type × Phone presence interaction was significant, we then compared the model fit of both models using the chi-square goodness of fit test.

With regard to Saccade errors, the Saccade type × Phone presence interaction was not significant, $\chi^2(1)=0.22$, $p=.641$. However, there was a main effect of Phone presence, such that participants were more likely to make Saccade errors when their own mobile phone was present, $z=2.48$, $p=.013$ (Figure 6.3E). With regard to Saccade latency, the interaction was again not significant, $\chi^2(1)=0.02$, $p=.895$. There was also no main effect of phone presence on saccade latencies, $t=1.48$, $p=.139$ (Figure 6.3F).

Together, the results showed that participants made more saccade errors in the conditions in which their phone was present, but this effect occurred regardless of whether participants made pro or antisaccades. Additionally, we found no effect of phone presence on saccade latency.

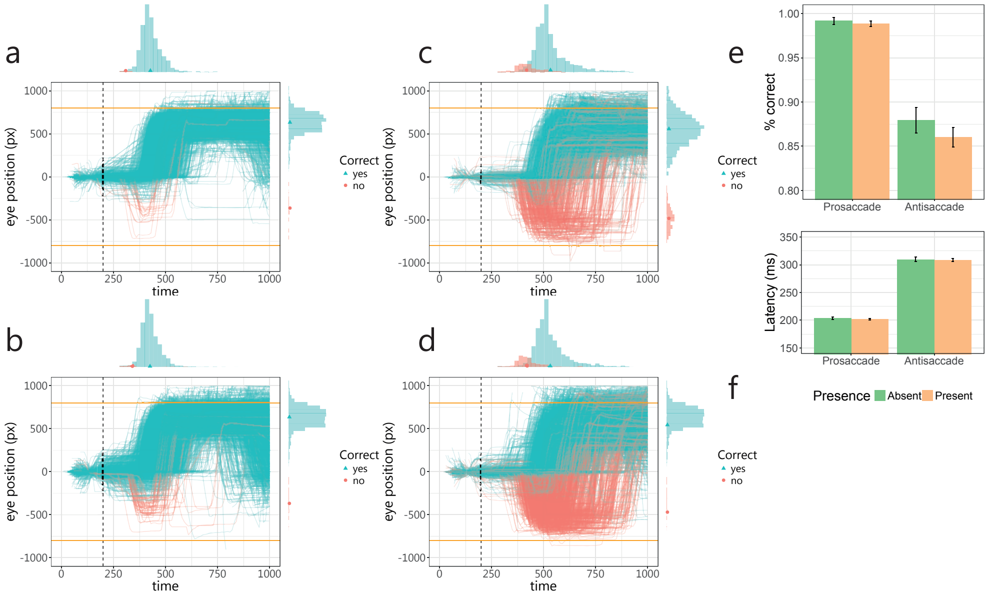

Figure 6.3. Eye-movement traces comparing the results across conditions for the raw (A-D) and averaged (E-F) data. The raw eye-movement traces are shown for the Prosaccade-Phone present (A), Prosaccade-Phone absent (B), Antisaccade-Phone Present (C), and Antisaccade-Phone Absent (D) conditions. The different colors reflect correct and incorrect saccades; the dashed line indicates the time at which the target was shown; the orange horizontal lines indicate the horizontal boundaries of the monitor. The blue and red histograms shown above each graph show the latency distributions of correct and incorrect saccades, respectively, and the blue and red dots show the mean latencies of correct and incorrect saccades, respectively. On the right-hand side of graph, the blue and red histograms show the amplitude distribution of correct and incorrect saccades, respectively and the blue and red dots show the amplitude means of correct and incorrect saccades, respectively. The average plots show saccade accuracy (E) and correct saccades latency (F) over different phone presence conditions. The error bars denote the 95% confidence intervals of the means.

Tests of Spatial Bias Effects

The spatial bias hypothesis predicts that participants make fewer saccade errors and faster saccades when making eye movements towards compared to away from their phone, if mobile phones serve as a spatial cue, or it predicts that participants make more saccade errors and slower saccades when making eye movements towards their phone, if mobile phones serve as a distractor. This effect might interact with saccade type as well, although we had no clear hypothesis about this. To test this, we compared two models for those trials in which the participant's phone was present: one with only main effects of Saccade type and Phone congruence, and one with also a Saccade type × Phone interaction. These models had Saccade type × Subjects as a random slope, Target location as a random intercept, and Saccade errors and Saccade latencies as the outcome variables. To test whether the Saccade type × Phone congruence interaction was significant, we then compared the fit of both models using the chi-square goodness of fit test.

With regard to Saccade errors, there was a significant Saccade type × Phone congruence interaction, $\chi^2(1)=3.89$, $p=.048$. This interaction was driven by the presence of a significant congruence effect for the Prosaccade Block, with more saccade errors in the Phone-incongruent than Phone-congruent condition, $z=2.00$, $p=.045$, whereas this effect was not observed in the Antisaccade block, $z=-0.36$, $p=.719$ (Figure 6.4E). In other words, participants were more accurate in making eye movements toward the position of their phone in the prosaccade block. With regard to Saccade latency, the Saccade type × Phone congruence interaction was not significant, $\chi^2(1)=0.03$, $p=.869$. There was a significant main effect of Phone congruence: Participants made faster saccades away from, as compared to towards, their phone, $t=2.17$, $p=.029$ (Figure 6.4F). In other words, participants were slower in making eye movements toward the position of their phone.

Together, these results show that participants were more accurate in making saccades towards their phone in the prosaccade block. At the same time, however, the results also show that participants made faster eye movements away from their phone, regardless of saccade type.

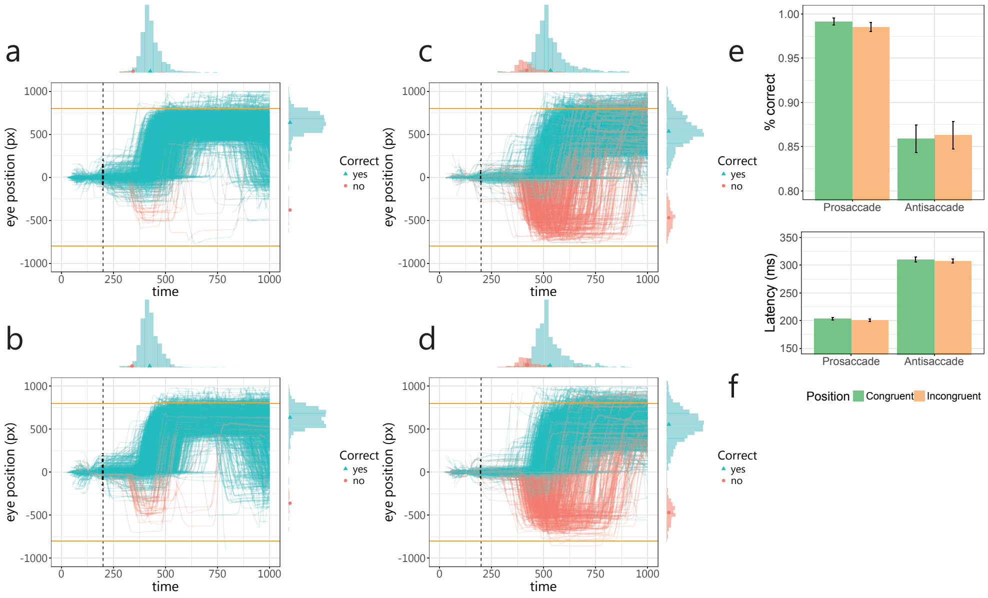

Figure 6.4. Eye movement traces comparing the results in raw (A-D) and averaged (E-F) scores. The raw eye movement traces are shown for the h the Prosaccade-Phone congruent (A), Prosaccade-Phone incongruent (B), Antisaccade-Phone congruent (C), and Antisaccade-Phone incongruent (D) conditions. The different colors reflect correct and incorrect saccades; the dashed line indicates the time in which the target was shown; the orange horizontal lines indicate the horizontal boundaries of the monitor. On top of each traces cell, the blue and red histograms show the latency distribution of correct and incorrect saccades, respectively and the blue and red dots show the latency means of correct and incorrect saccades, respectively. On the right-hand side of each traces cell, the blue and red histograms show the amplitude distribution of correct and incorrect saccades, respectively and the blue and red dots show the amplitude means of correct and incorrect saccades, respectively. The rows in the averaged plots show saccades accuracy (E) and correct saccades latency (F) over different phone position conditions. The error bars denote the 95% confidence intervals of the means.

Discussion

Previous studies showed that the mere presence of a mobile phone was associated with worse task performance, and that this might be due to either the depletion of attentional resources, or to a spatial bias of attention towards or away from the location of the phone. With regard to spatial bias, we proposed that this could either facilitate or reduce task performance. We tested these hypotheses in an antisaccade experiment in which participants made eye movements while their own phone was either absent or present (attached to the side of the display), at a location that was either congruent or incongruent with the saccade-target location. We hypothesized that 1) performance in the antisaccade blocks would be more strongly impaired by the mere-presence of a mobile phone than performance in the prosaccade blocks, and that 2) performance would be facilitated or disrupted in trials in which participants had to make saccades toward their phone, since the phones might induce a spatial bias toward or away from their location, respectively. We found partial support for both hypotheses. With regard to the mere-presence effect, participants made more saccadic errors under the presence of their own phones, but this occurred regardless of saccade type and there was no effect of phone presence on saccade latency. With regard to the spatial bias effect, participants made fewer errors in making saccades towards their phone in the prosaccade blocks. However, they also made slower saccades toward their phone. In addition, our exploratory analyses reported in the supplement showed that both the mere-presence and the spatial bias effects were modulated by participant's level of media multitasking. Frequent media multitaskers made faster saccades in the phone-present conditions and in the phone-congruent trials, but the error rates did not differ across conditions. Together, these findings show that the presence of the phone introduced a general reduction in saccade accuracy. On the other hand, the results for our tests of the spatial bias hypotheses appeared to be inconsistent, such that we found opposing results for error rates and latency, with the former suggesting that the location of the phone attracted attention whereas the latter suggested that attention might have been repelled away from the location of the phone.

Our results provided partial support for the mere-presence hypothesis, and are somewhat consistent with earlier findings: Compared to a condition in which a phone was absent or replaced by another object, people performed worse under the mere-presence of their phones (Ito & Kawahara, 2017; Przybylski & Weinstein, 2012; Thornton et al., 2014; Ward et al., 2016). At the same time, our mere-presence findings were somewhat different from the ones reported in the literature and from our initial predictions. We expected that the mere-presence of the participant's mobile phone would disrupt task performance more strongly in the antisaccade than in the prosaccade blocks. This was for two reasons. First, previous studies showed that the mere-presence effect occurred only when participants had to perform a cognitively demanding task (Thornton et al., 2014). Second and more importantly, performance on antisaccades, but not on prosaccades has been associated with higher-order cognitive functions such as goal maintenance (Nieuwenhuis et al., 2004) and working memory (Unsworth et al., 2004), although some studies have also found error rates in both in pro- and antisaccade trials to be associated with a successful implementation of goal-directed behavior (Barton, Pandita, Thakkar, Goff, & Manoach, 2008; Bowling, Hindman, & Donnelly, 2012). Thus, we expected that if the presence of participant's own mobile phones would result in an increase of cognitive load (e.g., as proposed by Ward et al., 2016), task performance would decrease in the anti- but not in the prosaccade blocks. We indeed observed that the magnitude of the mere-presence effect in our experiment was larger in the anti- compared to the prosaccade blocks, but this difference was not reliable.

We found mixed evidence for the spatial bias effect. On the one hand, the location of the participant's own mobile phone seems to facilitate task performance in the prosaccade blocks since participants made fewer errors in making saccades toward their phone. On the other hand, the location of participant's own mobile phone seems to disrupt task performance as well: Participants made slower saccades toward their phone. Therefore, mobile phones seem to both facilitate and disrupt task performance. It could be the case that two independent attention mechanisms were involved in this process. The participant's own mobile phone might act as a cue for the orientation of attention (Fan et al., 2002; Posner, 1980), therefore facilitating congruent saccades. At the same time, eye movements in congruent trials might also invoke a conflict between creating a correct saccade (i.e., looking at the target location) and trying to avoid looking directly at the phone. In other words, participants want to perform a correct saccade and at the same time try to avoid looking directly at their phone. Supporting this idea, our additional analysis on the amplitude gains (i.e., the ratio between desired and actual saccade amplitudes) showed that the gains for congruent trials were smaller than that of the incongruent trials, and this effect was driven by smaller amplitude gains in the antisaccade blocks. This indicates that our participants tried to avoid overshooting the target location in the phone-congruent trials. This result was in line with what was reported in Van Der Stigchel and Theeuwes (2006) that eye movement trajectories deviated away from the location of an actual or expected salient distractor.

The above said, the magnitude of the mere-presence effect in our experiment was also relatively small (*t*'s < 2.49). The small effect size might be due to several reasons. We contrasted the effect of the participant's own mobile phones to that of a 3D printed phone, rather than a different type of object, as a control object. In addition, we used a within-subject as opposed to a between-subjects design, and in the phone-absent condition, the phone was still located in the testing room, creating the possibility to produce notifications [24]. Altogether, the participants in our study were likely aware that it was the mere-presence and location of their mobile phone that were manipulated, and our manipulation of the mere-presence effect was weaker than that in previous studies since the participant's own phone remained present in the same room in our phone-absent conditions. Thus, the small effect size could be interpreted as evidence for the robustness of the mere-presence effect; we still observe an effect in spite of the possibility that participants might have been aware about the mere-presence of mobile phones being manipulated.

In summary, in an antisaccade experiment, we showed that the mere-presence of one's own mobile phone might be detrimental to task performance. The mere-presence of the participant's mobile phone increased the number of errors in both pro- and antisaccade blocks. Mobile phones might attract spatial attention as well, as eye movements toward the location of the mobile phones were somewhat facilitated, perhaps while participants at the same time tried to avoid looking directly at their phone. Considering that our findings suggest that the mere-presence of one's mobile phone has the potential to disrupt task performance, readers might want to consider restricting the presence of mobile phones, especially in situations in which one needs to maintain adequate level of task performance.

Supplementary Materials

Tests of Target-eccentricity Effects.

Prior to constructing the linear mixed models, we tested whether Target eccentricity had any effects of interest. To test the presence of any such effects, we constructed a repeated-measures ANOVA with Saccade type (pro vs. antisaccade), Target eccentricity (the distance from the center of the display), Phone Condition (i.e., Phone-absent, Phone-present

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[24] This was not the case: The experimenter did not note any perceivable notifications during the phone-absent condition for all participants.

congruent, and Phone-present incongruent) as within-subject factors and Saccade errors and Saccade latency as the outcome measures. The results showed that for saccade accuracy, Target eccentricy did not interact with Saccade type, $F(2, 391)=1.88$, $p=.154$, nor with Phone Condition, $F(4, 391)=0.36$, $p=.834$, and there was also no Target position × Saccade type × Phone Condition interaction, $F(4,391)=0.41$, $p=.799$. For saccade latency, we found a Target eccentricity × Saccade type interaction, $F(2, 391)=7.06$, $p<.001$, but importantly, we found no Target eccentricity × Phone Condition interaction, $F(4, 391)=0.14$, $p=.969$, and there was also no Target position × Saccade type × Phone Condition interaction, $F(4,391)=0.79$, $p=.532$. Therefore, we did not further consider Target eccentricity as a fixed effect for the analyses reported in the main text.

Phone Attachment and Media Multitasking Effects

Attachment to mobile phones. To test whether Attachment to mobile phones interacted with either Phone presence or Phone position, we categorized the participants based on their Attachment level into low (quartile 1 of the Attachment to mobile phones score distribution; N=10), intermediate (quartiles 2 and 3 of the distribution; N=9), and high (quartile 4 of the distribution; N=5) groups. We constructed two models, one with only main effects of Phone presence and Phone congruence, and one with Attachment × Phone presence and Attachment × Phone congruence, respectively. These models had Saccade type × Subjects as a random slope, Target position as a random intercept, and Saccade errors and Saccade latency as the outcome variables. To determine whether the interaction was significant, we evaluated the model fit using the chi-square goodness of fit test.

We found no Attachment × Phone presence interaction effect on Saccade errors and Saccade latency all $\chi^2<2.92$, all p's>.271. We also found no Attachment × Phone congruence interaction effect on Saccade errors and Saccade latency, all $\chi^2<.99$, all p's>.646. There results indicate that the magnitude of the Phone presence and Phone congruence effects did not vary as a function of one's Attachment to mobile phone.

Media multitasking. To test whether individual differences in media multitasking related to the effects of Phone presence or Phone position, we categorized the participants based on their MMS level into low (quartile 1 of the MMS distribution; N=9), intermediate (quartiles 2 and 3 of the distribution; N=10), and high (quartile 4 of the distribution; N=5) groups, and we constructed models with Media multitasking × Phone presence and Media multitasking × Phone congruence interaction and compared them with the models with Phone presence and Phone congruence as main effects. These models had Saccade type × Subjects as a random slope, Target location as a random intercept, and Saccade errors and Saccade latencies as the outcome variables. We used the chi-square goodness of fit test to determine whether or not the interaction was significant.

We found an MMS × Phone presence interaction on Saccade latency, $\chi^2(2)=30 .81$, $p<.001$, indicating that the effect of Phone presence varies as a function of one's level of media multitasking. Specifically, participants in the low MMS scores group were faster in making eye movements in the Phone-present condition, $t=-5.33$, $p<.001$. We also found an MMS × Phone congruence interaction on Saccade latency, $\chi^2(2)=30.81$, $p<.001$, indicating that the effect of Phone congruence varies as a function of one's level of media multitasking. Specifically, participants in the high MMS scores group were faster in making eye movements toward their phones, $t=-3.53$, $p<.001$. There was no MMS × Phone presence interaction on Saccade errors, $\chi^2(2)=2.61$, $p<.271$ and there were no MMS × Phone position interaction on Saccade errors $\chi^2(2)<3.93$, $p>.140$.

Chapter 7

General Discussion

Note: I thank Prof. Sander Nieuwenhuis and Dr. Susanne Baumgartner for their valuable input in our discussions on implementing the Adaptive Gain Theory in multitasking.

Summary of Findings

The studies presented in this thesis aimed to address three main questions: What constitutes media multitasking behavior, which domains of cognition and behavior differentiate heavy from light media multitaskers, and what is the extent to which the presence of media devices influences our ability to process information? In what follows, I outline the key findings from Chapters 2 to 6.

What Constitutes Media Multitasking Behavior?

As outlined in Chapter 2, I rendered the responses of Media Use Questionnaire (MUQ) into networks. The responses came from eight different datasets from samples that varied in age and geographical locations. The rendered networks showed that certain media combinations were more likely to be selected than others, and these combinations remained similar over samples of varying ages and geographical locations. The prominent combinations can be characterized by their adaptiveness (Z. Wang et al., 2015): These are combinations of media of which each medium draws from a different sensory modality (e.g., the visual and auditory modality, for instance texting while listening to music) and provide the users a certain degree of control over switching from one medium to another. Additionally, in responding to the questionnaire, participants did not make a distinction between primary and secondary media (i.e., there was no difference between watching television while texting and texting while watching television).

The rendered networks provided an important insight, namely that some media combinations are more prominent than others in media multitasking. Subsequently, instead of querying an overwhelming number of media (the original MUQ by Ophir, Nass, & Wagner, (2009) covers no fewer than 144 pairs of media), the MUQ can be shortened to a limited number of media combinations, as these combinations capture most of the variance of the larger set of media pairs (Baumgartner, Lemmens, et al., 2017). At the same time, it does not seem to be the case that in responding to MUQ questions participants considered which media was the main activity.

Minds of Media Multitaskers

In Chapters 3 and 4, I conducted small- and large-scale replication experiments and provided a meta-analysis on the association between media multitasking behavior and domains of cognition related to distractibility. The small-scale experiments, which aimed to replicate the findings of Ophir et al. (2009) showed that out of 14 critical findings reported in the original study, five could be replicated whereas the other nine showed null results. The large-scale experiment (N=261) aimed to resolve whether media multitasking is associated with distractibility related to the environment (i.e., external distraction) or to self-generated distractions (i.e., internal distraction). In this experiment, participants were required to encode the orientation of target objects while trying to ignore the distractor objects (external distraction) and we used thought-probes to determine to what extent participants were able to stay focused on the task during the experiment. The results showed that heavy media multitaskers (HMMs) did not perform worse in conditions in which the distractor objects were present. In addition and they did not report a lower focus of attention on the task during the experiment. These results indicate that media multitasking is not associated with external or internal distractibility. Consistent with this outcome, our meta-analysis of 39 tests of the association between media multitasking and external distractibility showed that the pooled effect size indicated a small effect in the direction of increased distractibility in HMMs (Cohen's *d*=0.17), but this effect disappeared upon accounting for study bias.

Together, the findings outlined in Chapters Three and Four indicate that media multitasking is not associated with distractibility. This is somewhat in contrast with a recent review which suggests that HMMs may experience increased attentional lapses, and that they thus perform worse in different tasks in which such lapses of attention are likely to occur (Uncapher & Wagner, 2018). Critically, however, the conclusions of this review were based on whether studies showed a difference in performance, regardless of the statistical significance of the effect in question. Thus, the conclusions of the review might have been based on an overestimation of the evidence in favor of the attentional-lapses account.

Behaviors of Media Multitaskers

In Chapter 5, I summarized findings in the literature which pertain to the association between media-multitasking behavior and self-reports of cognitive control, mental health, and personality traits. These self-reports were categorized in a series of mini-meta-analyses (Goh et al., 2016), that is, meta-analyses of a small number of studies pertaining to a similar theme.

The pooled effect sizes showed that HMMs have increased problems with behavior regulation and metacognition in everyday situations, more (severe) symptoms of ADHD, depression, and anxiety, and higher levels of impulsiveness and sensation-seeking traits. Overall, the pooled effect sizes were weak. They ranged between Fisher's z=0.15 to z=0.27. At the same time, there was a relatively low level of heterogeneity across studies, indicating that the findings were consistent across the different populations of participants that were sampled in the studies.

Overall, the mini-meta-analyses indicate certain behavioral characteristics which may demarcate HMMs from light media multitaskers (LMMs), namely the reported levels of behavioral regulation and metacognition, the reported (symptoms) of ADHD, depression, and anxiety-related symptoms, and the reported levels of impulsiveness and sensation-seeking traits. At the same time, while these correlates were statistically significant and robust across different populations, they accounted for a minimal amount of variance of the media multitasking behavior.

Media-induced Distractions

In Chapter 6, I evaluated the extent to which the presence of media devices interferes with our information processing (Thornton et al., 2014; Ward et al., 2016). In an antisaccade experiment, I instructed participants to make eye movements to a location that could be congruent or incongruent to the position of their mobile phone, and I compared performance with a condition in which the participant's phone was absent. Thus, I evaluated the effect of the presence of mobile phones in absence of direct interactions with it. I found that participants made more incorrect eye movements in the phone-present conditions, and especially in the less challenging condition (i.e., in the Prosaccade block), they made more correct eye movements if the target location was congruent with the location of their phone. This indicates that the mere-presence of mobile phones might be associated with a global cognitive cost (Ward et al., 2016), and additionally, the presence of mobile phone might also induce a spatial bias (i.e., because participants try to look at their phone more often; Ito & Kawahara, 2017).

In combination with my other findings, the mere-presence effect of mobile phones may demonstrate that while our interactions with contemporary media (i.e., the media-multitasking habit) might not interfere with our capabilities of filtering distractions, having a media device in view might still be distracting.

Media Multitasking: From Minds to Behavior

Together, the set of findings above suggest some characteristics of heavy and light media multitaskers. To start, the media multitasking behavior can be characterized by a rather limited set of media combinations, namely those with texting, browsing, listening to music, and accessing social media. Importantly, in responding to MUQ questions, participants did not seem to distinguish primary from secondary media activities. With regards to the correlates of the MMI, heavy, compared to light media multitaskers might not perform worse under externally-presented and internally-generated distractions, yet heavy media multitaskers reported more problems with regards to behavior regulations and metacognition, they reported more (severe) symptoms of ADHD, and higher impulsiveness and sensation-seeking traits. Lastly, having a mobile phone in view might be distracting, which suggests that the presence of media devices might influence task performance.

At present, the findings presented in the empirical chapters of this thesis can be said to be mixed. On the one hand, media multitasking, as assessed with the MUQ, was not correlated with laboratory task performance related to filtering distractions. On the other hand, media multitasking was correlated with higher self-reports of distractibility in everyday situations, and higher levels of mental health problem and psychological traits associated with distractibility, namely ADHD and impulsiveness, respectively. Why was this case? One consideration would be that these mixed findings relate to the difference in the performance level measured in performance-based tasks and self-reports. As alluded in Chapter 5, performance-based tasks measure one' efficiency in processing information while self-reports measure one's ability to successfully pursue a goal (see also Toplak et al., 2013). Therefore, although HMMs might experience more difficulties in monitoring and managing different thoughts, emotions, and actions in everyday situations (i.e., goal pursuits), this does not mean that they would also suffer from media-related or environmental distractions when they are required to stay on task (i.e., information processing efficiency), especially since in most of these tasks, the goals are relatively clear (e.g., which stimuli to be attended, which ones to be ignored). It could be the case that HMMs have an optimal task-performance level in the performance-based tasks since the goals of the task are clear, yet still experience problems in everyday situations, where they have to manage the goals themselves.

Another alternative to explain the mixed findings would be related to the types of behavior sampled in the MUQ. At present, as shown in Chapter 2, users do not seem to distinguish primary from secondary media activities in responding to the questionnaire. This might indicate that in considering the media pairs, they do not take into account which media is the main task and which one is a distraction. It would be interesting to investigate whether sampling media multitasking behaviors in which the distinction between primary and secondary tasks is clear (e.g., texting while driving) would result in a higher media multitasking-self reports of distractibility correlation and importantly, a correlation between media multitasking and task performance related to distractibility in the laboratory.

Yet another alternative to explain the mixed findings would be that at present HMMs are comprised of "good" and "distracted" multitaskers: Those who have a good multitasking skill and therefore, tend to frequently combine multiple media streams and those who combine multiple media streams because they are driven to it due to their proneness to distraction, respectively. This distinction that there exist good and distracted subgroups of heavy media multitaskers might provide a critical explanation to why some studies found a correlation between MMI and task performance while others, as outlined in Chapters 3 and 4, did not. In what follows, I propose a theoretical framework for explaining the individual differences in media multitasking, which might be proven to be invaluable for explaining why certain types of media multitasking behavior might be correlated with task performance both in the lab and in everyday situations (Baumgartner, van der Schuur, et al., 2017; Uncapher & Wagner, 2018). Additionally, I will present what this framework predicts for "good" and "distracted" multitaskers in term of task performance in more details. I hope this framework will help the field to move forward.

Everyday multitasking, that is, rapidly switching back and forth from one activity to another, can be broadly categorized into two types of behavior: Within-task exploitations and between-tasks explorations. Within-task exploitations are behaviors that relate to the goals of the current task at hand, and they help the organism to stay engaged to the task. Between-task explorations, on the other hand, are behaviors that relate to finding potential new goals and resources, and they help the organism to disengage from the current task. Keeping the balance between these two types of behavior is considered to be adaptive (Cohen, McClure, & Yu, 2007; Inzlicht, Schmeichel, & Macrae, 2014; Nieuwenhuis, Aston-Jones, & Cohen, 2005), since one's environment, which includes current goals and resources, might be limited. Therefore, there can be a benefit for switching from exploiting current resources to exploring for new ones. Recently, the biological system which seems to play a major role in regulating this so-called switching threshold has been identified (Bouret & Sara, 2005; Yu & Dayan, 2005) and an integrative theory which explains the role of this biological system has been proposed (Aston-Jones & Cohen, 2005). In the following sections, I outline the suggested roles of the locus coeruleus-norepinephrine (LC-NE) system in governing the control of behavior, and some predictions with regards to everyday multitasking and individual differences in media multitasking which we can derive from this framework.

The LC-NE System

A part of the brain stem, the LC-NE system comprises of serotonergic and noradrenergic neurons, of which the latter are the sole source of noradrenaline/norepinephrine in the brain (Berridge & Waterhouse, 2003; Sara, 2009). This system has a wide projection to the neocortex (Aston-Jones & Cohen, 2005; Berridge & Waterhouse, 2003; Bouret & Sara, 2005), and receives inputs from regions which have been implied in monitoring the utility of the current behavior , namely the Anterior Cingulate Cortex (ACC) and the Orbitofrontal Cortex (OFC; Aston-Jones & Cohen, 2005). Noradrenergic neurons are sensitive to changes in stimulus-reinforcement contingencies (e.g., in a visual discrimination task, they respond vigorously to the target stimuli but not to the distractors, e.g., Usher et al., 1999) and are known to be activated by acute stressors (Sara & Bouret, 2012). Releases of noradrenaline have also been known to help tuning neurons which respond specifically to a target, in turn resulting in correct task responses (Aston-Jones & Cohen, 2005; Sara, 2009). Importantly, LC neurons are known to be polymodal; they fire in two distinct modes: phasic and tonic (Aston-Jones & Cohen, 2005; Berridge & Waterhouse, 2003). The phasic mode is characterized by short-lasting, brief bursts of action potentials (Berridge & Waterhouse, 2003). This mode has been associated with accurate task performance (Aston-Jones & Cohen, 2005). In contrast, the tonic mode is characterized by a more sustained, regular discharge pattern (Berridge & Waterhouse, 2003). It has been associated with less engagement to a task. At the same time, the tonic discharge may promote the sampling of alternative behavior (Aston-Jones & Cohen, 2005). Accordingly, Aston-Jones and Cohen (2005) proposed that the transition of the two LC modes may play a significant role in performance optimization within a task and across different tasks, in other words, keeping the balance between within-task exploitation and between-tasks exploration behaviors.

LC phasic mode helps optimize performance within a task, thus promoting within-task exploitation behaviors. This mode is characterized by a brief bursts of action potentials and a short latency (Berridge & Waterhouse, 2003), and it has been found to occur following task-relevant stimuli and processes (Aston-Jones & Cohen, 2005; Berridge & Waterhouse, 2003; Bouret & Sara, 2005). For instance, in monkeys, during a visual oddball discrimination task, phasic activations of LC neurons were observed following the presentation of the target stimuli, but not to distractors (Rajkowski, Kubiak, & Aston-Jones, 1994; Usher et al., 1999). Using a computational model, Usher et al. (1999) suggested that phasic LC responses may signal releases of NE, which increases the responses of target-specific neurons, reduces the spontaneous (tonic) activity of LC, and inhibits the responses of the neighboring neurons which are less sensitive to the target (see also Sara, 2009), in turns, modulating performance of the organism. Since the LC-NE system has a wide projection to the neocortex, it has been suggested that this system also plays a role in cognitive control (Berridge & Waterhouse, 2003; Sara, 2009; Sara & Bouret, 2012). In humans, an administration of the pharmacological agent modafinil was associated with the increase of LC and Prefrontal Cortex (PFC) activation, in turns resulting in faster (correct) responses in subjects when they prepared to switch from a response with a compatible stimulus-response mapping to another with an incompatible stimulus-response mapping (Francisco & Health, 2009). Together, phasic LC mode is associated with the identification of task-relevant stimuli and the increase of cognitive control. Accordingly, LC phasic mode can be consistently observed when the organism is performing the task well.

LC tonic mode helps optimize performance across different tasks. This mode is characterized by relatively regular, sustained discharges (Berridge & Waterhouse, 2003), resulting in an increase of the baseline activity of the neurons. It has been found to be associated with periods of disengagements to a task (Aston-Jones & Cohen, 2005; Bouret & Sara, 2005). At the same time, during waking hours, it is associated with periods of high arousal and attentiveness (Berridge & Waterhouse, 2003). In monkeys, an increase of tonic LC activity during a visual oddball discrimination task was associated with increased distractibility, signaled by an increase of false alarms (Aston-Jones & Cohen, 2005). Meanwhile, increases of arousal during this period might signal the tendency to sample alternative behaviors and or to detect stimuli which are otherwise irrelevant. For instance, in anesthetized rats, tonic LC stimulation results in their whiskers responding to stimuli below and above their detection-level thresholds (i.e., uniform responses) while phasic LC discharges result in whisker responses to salient or novel stimulus only (Berridge & Waterhouse, 2003). Together, the tonic LC mode is associated with a decrease of sensitivity in discriminating relevant from irrelevant stimuli and an increase of arousal. In other words, organisms become more responsive, but less discriminative towards the incoming stimuli.

Together, the different LC-NE modes are proposed to signal changes in the sensitivity thresholds for detecting incoming stimuli. The LC phasic mode increases the sensitivity threshold, reducing interference from irrelevant stimuli and helping to produce accurate responses while the LC tonic mode decreases the sensitivity threshold, reducing accurate task responses but increasing arousal, potentially facilitating shifts from one task to another. Aston-Jones and Cohen (2005; see also Gilzenrat et al., 2010) propose that the mode transitions occur because the LC-NE system continuously monitors the utility of a task. The LC-NE system receives projections from two frontal structures affiliated with rewards and costs evaluation, the OFC and the ACC, respectively (Aston-Jones & Cohen, 2005). When task utility is high (i.e., when the reward for performing the task well is high and the cost of errors is low), the LC phasic mode promotes engagements to the task by facilitating accurate responses. In contrasts, when task utility is low, the LC tonic mode promotes disengagements to the task, facilitating explorations of alternative behaviors which might provide a better reward. Gilzenrat et al., (2010; see also Jepma & Nieuwenhuis, 2011) provided evidence for this task-utility monitoring account in a tone-discrimination task with an increasing difficulty and the means to reset (i.e., participants could disengage from the current series of tone discriminations and start anew). Overall, in this task, participants behaved adaptively: they chose to reset when the expected value of the task started to decline. Importantly, their pupil size reflected the mode transitions in the LC-NE system: accurate tone discriminations were coupled with task-evoked pupil dilations while resets were coupled with increases of the baseline pupil diameter. This finding suggests that task-utility monitoring (and consequently, behavioral shifts) occurs relatively frequent, in this case, changes in behavior can be observed within a few trials (see also Bouret & Sara, 2005).

Other examinations of the roles of the LC-NE system also support the notion that this system helps in modulating behavioral shifts. Bouret and Sara (2005) proposed that the LC-NE system provides a way to reset the current neural network in response to environmental demands. During optimal task performance, low (phasic) LC activity prevents spurious behavior shifts while long-lasting (tonic) LC activity promotes behavioral shifts. This persistent LC activity is associated with a network reset, thus allowing the organism to rapidly adapt to environmental changes (Bouret & Sara, 2005; Sara, 2009). Additionally, Yu and Dayan (2005) proposed that the neuromodulator NE is sensitive to unexpected uncertainty (i.e., uncertainties induced by changes in the environment). To this end, they run an extended Posner cueing task on simulated rats: reporting the location of targets following the presentation of a set of cue stimuli. In this task, the validity and the identity of the cues are manipulated, such that for the former, the stimulus set contains arrows of different colors, one of which predicts the location of the target with a significant probability. For the latter, the experimenter can suddenly change the relevant cue color. Together, the model had to infer both the identity of the relevant arrow and estimate its validity. The model predicted increased activations in NE while the simulated rats correctly infer the identity, but not the validity of the cues. Accordingly, Yu & Dayan (2005) concluded that NE acts as an alerting signal for contextual changes in the environment.

Detecting LC-NE-related Activities in the Brain

Despite of its position in the Pons, LC mode transitions can be observed in noninvasive ways, thanks to its wide and robust efferent projections. Using EEG, it has been found that the amplitude of the event-related potentials (ERPs) with the (positive) peak latency around 300ms following the presentation of stimuli, the P3, was associated with the phasic LC-NE mode (see Nieuwenhuis, Aston-Jones, & Cohen, 2005 for a review). The transition between the LC-NE modes is also correlated with pupil diameters (Gilzenrat et al., 2010; Jepma & Nieuwenhuis, 2011). Specifically, the LC phasic mode is associated with relatively smaller baseline pupil diameter and the presence of task-evoked pupil dilations while the LC tonic mode is associated with increases in the baseline pupil diameter (Gilzenrat et al., 2010; Jepma & Nieuwenhuis, 2011). Together, these findings suggest that the activity of the LC-NE system is coupled with activities of other systems in an organism, such as the pupil (see also Einhauser, Stout, Koch, & Carter, 2008; Murphy, O'Connell, O'Sullivan, Robertson, & Balsters, 2014).

To summarize, the LC-NE system plays an important role in ensuring an adaptive behavior. By evaluating inputs on the current task utility and environmental demands, the system provides an important signal for promoting optimal behavior within a task (i.e., within-task exploitations) or alternatively, facilitating shifts to a different task (i.e., between-tasks explorations). Accordingly, this function becomes important for dealing with the unexpected uncertainties in the environment and for generating adaptive behavior (Bouret & Sara, 2005; Yu & Dayan, 2005). Using known biological mechanisms (Berridge & Waterhouse, 2003) and computational models (Usher et al., 1999) of the LC-NE system, the adaptive gain theory (Aston-Jones & Cohen, 2005; Gilzenrat et al., 2010) provides an overarching framework for predicting behavior switches. Thus, this theory may explain many observed phenomena in media multitasking, which I will outline in the following sections.

Predictions for Media Multitasking

Multitasking in spite of performance cost. The adaptive gain theory assumes that task utility is not constant: When the task utility is high, there is a clear benefit of sticking to the current task instead of switching to another, but when the task utility decreases, there is a benefit of switching. Somewhat consistent with this assumption (and its consequences) of varying levels of task utility, studies have shown that people sometimes switch from one task to another despite their understanding of the (potential) performance costs (Bardhi et al., 2010; Hwang et al., 2014; Kessler et al., 2009). In a systematic interview, Bardhi et al. (2010) found that young consumers were aware of their paradoxical experience of media multitasking: they were aware that simultaneously consuming different media streams is associated with inefficient content processing, but at the same time they continue to do so because it provided a heightened sense of control and enjoyment, and it was perceived to be a more efficient way for processing information. Subsequent studies have tried providing explanations for this paradoxical relationship using the Uses and Gratifications theory (Katz, Blumler, & Guretvich, 1974): media multitasking might start with user control and efficiency as motivations, but it continues because it provides emotional gratifications (Hwang et al., 2014; Z. Wang & Tchernev, 2012).

The adaptive gain theory might provide a more parsimonious, alternative explanation for this multitasking paradox: Switches between different media are the natural consequences of the waxing and waning of task utilities. The adaptive gain theory predicts that when task utility is high (e.g., me trying to write the general discussion of my thesis), the phasic LC mode promotes task engagement. However, there might be a point when the task utility wanes (e.g., I am stuck trying to come up with a good sentence) and the LC-NE system fires in the tonic mode, promoting task disengagement. Consequently, switches between tasks occur in spite of the organism knowing the consequences (e.g., I am checking my emails instead of continue writing, in spite of knowing email-checking would not help me finish writing this discussion faster). This does not have to be necessarily harmful (e.g., that I am distracted); switching might help reset my network and renew my task engagement (Bouret & Sara, 2005).

Several pieces of evidence provide further support for the benefit of self-initiated switching. First, studies have shown that self-, as opposed to forced-interruptions in task-switching are associated with better performance (Kononova, Joo, & Yuan, 2016; Mcfarlane, 2002; but see Katidioti et al., 2014), indicating that individuals might be aware of their assessment of the current task utility and use that information to decide whether or not to switch. For instance, Kononova et al. (2016) showed that participants retained more information from an online article when they could choose to switch from article-reading to Facebook-checking at will, as opposed to when the switches were predetermined. Secondly, the presence of acute stress, which is associated with tonic LC mode (Sara & Bouret, 2012), has been shown to trigger task-switches. In this regard, one study found that negative feelings (i.e., obstructions, exhaustions, and frustrations), but not positive ones were reported preceding task switches in an experiment in which participants had to perform six unrelated tasks (Adler & Benbunan-Fich, 2013).

Interestingly, switches from one task to another may also occur in absence of changes in task utility. In a voluntary task-switching experiment, participants sometimes randomly switch from one task to another in spite no instructions over task orders: The spontaneous switching phenomenon (Kessler et al., 2009). In two voluntary task-switching experiments in which participants were asked to perform three categorization tasks, Kessler et al. (2009) showed that participants sometimes spontaneously switched from one categorization task to others in absence of explicit instructions for switching. They found that participants spontaneously switched in spite of their awareness of the switch cost (i.e., that they responded slower in trials following a switch as opposed to a repetition; Experiment 1) and in spite of their awareness of the difficulty of the task (i.e., switching from easier to more difficult categorization tasks; Experiment 2). The Uses & Gratification theory would predict no spontaneous switching in these experiments since more difficult, uncertain tasks are certainly less gratifying. However, according to the adaptive gain theory, random switches may occur due to the waning of the current task utility, i.e., since participants could no longer keep their task-engagement level high in repeating a similar task over and over again. In this sense, spontaneous switching might help ensuring a certain level of flexibility in individuals, especially for exploring alternative behaviors. It also prevents the organism to get attracted to a permanent state of behavior (Kessler et al., 2009).

Good and distracted multitaskers. Some individuals switch from one media stream to another more frequently than others. One line of evidence for this would be the variation in the MMI scores (Ophir et al., 2009; also see Chapter 2 of this thesis): HMMs could be considered to be frequent media switchers compared to LMMs. What drives this individual difference in switching? The studies presented in this thesis (Chapters 3-5) and others (see Uncapher et al., 2017; Uncapher & Wagner, 2018; van der Schuur, Baumgartner, Sumter, & Valkenburg, 2015 for reviews) have tried to find the cognitive, behavioral, and mental-health correlates of the MMI, and these studies have produced mixed results. The studies I presented in this thesis present an interesting contradiction. On the one hand, HMMs, compared to LMMs did not seem to perform worse in laboratory tasks involving distractions (Chapters 3 & 4). On the other hand, HMMs seem to experience more distraction-related problems and they reported higher levels of distraction-related mental health issues (ADHD) and personality traits (Impulsiveness, Sensation-seeking) in their daily life (Baumgartner et al., 2014; Magen, 2017; Ralph, Thomson, Cheyne, & Smilek, 2013; see Chapter 5 of this thesis for a meta-analysis). In other words: the rates of media multitasking in daily life are associated with self-reports measures of problems related to distractibility, but not with performance measures of distractibility.

Arguably, the discrepancies between findings from self-report and performance measures of cognitive control can be resolved by the different levels of sensitivity of self-report and performance measures (Stanovich, 2009; Toplak et al., 2013). Specifically, performance-based measures estimate the level of algorithmic thinking, i.e., the efficiency of different cognitive mechanisms, while self-report measures estimate the level of reflective thinking, i.e., the ability to successfully execute tasks given certain goals and constraints (Stanovich, 2009). Accordingly, individual differences in media multitasking are not associated with performance-based measures in the lab since the goals and constraints of the laboratory tasks are predetermined, thus, reducing the need to regulate switching behavior. Somewhat analogously, the adaptive gain theory would predict that in everyday situations, switch rates might indicate the waxing and waning of task utilities. Thus, individuals with problems in distractions might switch more often from one task to another (e.g., they might switch too fast, before the task utility of one task started to wane). In contrasts, since goals and constraints of laboratory tasks are predetermined, task utility remains relatively constant, thus, eliminating the need to regulate switches from one task to another. Therefore, MMI does not necessarily correlate with task performance.

In a sense, within the framework of the adaptive gain theory, the MMI might reflect individual differences in their ability to optimize between within-task exploitation and between-task exploration behaviors. Good multitaskers might be able to effectively engage to a task and therefore, they are less likely to miss opportunities within the task in which a maximum gain could be obtained. Conversely, they might be quick to switch to a different task once the utility of the current task starts to decline. For distracted multitaskers, on the other hand, frequent switching between tasks could indicate a bias toward explorations (see also: Uncapher & Wagner, 2018). Consequently, distracted multitaskers might decide to promptly switch from one activity to another, even though the utility level of the current activity is still high (or conversely, even though the utility level of the alternative activity is still uncertain).

There are some lines of evidence which support the notion that there exists an individual difference in optimizing task performance during multitasking. In a study on adaptation to task interference, Nijboer, Taatgen, Brands, Borst, and van Rijn (2013) asked their participants to perform two types of a multi-column subtraction task, which were presented at a random order. The subtraction task could require a carry (the hard condition) or not (the easy condition). Thus, the hard subtraction task would require the visual modality and produce a higher demand on working memory. At the beginning of each trial, participants could decide whether to combine the subtraction task with a tone counting task, which requires working memory and the auditory modality, or a dot-tracking task, which requires visual attention and the visual modality. Therefore, in easy subtraction trials, choosing the digit subtraction and tone-counting combination would be the optimal choice since it produces less interference (in working memory) while in hard subtraction trials, choosing the digit subtraction and dot-tracking tasks combination would be the optimal choice. They found that about half of the participants (~49%) choose only one combination of tasks during the experiment while the rest (~51%) switched over different combinations of tasks. For those who switched, the majority (60%) did so optimally (i.e., selecting the task combinations which produced less interference), while the rest did so randomly. These findings were somewhat in line with the good and distracted multitaskers distinction, since the former would switch between tasks adaptively while the latter would not.

There are also lines of evidence which support the notion that distracted multitaskers, who are likely to have high MMI scores, are biased toward explorations. First, there have been some indications that HMMs give up easily when facing adversity. They have been reported to omit their response on a larger number of trials in the N-back task (Ralph & Smilek, 2016) and they had lower Raven's matrices scores since they gave up earlier in the test (Minear et al., 2013). Secondly, HMMs have been reported to be more likely to endorse intuitive, but wrong answers in the Cognitive Reflection Task (Schutten et al., 2017). Together, these findings suggest that HMMs have a bias toward explorations; they tend to switch from one task (or thought) to another without deliberations. However, it is yet unclear how many HMMs actually are good multitaskers.

The adaptive gain framework could provide the means to distinguish good from distracted multitaskers among the HMM group, by monitoring whether one switches as a function of optimizing task performance in multitasking. Distracted multitaskers are likely to be biased toward between-task explorations regardless of their evaluations of the current task utility. In other words, they switch more frequently for no strategic reasons (perhaps because they are more impulsive or they have problems with behavioral control). In contrast, good multitaskers might only switch when it is strategic to do so. In laboratory tasks (e.g., when performing the N-back, Raven's, or Cognitive Reflection Task), distracted multitaskers disengage easily from the current task because there are no actual rewards for performing the task well. Accordingly, in a task in which we vary the current task utility (e.g., by increasing the monetary compensation for good performance), the distracted multitaskers would switch more often regardless of the utility level while the good multitaskers would only switch when the utility level of the current task diminishes significantly. One of such task is the four-armed bandit task (Cohen et al., 2007): In this task, participants were instructed to play four slot machines. Each of these machines has its own probability of producing a reward and this probability could change over time. To obtain the maximum reward in this task, the most optimal strategy would be to keep playing the arm which has a high reward probability and switch to another arm once the reward probability starts to decline.

Some Caveats and Unanswered Questions

The adaptive gain theory provides an explanation on why people switch from within-task exploitation to between-tasks explorations. However, the theory suggests that switching occurs spontaneously, that is, as a response to either the waning of current task utility (Aston-Jones & Cohen, 2005) or to unexpected uncertainty in the environment (e.g., Yu & Dayan, 2005). One open question in relation to media multitasking would be whether or not we take into account the utility of the alternative task in creating our decision to switch, and what are the mechanisms involved. For instance, why would it be the case that when writing becomes more difficult, suddenly, checking my social media accounts becomes even more tempting?

Two lines of evidence provide some insights on this issue. First, it has been known that attending to novel stimuli in the environment is also rewarding. Indeed, study has shown that the Substantia Nigra/Ventral Tegmental Area (SN/VTA) area in the brain, which has been known to play an important role in reward processing, showed an increased activation during a presentation of cues which would predict the presentation of a novel stimuli (Wittmann, Bunzeck, Dolan, & Düzel, 2007). This indicates that the anticipation of a novel stimulus might be rewarding. Second, it has been shown that the number of consecutive decisions people can make influences whether they would choose directed (i.e., utility seeking) or random explorations. Wilson, Geana, White, Ludvig, and Cohen (2017) asked their participants to play a modified two-armed-bandit task. In this task, participants start with a four forced-choice sequences which inform which arm would produce the larger reward. Following the forced-choice sequence, participants would either play one of the arms once (Horizon 1) or six (Horizon 6) more consecutive times. One of the important findings was that in the Horizon 6 condition, participants chose the arm with the smaller reward ~50% of the time, in spite of their awareness of the lesser reward. Similarly, in the Horizon 1 condition, participants chose the arm with the larger reward most of the times. Together, these indicate that the likelihood of switching randomly is influenced by the number of possible consecutive decisions one would have to make. In the context of media multitasking, this would mean that the number of alternative media-related activities might influence whether users would make a utility-based switch (e.g., from writing an email to checking a document related to that email) or a random (e.g., from writing an email to checking social network) one.

Somewhat relatedly to the mechanisms underlying how we monitor the utility level of a task and the individual differences in media multitasking behavior, it is still relatively unknown whether the bias toward sampling for alternative behaviors stems from the inability to monitor the current task utilities, the inability to appropriately respond to the changes of the task utilities, or the strategic responses to the changes of task utilities and environmental demands.

Conclusions

This thesis aimed to address three questions central to the discussion of the potential effects of media technologies in general and media multitasking in particular: What constitutes the media multitasking behavior, which domains of cognition and behavior differentiate heavy from light media multitaskers, and what is the extent to which the presence of media devices influences our ability to process information? To those ends, we found that 1) media multitasking behaviors, at least those sampled by the MMI, are confined to a set of combinations of activities with Social media, Listening to music, Texting, and Browsing; 2) the media multitasking behaviors which are sampled by the MMI do not correlate with distractibility during task performance, yet those who have high MMI scores do report more problems, more (severe) mental health symptoms, and higher levels of personality traits related to distractibility; 3) the mere-presence of media devices might be distracting regardless of one's level of habitual media multitasking. Together, this set of findings suggests that our everyday interactions with media devices might not always be related to cognitive processing and behavior. To explain these findings, I proposed that our everyday interactions with media devices might serve an adaptive function after all, namely to keep the homeostasis between exploitation- and exploration-related behaviors in our system. Individuals have different lim-its for processing information for the task at hand (exploitation), thus, interacting with media devices might provide a (quick) escape which allows the system to refresh (exploration). This exploitation-exploration threshold varies per individual, which might explain why some individual might media multitask more often in everyday situations than others.

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References

References

Aagaard, J. (2015). Media multitasking, attention, and distraction: a critical discussion. *Phenomenology and the Cognitive Sciences*, *14*(4), 885–896. http://doi.org/10.1007/s11097-014-9375-x

Adler, R. F., & Benbunan-Fich, R. (2012). Juggling on a high wire: Multitasking effects on performance. *International Journal of Human-Computer Studies*, *70*(2012), 156–168. http://doi.org/10.1016/j.ijhcs.2011.10.003

Adler, R. F., & Benbunan-Fich, R. (2013). Self-interruptions in discretionary multitasking. *Computers in Human Behavior*, *29*(4), 1441–1449. http://doi.org/10.1016/j.chb.2013.01.040

Altmann, E. M., Trafton, J. G., & Hambrick, D. Z. (2014). Momentary interruptions can derail the train of thought. *Journal of Experimental Psychology. General*, *143*(1), 215–26. http://doi.org/10.1037/a0030986

Alzahabi, R., & Becker, M. W. (2013). The association between media multitasking, task-switching, and dual-task performance. *Journal of Experimental Psychology: Human Perception and Performance*, *39*(5), 1485–1495. http://doi.org/10.1037/a0031208

Alzahabi, R., Becker, M. W., & Hambrick, D. Z. (2017). Investigating the Relationship Between Media Multitasking and Processes Involved in Task-Switching. *Journal of Experimental Psychology: Human Perception and Performance*, *43*(11), 1872–1894.

Anderson, M. (2015). Technology Device Ownership: 2015. *Pew Research Reports*, 1–26. http://doi.org/10.3916/C43-2014-17

Arrington, C. M., & Logan, G. D. (2004). The cost of a voluntary task switch. *Psychological Science*, *15*(9), 610–615. http://doi.org/10.1111/j.0956-7976.2004.00728.x

Arrington, C. M., Reiman, K. M., & Weaver, S. M. (2014). Voluntary Task Switching. In *Task Switching and Cognitive Control* (pp. 1–29). http://doi.org/10.1093/acprof

Aston-Jones, G., & Cohen, J. D. (2005). An Integrative Theory of Locus Coeruleus-Norepinephrine Function: Adaptive Gain and Optimal Performance. *Annual Review of Neuroscience*, *28*(1), 403–450. http://doi.org/10.1146/annurev.neuro.28.061604.135709

Baayen, R. H., Davidson, D. J., & Bates, D. M. (2008). Mixed-effects modeling with crossed random effects for subjects and items. *Journal of Memory and Language*, *59*(4), 390–412. http://doi.org/10.1016/j.jml.2007.12.005

Bakker, M., van Dijk, A., & Wicherts, J. M. (2012). The Rules of the Game Called Psychological Science. *Perspectives on Psychological Science*, *7*(6), 543–554. http://doi.org/10.1177/1745691612459060

Bardhi, F., Rohm, A. J., & Sultan, F. (2010). Tuning in and tuning out: media multitasking among young consumers. *Journal of Consumer Behaviour*, *9*, 316–332. http://doi.org/10.1002/cb

Barrat, A., Barthelemy, M., Pastor-Satorras, R., & Vespignani, A. (2003). The architecture of complex weighted networks. *Proceedings of the National Academy of Sciences of the United States of America*, *101*(11), 3747–3752. http://doi.org/10.1073/pnas.0400087101

Barton, J. J. S., Pandita, M., Thakkar, K., Goff, D. C., & Manoach, D. S. (2008). The relation between antisaccade errors, fixation stability and prosaccade errors in schizophrenia. *Experimental Brain Research*, *186*(2), 273–282. http://doi.org/10.1007/s00221-007-1235-2

Bates, D., Mächler, M., Bolker, B. M., & Walker, S. C. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1), 1–48. http://doi.org/10.18637/jss.v067.i01

Baumgartner, S. E., Lemmens, J. S., Weeda, W. D., & Huizinga, M. (2017). Measuring Media Multitasking. *Journal of Media Psychology*, *29*, 188–197. http://doi.org/10.1027/1864-1105/a000167

Baumgartner, S. E., van der Schuur, W. A., Lemmens, J. S., & te Poel, F. (2017). The Relationship Between Media Multitasking and Attention Problems in Adolescents: Results of Two Longitudinal Studies. *Human Communication Research*, 1–27. http://doi.org/10.1111/hcre.12111

Baumgartner, S. E., Weeda, W. D., van der Heijden, L. L., & Huizinga, M. (2014). The relationship between media multitasking and executive function in early adolescents. *The Journal of Early Adolescence*, *34*(8), 1120–1144. http://doi.org/10.1177/0272431614523133

Bavelier, D., Green, C. S., & Dye, M. W. G. (2010). Children, Wired: For Better and for Worse. *Neuron*, *67*(5), 692–701. http://doi.org/10.1016/j.neuron.2010.08.035

Becker, M. W., Alzahabi, R., & Hopwood, C. J. (2013). Media multitasking is associated with symptoms of depression and social anxiety. *Cyberpsychology, Behavior and Social Networking*, *16*(2), 132–5. http://doi.org/10.1089/cyber.2012.0291

Beentjes, J. W. J., Koolstra, C. M., & van der Voort, T. H. A. (1996). Combining background media with doing homework: Incidence of background media use and perceived effects. *Communication Education*, *45*, 59–72. http://doi.org/10.2105/AJPH,2008

Bell, C., Compeau, D., & Olivera, F. (2005). Understanding the social implications of technological multitasking: A conceptual model. *SIGHCI 2005 Proceedings*, *2*. Retrieved from https://aisel.aisnet.org/sighci2005/2

Berridge, C. W., & Waterhouse, B. D. (2003). The locus coeruleus-noradrenergic system: Modulation of behavioral state and state-dependent cognitive processes. *Brain Research Reviews*, *42*(1), 33–84. http://doi.org/10.1016/S0165-0173(03)00143-7

Bolker, B. M., Brooks, M. E., Clark, C. J., Geange, S. W., Poulsen, J. R., Stevens, M. H. H., & White, J. S. S. (2009). Generalized linear mixed models: a practical guide for ecology and evolution. *Trends in Ecology and Evolution*, *24*(3), 127–135. http://doi.org/10.1016/j.tree.2008.10.008

Boonstra, M. A., Oosterlaan, J., Sergeant, J. A., & Buitelaar, J. K. (2005). Executive functioning in adult ADHD: a meta-analytic review. *Psychological Medicine*, *35*(8), 1097–1108. http://doi.org/10.1017/S003329170500499X

Borenstein, M., Hedges, L. V, Higgins, J. P. T., & Rothstein, H. R. (2009). *Introduction to Meta-Analysis*. West Sussex: John Wiley & Sons.

Borgatti, S. P., Mehra, A., Brass, D. J., & Labianca, G. (2009). Network analysis in the social sciences. *Science (New York, N.Y.)*, *323*(5916), 892–895. http://doi.org/10.1126/science.1165821

Borst, J. P., Taatgen, N. A., & van Rijn, H. (2010). The problem state: a cognitive bottleneck in multitasking. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *36*(2), 363–82. http://doi.org/10.1037/a0018106

Botvinick, M. M., Braver, Barch, D. M., Carter, C. S., & Cohen, J. D. (2001). Conflict monitoring and cognitive control. *Psychological Review*, *108*(3), 624–52. http://doi.org/10.1037//0033-295X.I08.3.624

Botvinick, M. M., Cohen, J. D., & Carter, C. S. (2004). Conflict monitoring and anterior cingulate cortex: an update. *Trends in Cognitive Sciences*, *8*(12), 539–46. http://doi.org/10.1016/j.tics.2004.10.003

Bouret, S., & Sara, S. J. (2005). Network reset: A simplified overarching theory of locus coeruleus noradrenaline function. *Trends in Neurosciences*, *28*(11), 574–582. http://doi.org/10.1016/j.tins.2005.09.002

Bowling, A. C., Hindman, E. A., & Donnelly, J. F. (2012). Prosaccade errors in the antisaccade task: Differences between corrected and uncorrected errors and links to neuropsychological tests. *Experimental Brain Research*, *216*(2), 169–179. http://doi.org/10.1007/s00221-011-2921-7

Brandt, M. J., IJzerman, H., Dijksterhuis, A., Farach, F. J., Geller, J., Giner-Sorolla, R., … van 't Veer, A. (2014). The Replication Recipe: What makes for a convincing replication? *Journal of Experimental Social Psychology*, *50*(1), 217–224. http://doi.org/10.1016/j.jesp.2013.10.005

Brasel, S. A., & Gips, J. (2011). Media multitasking behavior: concurrent television and computer usage. *Cyberpsychology, Behavior and Social Networking*, *14*(9), 527–534. http://doi.org/10.1089/cyber.2010.0350

Broadbent, D., & Cooper, P. (1982). The cognitive failures questionnaire (CFQ) and its correlates.

British Journal of Clinical Psychology, *21*(1), 1–16. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/j.2044-8260.1982.tb01421.x/full

Brown, K. W., & Ryan, R. M. (2003). The benefits of being present: mindfulness and its role in psychological well-being. *Jounal of Personality and Social Psychology*, *84*(4), 822–848. http://doi.org/10.1037/0022-3514.84.4.822

Burgess, P. W., Alderman, N., Forbes, C., Costello, A., Coates, L. M., Dawson, D. R., … Channon, S. (2006). The case for the development and use of "ecologically valid" measures of executive function in experimental and clinical neuropsychology. *Journal of the International Neuropsychological Society : JINS*, *12*(2), 194–209. http://doi.org/10.1017/S1355617706060310

Button, K. S., Ioannidis, J. P. A., Mokrysz, C., Nosek, B. A., Flint, J., Robinson, E. S. J., & Munafò, M. R. (2013). Power failure: why small sample size undermines the reliability of neuroscience. *Nature Reviews Neuroscience*, *14*(5), 365–76. http://doi.org/10.1038/nrn3475

Cain, M. S., Leonard, J. A., Gabrieli, J. D. E., & Finn, A. S. (2016). Media multitasking in adolescence. *Psychonomic Bulletin & Review*, *23*(6), 1932–1941. http://doi.org/10.3758/s13423-016-1036-3

Cain, M. S., & Mitroff, S. R. (2011). Distractor filtering in media multitaskers. *Perception*, *40*(10), 1183–1192. http://doi.org/10.1068/p7017

Calamaro, C. J., Mason, T. B. A., & Ratcliffe, S. J. (2009). Adolescents Living the 24/7 Lifestyle: Effects of Caffeine and Technology on Sleep Duration and Daytime Functioning. *Pediatrics*, *123*(6), e1005–e1010. http://doi.org/10.1542/peds.2008-3641

Cardoso-Leite, P., Kludt, R., Vignola, G., Ma, W. J., Green, C. S., & Bavelier, D. (2015). Technology consumption and cognitive control: Contrasting action video game experience with media multitasking. *Attention, Perception, & Psychophysics*, *78*(1), 218–241. http://doi.org/10.3758/s13414-015-0988-0

Carrier, L. M., Cheever, N. A., Rosen, L. D., Benitez, S., & Chang, J. (2009). Multitasking across generations: Multitasking choices and difficulty ratings in three generations of Americans. *Computers in Human Behavior*, *25*(2), 483–489. http://doi.org/10.1016/j.chb.2008.10.012

Carrier, L. M., Rosen, L. D., Cheever, N. A., & Lim, A. F. (2015). Causes, effects, and practicalities of everyday multitasking. *Developmental Review*, *35*, 64–78. http://doi.org/10.1016/j.dr.2014.12.005

Carriere, J. S. A., Cheyne, J. A., & Smilek, D. (2008). Everyday attention lapses and memory failures: The affective consequences of mindlessness. *Consciousness and Cognition*, *17*(3), 835–847. http://doi.org/10.1016/j.concog.2007.04.008

Carriere, J. S. A., Seli, P., & Smilek, D. (2013). Wandering in both mind and body: Individual differences in mind wandering and inattention predict fidgeting. *Canadian Journal of Experimental Psychology/Revue Canadienne de Psychologie Expérimentale*, *67*(1), 19–31. http://doi.org/10.1037/a0031438

Carter, E. C., & McCullough, M. E. (2014). Publication bias and the limited strength model of self-control: has the evidence for ego depletion been overestimated? *Frontiers in Psychology*, *5*(July), 1–11. http://doi.org/10.3389/fpsyg.2014.00823

Chan, R. C. K., Shum, D., Toulopoulou, T., & Chen, E. Y. H. (2008). Assessment of executive functions: Review of instruments and identification of critical issues. *Archives of Clinical Neuropsychology*, *23*(2), 201–216. http://doi.org/10.1016/j.acn.2007.08.010

Cheever, N. A., Peviani, K., & Rosen, L. D. (2018). Media Multitasking and Mental Health. In M. A. Moreno & A. Radovic (Eds.), *Technology and Adolescent Mental Health* (pp. 101–112). Springer, Cham.

Chen, Q., & Yan, Z. (2016). Does multitasking with mobile phones affect learning? A review. *Computers in Human Behavior*, *54*, 34–42. http://doi.org/10.1016/j.chb.2015.07.047

Chinchanachokchai, S., Duff, B. R. L., & Sar, S. (2015). The effect of multitasking on time perception, enjoyment, and ad evaluation. *Computers in Human Behavior*, *45*, 185–191. http://doi.org/10.1016/j.chb.2014.11.087

Christoff, K., Gordon, A. M., Smallwood, J., Smith, R., & Schooler, J. W. (2009). Experience sampling during fMRI reveals default network and executive system contributions to mind wandering. *Proceedings of the National Academy of Sciences of the United States of America*, *106*(21), 8719–24. http://doi.org/10.1073/pnas.0900234106

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences. Statistical Power Analysis for the Behavioral Sciences* (Vol. 2nd). http://doi.org/10.1234/12345678

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*(1), 155–159. http://doi.org/10.1037/0033-2909.112.1.155

Cohen, J. D., McClure, S. M., & Yu, A. J. (2007). Should I stay or should I go? How the human brain manages the trade-off between exploitation and exploration. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *362*(1481), 933–942. http://doi.org/10.1098/rstb.2007.2098

Cohn, L. D., & Becker, B. J. (2003). How meta-analysis increases statistical power. *Psychological Methods*, *8*(3), 243–253. http://doi.org/10.1037/1082-989X.8.3.243

Courage, M. L., Bakhtiar, A., Fitzpatrick, C., Kenny, S., & Brandeau, K. (2015). Growing up multitasking: The costs and benefits for cognitive development. *Developmental Review*, *35*, 5–41. http://doi.org/10.1016/j.dr.2014.12.002

Cowan, N. (2000). The magical number 4 in short-term memory: A reconsideration of mental storage capacity. *Behavioral and Brain Sciences*, *24*(1), 87–185. http://doi.org/10.1017/S0140525X01003922

Csárdi, G., & Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal Complex Systems*, *1695*, 1–9. http://doi.org/10.3724/SP.J.1087.2009.02191

Daamen, J., van Vugt, M. K., & Taatgen, N. A. (2016). Measuring and modeling distraction by self-referential processing in a complex working memory span task. *Proceedings 38th Annual Meeting of the Cognitive Science Society*, 2147–2152.

Dalley, J. W., Everitt, B. J., & Robbins, T. W. (2011). Impulsivity, Compulsivity, and Top-Down Cognitive Control. *Neuron*, *69*(4), 680–694. http://doi.org/10.1016/j.neuron.2011.01.020

David, P., Kim, J.-H., Brickman, J. S., Ran, W., & Curtis, C. M. (2014). Mobile phone distraction while studying. *New Media Society*, 1461444814531692-. http://doi.org/10.1177/1461444814531692

Deloitte Southeast Asia. (2017). Global Mobile Consumer Survey Southeast Asia Edition. Accessed online in 27/11/2017.

Deng, T., Meng, J., Kononova, A., & David, P. (2018). Measuring smartphone usage and task switching with log tracking and self-reports. *Mobile Media & Communication*, 1–21. http://doi.org/10.1177/2050157918761491

Diamond, A. (2013). Executive functions. *The Annual Review of Psychology*, *64*, 135–168. http://doi.org/10.1146/annurev-psych-113011-143750

Duff, B. R.-L., Yoon, G., Wang, Z. (Glenn), & Anghelcev, G. (2014). Doing It All: An Exploratory Study of Predictors of Media Multitasking. *Journal of Interactive Advertising*, *14*(1), 11–23. http://doi.org/10.1080/15252019.2014.884480

Duggan, M., & Brenner, J. (2013). *The Demographics of Social Media Users-2012. Washington, DC: Pew Research Center's Internet & American Life Project, 2013.* Retrieved from http://pewinternet.org/Reports/2013/Social-media-users.aspx

Duval, S. J., & Tweedie, R. L. (2000). Trim and fill: A simple funnel-plot-based method of testing and adjusting for publication bias in meta-analysis. *Biometrics*, *56*(2), 455–463. http://doi.org/10.1111/j.0006-341x.2000.00455.x

Edwards, K. S., & Shin, M. (2017). Media multitasking and implicit learning. *Attention, Perception, & Psychophysics*, *79*(5), 1535–1549. http://doi.org/10.3758/s13414-017-1319-4

Egger, M., Davey Smith, G., Schneider, M., & Minder, C. (1997). Bias in meta-analysis detected by a simple, graphical test. *BMJ (Clinical Research Ed.)*, *315*(7109), 629–34. http://doi.org/10.1136/bmj.316.7129.469

Einhauser, W., Stout, J., Koch, C., & Carter, O. (2008). Pupil dilation reflects perceptual selection and predicts subsequent stability in perceptual rivalry. *Proceedings of the National Academy of Sciences*, *105*(5), 1704–1709. http://doi.org/10.1073/pnas.0707727105

Engle, R. W., Tuholski, S. W., Laughlin, J. E., & Conway, A. R. A. (1999). Working memory, short-term memory, and general fluid intelligence: a latent-variable approach. *Journal of Experimental Psychology. General*, *128*(3), 309–331. http://doi.org/10.1037/0096-3445.128.3.309

Everling, S., & Fischer, B. (1998). The antisaccade: a review of basic research and clinical studies. *Neuropsychologia*, *36*(9), 885–899. http://doi.org/10.1016/S0028-3932(98)00020-7

Fairchild, A. J., & MacKinnon, D. P. (2009). A general model for testing mediation and moderation effects. *Prevention Science*, *10*(2), 87–99. http://doi.org/10.1007/s11121-008-0109-6

Fan, J., McCandliss, B. D., Sommer, T., Raz, A., & Posner, M. I. (2002). Testing the efficiency and independence of attentional networks. *Journal of Cognitive Neuroscience*, *14*(3), 340–347. http://doi.org/10.1162/089892902317361886

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–91. http://doi.org/10.3758/bf03193146

Foehr, U. G. (2006). *Media multitasking among American youth: Prevalence, predictors, and pairings. The Henry J. Kaiser Family Foundation.*

Fox, A. B., Rosen, J., & Crawford, M. (2009). Distractions, distractions: does instant messaging affect college students' performance on a concurrent reading comprehension task? *Cyberpsychology & Behavior : The Impact of the Internet, Multimedia and Virtual Reality on Behavior and Society*, *12*(1), 51–3. http://doi.org/10.1089/cpb.2008.0107

Francisco, S., & Health, T. (2009). Modafinil Shifts Human Locus Coeruleus to Low- Tonic , High-Phasic Activity During Functional MRI, *322*(October 2015), 1700–1703. http://doi.org/10.1126/science.1164908

Fruchterman, T. M. J., & Reingold, E. M. (1991). Graph drawing by force-directed placement. *Software:*

Practice and Experience, *21*(11), 1129–1164. http://doi.org/10.1002/spe.4380211102

Gilzenrat, M. S., Nieuwenhuis, S., Jepma, M., & Cohen, J. D. (2010). Pupil diameter tracks changes in control state predicted by the adaptive gain theory of locus coeruleus function. *Cognitive, Affective and Behavioral Neuroscience*, *10*(2), 252–269. http://doi.org/10.3758/CABN.10.2.252

Gioia, G. A., Isquith, P. K., Guy, S. C., & Kenworthy, L. (2000). TEST REVIEW Behavior Rating Inventory of Executive Function Behavior Rating Inventory of Executive Function. *Child Neuropsychology*, *6*(3), 235–238. http://doi.org/10.1076/chin.6.3.235.3152

Gioia, G. A., Isquith, P. K., Retzlaff, P. D., & Espy, K. A. (2002). Confirmatory factor analysis of the behavior rating inventory of executive function (BRIEF) in a clinical sample. *Child Neuropsychology*, *8*(4), 249–257. http://doi.org/10.1076/chin.8.4.249.13513

Goh, J. X., Hall, J. A., & Rosenthal, R. (2016). Mini Meta-Analysis of Your Own Studies: Some Arguments on Why and a Primer on How. *Social and Personality Psychology Compass*, *10*(10), 535–549. http://doi.org/10.1111/spc3.12267

González, V. M., & Mark, G. (2004). “Constant, Constant, Multi-tasking Craziness”: Managing Multiple Working Spheres. In *CHI ’04 Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Vol. 6, pp. 113–120). http://doi.org/10.1145/985692.985707

Goodman, S. N., Fanelli, D., & Ioannidis, J. P. A. (2016). What does research reproducibility mean? *Science Translational Medicine*, *8*(341), 341ps12-341ps12. http://doi.org/10.1126/scitranslmed.aaf5027

Gorman, T. E., & Green, C. S. (2016). Short-term mindfulness intervention reduces the negative attentional effects associated with heavy media multitasking. *Scientific Reports*, *6*(April), 24542. http://doi.org/10.1038/srep24542

Hadlington, L., & Murphy, K. (2018). Is Media Multitasking Good for Cybersecurity ? Exploring the Relationship Between Media Multitasking and Everyday Cognitive Failures on Self-Reported Risky Cybersecurity Behaviors. *Cyberpsychology, Behavior and Social Networking*, *21*(3), 168–172. http://doi.org/10.1089/cyber.2017.0524

Hanson, J. (2007). *24/7: How Cell Phones and the Internet Change the Way We Live, Work, and Play*. Wesport: Praeger.

Hatchel, T., Negriff, S., & Subrahmanyam, K. (2018). The relation between media multitasking, intensity of use, and well-being in a sample of ethnically diverse emerging adults. *Computers in Human Behavior*, *81*, 115–123. http://doi.org/10.1016/j.chb.2017.12.012

Hedges, L. V., Tipton, E., & Johnson, M. C. (2010). Robust variance estimation in meta-regression with dependent effect size estimates. *Research Synthesis Methods*, *1*(1), 39–65. http://doi.org/10.1002/jrsm.5

Hedges, L. V, & Pigott, T. D. (2004). The power of statistical tests for moderators in meta-analysis. *Psychological Methods*, *9*(4), 426–445. http://doi.org/10.1037/1082-989X.9.4.426

Hembrooke, H., & Gay, G. (2003). The laptop and the lecture: The effects of multitasking in learning environments. *Journal of Computing in Higher Education*, *15*(1), 1–19. Retrieved from http://link.springer.com/article/10.1007/BF02940852

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). The weirdest people in the world? *Behavioral and Brain Sciences*, *33*(2–3), 61–83. http://doi.org/10.1017/S0140525X0999152X

Heppner, P. P., & Petersen, C. H. (1982). The development and implications of a personal problem-solving inventory. *Journal of Counseling Psychology*, *29*(1), 66–75. http://doi.org/10.1037/0022-0167.29.1.66

Horrey, W. J., & Wickens, C. D. (2006). Examining the impact of cell phone conversations on driving using meta-analytic techniques. *Human Factors*, *48*(1), 196–205. http://doi.org/10.1518/001872006776412135

Hoyle, R. H., Stephenson, M. T., Palmgreen, P., Lorch, E. P., & Donohew, R. L. (2002). Reliability and validity of a brief measure of sensation seeking. *Personality and Individual Differences*, *32*(3), 401–414. http://doi.org/10.1016/S0191-8869(01)00032-0

Huff, C., & Tingley, D. (2015). “Who are these people?” Evaluating the demographic characteristics and political preferences of MTurk survey respondents. *Research and Politics*, *2*(3). http://doi.org/10.1177/2053168015604648

Huizinga, M., & Smidts, D. P. (2010). Age-Related Changes in Executive Function: A Normative Study with the Dutch Version of the Behavior Rating Inventory of Executive Function (BRIEF). *Child Neuropsychology*, *17*(1), 51–66. http://doi.org/10.1080/09297049.2010.509715

Hutton, S. B., & Ettinger, U. (2006). The antisaccade task as a research tool in psychopathology: A critical review. *Psychophysiology*, *43*(3), 302–313. http://doi.org/10.1111/j.1469-8986.2006.00403.x

Hwang, Y., Kim, H., & Jeong, S. H. (2014). Why do media users multitask?: Motives for general, medium-specific, and content-specific types of multitasking. *Computers in Human Behavior*, *36*, 542–548. http://doi.org/10.1016/j.chb.2014.04.040

Inzlicht, M., Schmeichel, B. J., & Macrae, C. N. (2014). Why self-control seems (but may not be) limited.

Trends in Cognitive Sciences, *18*(3), 127–133. http://doi.org/10.1016/j.tics.2013.12.009

Ioannidis, J. P. A. (2005). Why most published research findings are false. *PLoS Medicine*, *2*(8), e124. http://doi.org/10.1371/journal.pmed.0020124

Ioannidis, J. P. A., Munafò, M. R., Fusar-Poli, P., Nosek, B. A., & David, S. P. (2014). Publication and other reporting biases in cognitive sciences: Detection, prevalence, and prevention. *Trends in Cognitive Sciences*, *18*(5), 235–241. http://doi.org/10.1016/j.tics.2014.02.010

Ito, M., & Kawahara, J. I. (2017). Effect of the Presence of a Mobile Phone during a Spatial Visual Search. *Japanese Psychological Research*, *59*(2), 188–198. http://doi.org/10.1111/jpr.12143

Jarosz, A., & Wiley, J. (2014). What are the odds? A practical guide to computing and reporting Bayes Factors. *The Journal of Problem Solving*, *7*, 2–9. Retrieved from http://docs.lib.purdue.edu/jps/vol7/iss1/2/

Jeffreys, H. (1961). *Theory of Probability*. *Theory of Probability* (Vol. 2). Retrieved from http://ocw.mit.edu/OcwWeb/Mathematics/18-175Spring-2007/LectureNotes/Index.htm

Jeong, S.-H., & Fishbein, M. (2007). Predictors of Multitasking with Media: Media Factors and Audience Factors. *Media Psychology*, *10*(3), 364–384. http://doi.org/10.1080/15213260701532948

Jeong, S.-H., & Hwang, Y. (2016). Media Multitasking Effects on Cognitive vs. Attitudinal Outcomes: A Meta-Analysis. *Human Communication Research*, *42*(4), 599–618. http://doi.org/10.1111/hcre.12089

Jepma, M., & Nieuwenhuis, S. (2011). Pupil Diameter Predicts Changes in the Exploration–Exploitation Trade-off: Evidence for the Adaptive Gain Theory. *Journal of Cognitive Neuroscience*, *23*(7), 1587–1596. http://doi.org/10.1162/jocn.2010.21548

Judd, T. (2013). Making sense of multitasking: Key behaviours. *Computers and Education*, *63*, 358–367. http://doi.org/10.1016/j.compedu.2012.12.017

Judd, T., & Kennedy, G. (2011). Measurement and evidence of computer-based task switching and multitasking by ‘Net Generation’ students. *Computers & Education*, *56*(3), 625–631. http://doi.org/10.1016/j.compedu.2010.10.004

Junco, R. (2012). In-class multitasking and academic performance. *Computers in Human Behavior*, *28*(6), 2236–2243. http://doi.org/10.1016/j.chb.2012.06.031

Junco, R. (2015). Student class standing, Facebook use, and academic performance. *Journal of Applied Developmental Psychology*, *36*, 18–29. http://doi.org/10.1016/j.appdev.2014.11.001

Junco, R., & Cotten, S. R. (2011). Perceived academic effects of instant messaging use. *Computers and*

Education, *56*(2), 370–378. http://doi.org/10.1016/j.compedu.2010.08.020

Junco, R., & Cotten, S. R. (2012). No A 4 U: The relationship between multitasking and academic performance. *Computers and Education*, *59*(2), 505–514. http://doi.org/10.1016/j.compedu.2011.12.023

Kass, R. E., & Raftery, A. E. (1995). Bayes Factors. *Journal of the American Statistical Association*, *90*(430), 773–795.

Katidioti, I., Borst, J. P., & Taatgen, N. A. (2014). What happens when we switch tasks: Pupil dilation in multitasking. *Journal of Experimental Psychology: Applied*, *20*(4), 380–396. http://doi.org/10.1037/xap0000031

Katidioti, I., & Taatgen, N. A. (2013). Choice in Multitasking: How Delays in the Primary Task Turn a Rational Into an Irrational Multitasker. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *56*(4), 728–736. http://doi.org/10.1177/0018720813504216

Katz, E., Blumler, J., & Guretvich, M. (1974). Uses of Mass Communication by the Individual. In *The Uses of Mass Communications: Current Perspectives on Gratifications Research* (pp. 19–32).

Kazakova, S., Cauberghe, V., Pandelaere, M., & De Pelsmacker, P. (2015). Can't See the Forest for the Trees? The Effect of Media Multitasking on Cognitive Processing Style. *Media Psychology*, *18*(4), 425–450. http://doi.org/10.1080/15213269.2015.1006789

Kessler, Y., Shencar, Y., & Meiran, N. (2009). Choosing to switch: Spontaneous task switching despite associated behavioral costs. *Acta Psychologica*, *131*(2), 120–128. http://doi.org/10.1016/j.actpsy.2009.03.005

Kiesel, A., Steinhauser, M., Wendt, M., Falkenstein, M., Jost, K., Philipp, A. M., & Koch, I. (2010). Control and interference in task switching-a review. *Psychological Bulletin*, *136*(5), 849–74. http://doi.org/10.1037/a0019842

König, C. J., & Waller, M. J. (2010). Time for Reflection: A Critical Examination of Polychronicity. *Human Performance*, *23*(2), 173–190. http://doi.org/10.1080/08959281003621703

Kononova, A. (2013). Multitasking across borders: a cross-national study of media multitasking behaviors, its antecedents, and outcomes. *International Journal of Communication*, *7*(2013), 1688–1710. Retrieved from http://libproxy.albany.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edsgao&AN=edsgcl.346926476&site=eds-live&scope=site

Kononova, A., & Chiang, Y. H. (2015). Why do we multitask with media? Predictors of media multitasking among Internet users in the United States and Taiwan. *Computers in Human Behavior*, *50*, 31–41. http://doi.org/10.1016/j.chb.2015.03.052

Kononova, A., Joo, E., & Yuan, S. (2016). If I choose when to switch: Heavy multitaskers remember online content better than light multitaskers when they have the freedom to multitask. *Computers in Human Behavior*, *65*, 567–575. http://doi.org/10.1016/j.chb.2016.09.011

Kononova, A., Zasorina, T., Diveeva, N., Kokoeva, A., & Chelokyan, A. (2014). Multitasking goes global: Multitasking with traditional and new electronic media and attention to media messages among college students in Kuwait, Russia, and the USA. *International Communication Gazette*, *76*(8), 617–640. http://doi.org/10.1177/1748048514548533

Kuznetsova, A., Brockhoff, P. A., & Bojesen, R. H. (2018). lmerTest Package: Tests in Linear Mixed Effects Models. *Journal of Statistical Software*, *83*(13), 1–26. http://doi.org/10.1111/jocn.13257

Lakens, D. (2013). Calculating and reporting effect sizes to facilitate cumulative science: A practical primer for t-tests and ANOVAs. *Frontiers in Psychology*, *4*(NOV), 1–12. http://doi.org/10.3389/fpsyg.2013.00863

Lee, H., Boot, W. R., Basak, C., Voss, M. W., Prakash, R. S., Neider, M., … Kramer, A. F. (2012). Performance gains from directed training do not transfer to untrained tasks. *Acta Psychologica*, *139*(1), 146–158. http://doi.org/10.1016/j.actpsy.2011.11.003

Lenhart, A. (2015). *Teens, Social Media & Technology Overview 2015. Pew Research Center's Internet & American Life Project*. Retrieved from http://www.pewinternet.org/2015/04/09/teens-social-media-technology-2015/

Lepp, A., Barkley, J. E., & Karpinski, A. C. (2014). The relationship between cell phone use, academic performance, anxiety, and Satisfaction with Life in college students. *Computers in Human Behavior*, *31*(1), 343–350. http://doi.org/10.1016/j.chb.2013.10.049

Liberati, A., Altman, D. G., Tetzlaff, J., Mulrow, C., Gøtzsche, P. C., Ioannidis, J. P. A., … Moher, D. (2009). The PRISMA Statement for Reporting Systematic Reviews and Meta-Analyses of Studies That Evaluate Health Care Interventions: Explanation and Elaboration. *PLoS Medicine*, *6*(7), e1000100. http://doi.org/10.1371/journal.pmed.1000100

Liepelt, R., Strobach, T., Frensch, P., & Schubert, T. (2011). Improved intertask coordination after extensive dual-task practice. *Quarterly Journal of Experimental Psychology (2006)*, *64*(7), 1251–1272. http://doi.org/10.1080/17470218.2010.543284

Lin, L. (2009). Breadth-biased versus focused cognitive control in media multitasking behaviors. *Proceedings of the National Academy of Sciences of the United States of America*, *106*(37), 15521–15522. http://doi.org/10.1073/pnas.0908642106

Lin, L., Robertson, T., & Lee, J. (2009). Reading Performances Between Novices and Experts in Different Media Multitasking Environments. *Computers in the Schools*, *26*(3), 169–186. http://doi.org/10.1080/07380560903095162

Liu, J., Smeesters, D., & Trampe, D. (2012). **RETRACTED:** Effects of Messiness on Preferences for Simplicity. *Journal of Consumer Research*, *39*(1), 199–214. http://doi.org/10.1086/662139

Loh, K. K., & Kanai, R. (2014). Higher media multi-tasking activity is associated with smaller gray-matter density in the anterior cingulate cortex. *PloS One*, *9*(9), e106698. http://doi.org/10.1371/journal.pone.0106698

Loh, K. K., & Kanai, R. (2016). How Has the Internet Reshaped Human Cognition? *The Neuroscientist*, *5*, 506–520. http://doi.org/10.1177/1073858415595005

Loh, K. K., Tan, B. Z. H., & Lim, S. W. H. (2016). Media multitasking predicts video-recorded lecture learning performance through mind wandering tendencies. *Computers in Human Behavior*, *63*, 943–947. http://doi.org/10.1016/j.chb.2016.06.030

Lui, K. F. H., & Wong, A. C.-N. (2012). Does media multitasking always hurt? A positive correlation between multitasking and multisensory integration. *Psychonomic Bulletin & Review*, *19*(4), 647–53. http://doi.org/10.3758/s13423-012-0245-7

MacWhinney, B., St James, J., Schunn, C., Li, P., & Schneider, W. (2001). STEP--a System for Teaching Experimental Psychology using E-Prime. *Behavior Research Methods, Instruments, & Computers : A Journal of the Psychonomic Society, Inc*, *33*(2), 287–96. http://doi.org/Article

Magen, H. (2017). The relations between executive functions, media multitasking and polychronicity. *Computers in Human Behavior*, *67*, 1–9. http://doi.org/10.1016/j.chb.2016.10.011

Mahone, E. M., Cirino, P. T., Cutting, L. E., Cerrone, P. M., Hagelthorn, K. M., Hiemenz, J. R., … Denckla, M. B. (2002). Validity of the behavior rating inventory of executive function in children with ADHD and/or Tourette syndrome. *Archives of Clinical Neuropsychology*, *17*(7), 643–662. http://doi.org/10.1016/S0887-6177(01)00168-8

Marius, P., & Anggoro, S. (2014). *Profil Pengguna Internet Indonesia 2014*. Asosiasi Penyelenggara Jasa Internet Indonesia.

Mark, G., Gudith, D., & Klocke, U. (2008). The Cost of Interrupted Work: More Speed and Stress. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 107–110. http://doi.org/10.1145/1357054.1357072

Mark, G., Iqbal, S., Czerwinski, M., & Johns, P. (2015). Focused, Aroused, but so Distractible: A Temporal Perspective on Multitasking and Communications. *CSCW '15 Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, 903–916. http://doi.org/10.1145/2675133.2675221

Mark, G., Wang, Y., & Niiya, M. (2014). Stress and multitasking in everyday college life. *Proceedings of the 32nd Annual ACM Conference on Human Factors in Computing Systems - CHI '14*, 41–50. http://doi.org/10.1145/2556288.2557361

Mathôt, S., Schreij, D., & Theeuwes, J. (2012). OpenSesame: An open-source, graphical experiment builder for the social sciences. *Behavior Research Methods*, *44*(2), 314–324. http://doi.org/10.3758/s13428-011-0168-7

Mcauley, T., Chen, S., Goos, L., Schachar, R., & Crosbie, J. (2010). Is the behavior rating inventory of executive function more strongly associated with measures of impairment or executive function? *Journal of the International Neuropsychological Society*, *16*(03), 495. http://doi.org/10.1017/S1355617710000093

McCandless, S., & O'Laughlin, L. (2007). The Clinical Utility of the Behavior Rating Inventory of Executive Function (BRIEF) in the diagnosis of ADHD. *Journal of Attention Disorders*, *10*(4), 381–389. http://doi.org/10.1177/1087054706292115

Mcfarlane, D. C. (2002). Comparison of Four Primary Methods for Coordinating the Interruption of People in Human – Computer Interaction Lockheed Martin Advanced Technology Laboratories, *17*, 63–139.

Medeiros-Ward, N., Watson, J. M., & Strayer, D. L. (2015). On Supertaskers and the Neural Basis of Efficient Multitasking. *Psychonomic Bulletin & Review*, *22*, 876–883. http://doi.org/10.3758/s13423-014-0713-3

Minear, M., Brasher, F., McCurdy, M., Lewis, J., & Younggren, A. (2013). Working memory, fluid intelligence, and impulsiveness in heavy media multitaskers. *Psychonomic Bulletin & Review*, *20*, 1274–81. http://doi.org/10.3758/s13423-013-0456-6

Moisala, M., Salmela, V., Hietajärvi, L., Salo, E., Carlson, S., Salonen, O., … Alho, K. (2016). Media multitasking is associated with distractibility and increased prefrontal activity in adolescents and young adults. *NeuroImage*, *134*, 113–121. http://doi.org/10.1016/j.neuroimage.2016.04.011

Monsell, S. (2003). Task switching. *Trends in Cognitive Sciences*, *7*(3), 134–140. http://doi.org/10.1016/S1364-6613(03)00028-7

Moreno, S. G., Sutton, A. J., Ades, A., Stanley, T. D., Abrams, K. R., Peters, J. L., & Cooper, N. J. (2009).

Assessment of regression-based methods to adjust for publication bias through a comprehensive simulation study. *BMC Medical Research Methodology*, *9*(2), 1–17. http://doi.org/10.1186/1471-2288-9-2

Morey, R. D. (2008). Confidence Intervals from Normalized Data: A correction to Cousineau (2005). *Tutorials in Quantitative Methods for Psychology*, *4*(2), 61–64. http://doi.org/10.3758/s13414-012-0291-2

Morey, R. D., Rouder, J. N., & Jamil, T. (2015). Computation of Bayes Factors for Common Design. *R Package Version 0.9.12-2*. Retrieved from http://cran.r-project.org/package=BayesFactor

Munoz, D. P., & Everling, S. (2004). Look away: the anti-saccade task and the voluntary control of eye movement. *Nature Reviews Neuroscience*, *5*(3), 218–228. http://doi.org/10.1038/nrn1345

Murphy, K., McLauchlan, S., & Lee, M. (2017). Is there a link between media-multitasking and the executive functions of filtering and response inhibition? *Computers in Human Behavior*, *75*, 667–677. http://doi.org/10.1016/j.chb.2017.06.001

Murphy, P. R., O'Connell, R. G., O'Sullivan, M., Robertson, I. H., & Balsters, J. H. (2014). Pupil diameter covaries with BOLD activity in human locus coeruleus. *Human Brain Mapping*, *35*(8), 4140–4154. http://doi.org/10.1002/hbm.22466

Nieuwenhuis, S., Aston-Jones, G., & Cohen, J. D. (2005). Decision making, the P3, and the locus coeruleus-norepinephrine system. *Psychological Bulletin*, *131*(4), 510–532. http://doi.org/10.1037/0033-2909.131.4.510

Nieuwenhuis, S., Broerse, A., Nielen, M. M. A., & de Jong, R. (2004). A goal activation approach to the study of executive function: An application to antisaccade tasks. *Brain and Cognition*, *56*(2 SPEC. ISS.), 198–214. http://doi.org/10.1016/j.bandc.2003.12.002

Nieuwenstein, M. R., Blom, T. N., Morey, R. D., & Wicherts, J. M. (2015). On making the right choice: A meta-analysis and large-scale replication attempt of the unconscious thought advantage. *Judgement and Decision Making*, *10*(1), 1–17.

Nijboer, M., Taatgen, N. A., Brands, A., Borst, J. P., & van Rijn, H. (2013). Decision making in concurrent multitasking: do people adapt to task interference? *PloS One*, *8*(11), e79583. http://doi.org/10.1371/journal.pone.0079583

Nikkelen, S. W., Valkenburg, P. M., Huizinga, M., & Bushman, B. J. (2014). Media use and ADHD-related behaviors in children and adolescents: A meta-analysis. *Developmental Psychology*, *50*(9), 2228–2241. http://doi.org/10.1111/jcom.12073

Open Science Collaboration. (2015). Estimating the reproducibility of psychological science. *Science*, *349*(6251), aac4716-aac4716. http://doi.org/10.1126/science.aac4716

Ophir, E., Nass, C., & Wagner, A. D. (2009). Cognitive control in media multitaskers. *Proceedings of the National Academy of Sciences of the United States of America*, *106*(37), 15583–7. http://doi.org/10.1073/pnas.0903620106

Otte, E., & Rousseau, R. (2002). Social network analysis: a powerful strategy, also for the information sciences. *Journal of Information Science*, *28*(6), 441–453. http://doi.org/10.1177/016555150202800601

Palfrey, J., & Gasser, U. (2008). *Born Digital*. *New York*. Retrieved from http://books.google.ca/books?id=hqJi8FaayN8C

Patton, J. H., Stanford, M. S., & Barratt, E. S. (1995). Factor Structure of the Barratt Impulsiveness Scale. *Journal of Clinical Psychology*, *51*(6), 768–774.

Pea, R., Nass, C., Meheula, L., Rance, M., Kumar, A., Bamford, H., … Zhou, M. (2012). Media use, face-to-face communication, media multitasking, and social well-being among 8- to 12-year-old girls. *Developmental Psychology*, *48*(2), 327–36. http://doi.org/10.1037/a0027030

Peirce, J. W. (2007). PsychoPy-Psychophysics software in Python. *Journal of Neuroscience Methods*, *162*(1–2), 8–13. http://doi.org/10.1016/j.jneumeth.2006.11.017

Peters, J. L., Sutton, A. J., Jones, D. R., Abrams, K. R., & Rushton, L. (2007). Performance of the trim and fill method in the presence of publication bias and between-study heterogeneity. *Statistics in Medicine*, *26*(May), 4544–4562. http://doi.org/10.1002/sim

PEW Research Center. (2018). Mobile Fact Sheet. Retrieved March 10, 2018, from http://www.pewinternet.org/fact-sheet/mobile/

Pool, M. M., Koolstra, C. M., & van der Voort, T. H. A. (2003). The impact of background radio and television on high school students' homework performance. *Journal of Communication*, *53*(1), 74–87. http://doi.org/10.1093/joc/53.1.74

Poposki, E. M., & Oswald, F. L. (2010). The Multitasking Preference Inventory: Toward an Improved Measure of Individual Differences in Polychronicity. *Human Performance*, *23*(3), 247–264. http://doi.org/10.1080/08959285.2010.487843

Posner, M. I. (1980). Orienting of attention. *Quarterly Journal of Experimental Psychology*, *32*(1), 3–25. http://doi.org/10.1080/00335558008248231

Primack, B. A., Shensa, A., Escobar-Viera, C. G., Barrett, E. L., Sidani, J. E., Colditz, J. B., & James, A. E.

(2017). Use of multiple social media platforms and symptoms of depression and anxiety: A nationally-representative study among U.S. young adults. *Computers in Human Behavior*, *69*, 1–9. http://doi.org/10.1016/j.chb.2016.11.013

Przybylski, A. K., & Weinstein, N. (2012). Can you connect with me now? How the presence of mobile communication technology influences face-to-face conversation quality. *Journal of Social and Personal Relationships*, *30*(3), 237–246. http://doi.org/10.1177/0265407512453827

Psychonomic Society. (2012). Psychonomic Society Guidelines on Statistical Issues. Retrieved July 26, 2017, from http://www.psychonomic.org/page/statisticalguideline

Quan-Haase, A., & Young, A. L. (2010). Uses and Gratifications of Social Media: A Comparison of Facebook and Instant Messaging. *Bulletin of Science, Technology & Society*, *30*(5), 350–361. http://doi.org/10.1177/0270467610380009

R Core team. (2015). R Core Team. *R: A Language and Environment for Statistical Computing*. Retrieved from http://www.r-project.org/

R Core Team. (2017). R Development Core Team. *R: A Language and Environment for Statistical Computing*. Retrieved from https://www.r-project.org/

Rajkowski, J., Kubiak, P., & Aston-Jones, G. (1994). Locus coeruleus activity in monkey: Phasic and tonic changes are associated with altered vigilance. *Brain Research Bulletin*, *35*(5–6), 607–616. http://doi.org/10.1016/0361-9230(94)90175-9

Ralph, B. C. W., & Smilek, D. (2016). Individual differences in media multitasking and performance on the n-back. *Attention, Perception, & Psychophysics*, *79*(2), 582–592. http://doi.org/10.3758/s13414-016-1260-y

Ralph, B. C. W., Thomson, D. R., Cheyne, J. A., & Smilek, D. (2013). Media multitasking and failures of attention in everyday life. *Psychological Research*, *78*(5), 661–9. http://doi.org/10.1007/s00426-013-0523-7

Ralph, B. C. W., Thomson, D. R., Seli, P., Carriere, J. S. A., & Smilek, D. (2015). Media multitasking and behavioral measures of sustained attention. *Attention, Perception, & Psychophysics*, *77*(2), 390–401. http://doi.org/10.3758/s13414-014-0771-7

Rideout, V. J., Foehr, U. G., & Roberts, D. F. (2010). *Generation M2: Media in the Lives of 8 to 18 Year-Olds. The Henry J. Kaiser Family Foundation*. Retrieved from http://kff.org/other/report/generation-m2-media-in-the-lives-of-8-to-18-year-olds/

Rideout, V. J., Vandewater, E. a., & Wartella, E. a. (2003). Zero to Six Electronic media in the lives of infants, toddlers and preschoolers. *Kaiser Family Foundation*, 1–40. http://doi.org/10.1177/0002764204271511

Rigby, J. M., Brumby, D. P., Gould, S. J. J., & Cox, A. L. (2017). Media Multitasking at Home: A Video Observation Study of Concurrent TV and Mobile Device Usage. In *Proceedings of the 2017 ACM International Conference on Interactive Experiences for TV and Online Video* (pp. 3–10). http://doi.org/10.1145/3077548.3077560

Roberts, D. F., & Foehr, U. G. (2008). Trends in media use. *Future of Children*, *18*(1), 11–37. http://doi.org/10.1353/foc.0.0000

Rosen, L. D., Whaling, K., Carrier, L. M., Cheever, N. A., & Rokkum, J. (2013). The Media and Technology Usage and Attitudes Scale: An empirical investigation. *Computers in Human Behavior*, *29*(6), 2501–2511. http://doi.org/10.1016/j.chb.2013.06.006

Rouder, J. N., & Morey, R. D. (2011). A Bayes factor meta-analysis of Bem's ESP claim. *Psychonomic Bulletin & Review*, *18*(4), 682–689. http://doi.org/10.3758/s13423-011-0088-7

Rouder, J. N., Morey, R. D., Speckman, P. L., & Province, J. M. (2012). Default Bayes factors for ANOVA designs. *Journal of Mathematical Psychology*, *56*(5), 356–374. http://doi.org/10.1016/j.jmp.2012.08.001

Rouder, J. N., Speckman, P. L., Sun, D., Morey, R. D., & Iverson, G. (2009). Bayesian t tests for accepting and rejecting the null hypothesis. *Psychonomic Bulletin & Review*, *16*(2), 225–237. http://doi.org/10.3758/PBR.16.2.225

Salvucci, D. D., & Bogunovich, P. (2010). Multitasking and monotasking: The effects of mental workload on deferred task interruptions. *CHI '10 Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 85–88. http://doi.org/10.1145/1753326.1753340

Salvucci, D. D., & Taatgen, N. A. (2008). Threaded cognition: an integrated theory of concurrent multitasking. *Psychological Review*, *115*(1), 101–30. http://doi.org/10.1037/0033-295X.115.1.101

Salvucci, D. D., & Taatgen, N. A. (2011). *The Multitasking Mind. Oxford University Press*. Retrieved from http://www.ai.rug.nl/~niels/publications/BorstTaatgen.pdf

Sanbonmatsu, D. M., Strayer, D. L., Medeiros-Ward, N., & Watson, J. M. (2013). Who multi-tasks and why? Multi-tasking ability, perceived multi-tasking ability, impulsivity, and sensation seeking. *PloS One*, *8*(1), e54402. http://doi.org/10.1371/journal.pone.0054402

Sara, S. J. (2009). The locus coeruleus and noradrenergic modulation of cognition. *Nature Reviews Neuroscience*, *10*(3), 211–223. http://doi.org/10.1038/nrn2573

Sara, S. J., & Bouret, S. (2012). Orienting and Reorienting: The Locus Coeruleus Mediates Cognition through Arousal. *Neuron*, *76*(1), 130–141. http://doi.org/10.1016/j.neuron.2012.09.011

Scammacca, N., Roberts, G., & Stuebing, K. K. (2013). Meta-Analysis With Complex Research Designs: Dealing With Dependence From Multiple Measures and Multiple Group Comparisons. *Review of Educational Research*, *84*(3), 0034654313500826. http://doi.org/10.3102/0034654313500826

Schlehofer, M. M., Thompson, S. C., Ting, S., Ostermann, S., Nierman, A., & Skenderian, J. (2010). Psychological predictors of college students' cell phone use while driving. *Accident; Analysis and Prevention*, *42*(4), 1107–12. http://doi.org/10.1016/j.aap.2009.12.024

Schooler, J. W., Smallwood, J., Christoff, K., Handy, T. C., Reichle, E. D., & Sayette, M. A. (2011). Meta-awareness, perceptual decoupling and the wandering mind. *Trends in Cognitive Sciences*, *15*(7), 319–326. http://doi.org/10.1016/j.tics.2011.05.006

Schutten, D., Stokes, K. A., & Arnell, K. M. (2017). I want to media multitask and I want to do it now: Individual differences in media multitasking predict delay of gratification and system-1 thinking. *Cognitive Research: Principles and Implications*, *2*(1), 8. http://doi.org/10.1186/s41235-016-0048-x

Scott, J. (2011). Social network analysis: developments, advances, and prospects. *Social Network Analysis and Mining*, *1*(1), 21–26. http://doi.org/10.1007/s13278-010-0012-6

Selst, M. Van, & Jolicoeur, P. (1994). A solution to the effect of sample size on outlier elimination. *The Quarterly Journal of Experimental Psychology Section A*, *47*(3), 631–650. http://doi.org/10.1080/14640749408401131

Shih, S. I. (2013). A Null Relationship between Media Multitasking and Well-Being. *PLoS ONE*, *8*(5). http://doi.org/10.1371/journal.pone.0064508

Small, G. W., & Vorgan, G. (2008). *iBrain: Surviving the technological alteration of the modern mind.* Collins Living New York.

Smallwood, J., & Schooler, J. W. (2006). The restless mind. *Psychological Bulletin*, *132*(6), 946–958. http://doi.org/10.1037/0033-2909.132.6.946

Smallwood, J., & Schooler, J. W. (2015). The Science of Mind Wandering: Empirically Navigating the Stream of Consciousness. *Annual Review of Psychology*, *66*(1), 487–518. http://doi.org/10.1146/annurev-psych-010814-015331

Srivastava, J., Nakazawa, M., & Chen, Y. W. (2016). Online, mixed, and offline media multitasking: Role of cultural, socio-demographic, and media factors. *Computers in Human Behavior*, *62*, 720–729. http://doi.org/10.1016/j.chb.2016.04.040

Standard Eurobarometer 86. (2016). *Media use in the European Union*. Accessed online in 27/11/2017.

Stanovich, K. E. (2009). Distinguishing the reflective, algorithmic, and autonomous minds: Is it time for a tri-process theory? In J. S. B. T. Evans & K. Frankish (Eds.), *In Two Minds: Dual Processes and Beyond* (pp. 55–88). http://doi.org/10.1093/acprof:oso/9780199230167.003.0003

Stening, B. W., & Everett, J. E. (1984). Response styles in a cross-cultural managerial study. *The Journal of Social Psychology*, *122*, 151–156.

Sterne, J. A. C., & Egger, M. (2001). Funnel plots for detecting bias in meta-analysis: guidelines on choice of axis. *Journal of Clinical Epidemiology*, *54*(10), 1046–55. http://doi.org/10.1016/S0895-4356(01)00377-8

Sterne, J. A. C., Gavaghan, D., & Egger, M. (2000). Publication and related bias in meta-analysis: Power of statistical tests and prevalence in the literature. *Journal of Clinical Epidemiology*, *53*(11), 1119–1129. http://doi.org/10.1016/S0895-4356(00)00242-0

Sterne, J. A. C., Sutton, A. J., Ioannidis, J. P. A., Terrin, N., Jones, D. R., Lau, J., … Higgins, J. P. T. (2011). Recommendations for examining and interpreting funnel plot asymmetry in meta-analyses of randomised controlled trials. *BMJ (Clinical Research Ed.)*, *343*, d4002. http://doi.org/10.1136/bmj.d4002

Strayer, D. L., Drews, F. A., & Johnston, W. A. (2003). Cell phone-induced failures of visual attention during simulated driving. *Journal of Experimental Psychology: Applied*, *9*(1), 23–32. http://doi.org/10.1037/1076-898X.9.1.23

Strayer, D. L., & Johnston, W. A. (2001). Driven to distraction: dual-Task studies of simulated driving and conversing on a cellular telephone. *Psychological Science*, *12*(6), 462–6. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/11760132

Strayer, D. L., & Watson, J. M. (2012). Supertaskers and the multitasking brain. *Scientific American Mind*, *23*(1), 22–29. http://doi.org/10.1038/scientificamericanmind0312-22

Strobach, T., Frensch, P. A., Soutschek, A., & Schubert, T. (2012). Investigation on the improvement and transfer of dual-task coordination skills. *Psychological Research*, *76*(6), 794–811. http://doi.org/10.1007/s00426-011-0381-0

Thompson, S. G., & Sharp, S. J. (1999). Explaining heterogeneity in meta-analysis: A comparison of methods. *Statistics in Medicine*, *18*(20), 2693–2708. http://doi.org/10.1002/(SICI)1097-0258(19991030)18:20<2693::AID-SIM235>3.0.CO;2-V

Thornton, B., Faires, A., Robbins, M., & Rollins, E. (2014). The Mere Presence of a Cell Phone May be

Distracting. *Social Psychology*, *45*(6), 479–488. http://doi.org/10.1027/1864-9335/a000216

Toplak, M. E., Bucciarelli, S. M., Jain, U., & Tannock, R. (2009). Executive functions: Performance-based measures and the behavior rating inventory of executive function (BRIEF) in adolescents with attention deficit/hyperactivity disorder (ADHD). *Child Neuropsychology*, *15*(1), 53–72. http://doi.org/10.1080/09297040802070929

Toplak, M. E., West, R. F., & Stanovich, K. E. (2013). Practitioner Review: Do performance-based measures and ratings of executive function assess the same construct? *Journal of Child Psychology and Psychiatry and Allied Disciplines*, *54*(2), 131–143. http://doi.org/10.1111/jcpp.12001

Tsukayama, E., Duckworth, A. L., & Kim, B. (2013). Domain-specific impulsivity in school-age children. *Developmental Science*, *16*(6), 879–893. http://doi.org/10.1111/desc.12067

Uncapher, M. R., Lin, L., Rosen, L. D., Kirkorian, H. L., Baron, N. S., Bailey, K., … Wagner, A. D. (2017). Media Multitasking and Cognitive, Psychological, Neural, and Learning Differences. *Pediatrics*, *140*(November). http://doi.org/10.1542/peds.2016-1758D

Uncapher, M. R., Thieu, M. K., & Wagner, A. D. (2016). Media multitasking and memory: Differences in working memory and long-term memory. *Psychonomic Bulletin & Review*, *23*(2), 483–490. http://doi.org/10.3758/s13423-015-0907-3

Uncapher, M. R., & Wagner, A. D. (2018). The minds and brains of media multitaskers: Current findings and future directions. *Proceedings of the National Academy of Sciences*, *115*(40), 9889–9896. http://doi.org/10.1073/pnas.1611612115

Unsworth, N., Schrock, J. C., & Engle, R. W. (2004). Working Memory Capacity and the Antisaccade Task: Individual Differences in Voluntary Saccade Control. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *30*(6), 1302–1321. http://doi.org/10.1037/0278-7393.30.6.1302

Usher, M., Cohen, J. D., Servan-Schreiber, D., Rajkowski, J., Aston-Jones, G., & Aston-Jones, G. (1999). The role of locus coeruleus in the regulation of cognitive performance. *Science*, *283*(January), 549–554. http://doi.org/10.1126/science.283.5401.549

van der Burg, E., Olivers, C. N. L., Bronkhorst, A. W., & Theeuwes, J. (2008). Pip and pop: nonspatial auditory signals improve spatial visual search. *Journal of Experimental Psychology. Human Perception and Performance*, *34*(5), 1053–65. http://doi.org/10.1037/0096-1523.34.5.1053

van der Schuur, W. A., Baumgartner, S. E., Sumter, S. R., & Valkenburg, P. M. (2015). The consequences of media multitasking for youth: A review. *Computers in Human Behavior*, *53*, 204–215. http://doi.org/10.1016/j.chb.2015.06.035

van der Schuur, W. A., Baumgartner, S. E., Sumter, S. R., & Valkenburg, P. M. (2018). Media multitasking and sleep problems: A longitudinal study among adolescents. *Computers in Human Behavior*, *81*, 316–324. http://doi.org/10.1016/j.chb.2017.12.024

van der Stigchel, S., & Theeuwes, J. (2006). Our eyes deviate away from a location where a distractor is expected to appear. *Experimental Brain Research*, *169*(3), 338–349. http://doi.org/10.1007/s00221-005-0147-2

Vera, E. R., & Schupp, T. (2006). Network analysis in comparative social sciences. *Comparative Education*, *42*(3), 405–429. http://doi.org/10.1080/03050060600876723

Viechtbauer, W. (2010). Conducting Meta-Analyses in R with the metafor Package. *Journal of Statistical Software*, *36*(3), 1–48.

Vogel, E. K., McCollough, A. W., & Machizawa, M. G. (2005). Neural measures reveal individual differences in controlling access to working memory. *Nature*, *438*(7067), 500–3. http://doi.org/10.1038/nature04171

Voorveld, H. A. M. (2011). Media multitasking and the effectiveness of combining online and radio advertising. *Computers in Human Behavior*, *27*(6), 2200–2206. http://doi.org/10.1016/j.chb.2011.06.016

Voorveld, H. A. M., & Goot, M. van der. (2013). Age Differences in Media Multitasking: A Diary Study. *Journal of Broadcasting & Electronic Media*, *57*(3), 392–408. http://doi.org/10.1080/08838151.2013.816709

Voorveld, H. A. M., Segijn, C. M., & Ketelaar, P. M. (2014). Investigating the Prevalence and Predictors of Media Multitasking Across Countries. *International Journal of Communication*, *8*, 2755–2777.

Wagenmakers, E.-J. (2007). A practical solution to the pervasive problems of p values. *Psychonomic Bulletin & Review*, *14*(5), 779–804. http://doi.org/10.3758/BF03194105

Wang, R., Bianchi, S. M., & Raley, S. B. (2005). Teenagers' Internet use and family rules: A research note. *Journal of Marriage and Family*, *67*(5), 1249–1258. http://doi.org/10.1111/j.1741-3737.2005.00214.x

Wang, Z., Irwin, M., Cooper, C., & Srivastava, J. (2015). Multidimensions of media multitasking and adaptive media selection. *Human Communication Research*, *41*(1), 102–127. http://doi.org/10.1111/hcre.12042

Wang, Z., & Tchernev, J. M. (2012). The "Myth" of Media Multitasking: Reciprocal Dynamics of Media Multitasking, Personal Needs, and Gratifications. *Journal of Communication*, *62*(3), 493–513.

http://doi.org/10.1111/j.1460-2466.2012.01641.x

Ward, A., Duke, K., Gneezy, A., & Bos, M. (2016). Brain Drain: The Mere Presence of Smartphones Reduces Cognitive Capacity. *Journal of the Association for Consumer Research*, *2*(2). http://doi.org/10.1017/CBO9781107415324.004

Watson, J. M., & Strayer, D. L. (2010). Supertaskers: Profiles in extraordinary multitasking ability. *Psychonomic Bulletin & Review*, *17*(4), 479–85. http://doi.org/10.3758/PBR.17.4.479

Wetzels, R., Matzke, D., Lee, M. D., Rouder, J. N., Iverson, G. J., & Wagenmakers, E.-J. (2011). Statistical Evidence in Experimental Psychology: An Empirical Comparison Using 855 t Tests. *Perspectives on Psychological Science : A Journal of the Association for Psychological Science*, *6*(3), 291–8. http://doi.org/10.1177/1745691611406923

Whiteside, S. P., & Lynam, D. R. (2001). The five factor model and impulsivity: Using a structural model of personality to understand impulsivity. *Personality and Individual Differences*, *30*(4), 669–689. http://doi.org/10.1016/S0191-8869(00)00064-7

Wickham, H. (2010). A Layered Grammar of Graphics. *Journal of Computational and Graphical Statistics*, *19*(1), 3–28. http://doi.org/10.1198/jcgs.2009.07098

Wilson, R. C., Geana, A., White, J. M., Ludvig, E. A., & Cohen, J. D. (2017). Humans Use Directed and Random Exploration to Solve the Explore – Exploit Dilemma. *Journal of Experimental Psychology : General*.

Wiradhany, W., & Nieuwenstein, M. R. (2017). Cognitive control in media multitaskers: Two replication studies and a meta-Analysis. *Attention, Perception, & Psychophysics*, *79*(8), 2620–2641. http://doi.org/10.3758/s13414-017-1408-4

Wittmann, B. C., Bunzeck, N., Dolan, R. J., & Düzel, E. (2007). Anticipation of novelty recruits reward system and hippocampus while promoting recollection. *NeuroImage*, *38*(1), 194–202. http://doi.org/10.1016/j.neuroimage.2007.06.038

Wood, E., Zivcakova, L., Gentile, P., Archer, K., De Pasquale, D., & Nosko, A. (2012). Examining the impact of off-task multi-tasking with technology on real-time classroom learning. *Computers and Education*, *58*, 365–374. http://doi.org/10.1016/j.compedu.2011.08.029

Wood, J., Freemantle, N., King, M., & Nazareth, I. (2014). Trap of trends to statistical significance: likelihood of near significant P value becoming more significant with extra data. *BMJ (Clinical Research Ed.)*, *348*(March), g2215. http://doi.org/10.1136/bmj.g2215

World Health Organization. (2001). International Classification of Funcitoning, Disabiltiy and Health:

Short version. Retrieved from http://apps.who.int/iris/bitstream/10665/42417/1/9241545445_eng.pdf

Wu, J. Y. (2017). The indirect relationship of media multitasking self-efficacy on learning performance within the personal learning environment: Implications from the mechanism of perceived attention problems and self-regulation strategies. *Computers and Education*, *106*, 56–72. http://doi.org/10.1016/j.compedu.2016.10.010

Yang, J., Zaitlen, N. A., Goddard, M. E., Visscher, P. M., & Price, A. L. (2014). Advantages and pitfalls in the application of mixed-model association methods. *Nature Genetics*, *46*(2), 100–106. http://doi.org/10.1038/ng.2876

Yang, X., & Zhu, L. (2016). Predictors of media multitasking in Chinese adolescents. *International Journal of Psychology*, *51*(6), 430–438. http://doi.org/10.1002/ijop.12187

Yap, J. J. Y., & Lim, S. S. W. H. (2013). Media multitasking predicts unitary versus splitting visual focal attention. *Journal of Cognitive Psychology*, *25*(7), 889–902. http://doi.org/10.1080/20445911.2013.835315

Yeykelis, L., Cummings, J. J., & Reeves, B. (2014). Multitasking on a Single Device: Arousal and the Frequency, Anticipation, and Prediction of Switching Between Media Content on a Computer. *Journal of Communication*, *64*(1), 167–192. http://doi.org/10.1111/jcom.12070

Yu, A. J., & Dayan, P. (2005). Uncertainty, neuromodulation, and attention. *Neuron*, *46*(4), 681–692. http://doi.org/10.1016/j.neuron.2005.04.026

Zuckerman, M. (2007). *Sensation seeking and risky behavior*. Washington DC: American Psychological Association. http://doi.org/10.1037/11555-000

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Summary/Samenvatting/Intisari

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Summary

Recent developments of media technologies have provided us with affordable, yet powerful devices. Given the ubiquity of these devices and the plasticity of our brain, our media-related activities might have consequences for various cognitive and psychological domains. Critically, these consequences may vary from one individual to another. For instance, for people with good multitasking ability (i.e., good multitaskers), media devices would help them accomplish their tasks more efficiently. However, for people with cognitive control problems (i.e., distracted multitaskers), media devices might distract them from accomplishing their tasks. This thesis aims to address three questions central to the discussion of the effects of media technologies in general and media multitasking, consuming multiple streams of information from media in particular: What constitutes the media multitasking behavior, which domains of cognition and behavior differentiate heavy from light media multitaskers, and to what extent does the presence of media devices influence our ability to process information?

Which media activities do people combine in multitasking? In Chapter 2, we rendered the responses from the widely-used media use questionnaire (MUQ) into networks. The MUQ asks how often people combine one media activity with another. The network analyses showed that media multitasking revolves around a small set of prominent media combinations involving Texting, Browsing, Listening to music, and Accessing social media. These prominent combinations were somewhat agreed with what has been proposed as the adaptive combinations of multitasking: they are typically characterized by combinations of media for which each medium is received through a different sensory modality and they comprise information that remains available for later access (e.g., messages received through social media), thus allowing users to easily switch between one medium and another without losing any information.

Which domains of cognition differentiate heavy from light media multitaskers? In Chapters 3 and 4, we looked into the correlates of media multitasking with different domains of cognition that were assessed with measures of task performance. Here, we found no evidence that heavy and light media multitaskers can be distinguished in terms of differences in cognitive functions relating to the ability to prevent distraction. Our studies and meta-analysis showed that, unlike what has been suggested in several studies and a recent review, heavy media multitaskers are not more susceptible to distractions present in their immediate environment, or to distractions from their memory, or to distractions from changing from one task-set to another, or to distractions caused by mind-wandering.

In Chapter 5, we looked into the correlates of media multitasking behavior with self-report measures of cognitive functioning in daily life in a series of mini meta-analyses. That is, we search the literature for studies that reported correlates of media multitasking with self-reports of everyday functioning and we categorized the findings based on their similar themes. Here, we found that heavy media multitaskers reported more problems related to behavior regulation and metacognition, more (severe) symptoms related to ADHD, depression, and anxiety, and a higher level of impulsiveness and sensation-seeking traits.

To what extent does the presence of media devices influence our ability to process information? In Chapter 6, we examined the potential effects of the presence of a media device, in particular, one's own mobile phone, in absence of any interactions with this device in an antisaccade experiment. We found that the mere presence of one's mobile phone was associated with worse performance in the task. Additionally, we found that mobile phones might induce a spatial bias. In trials in which participants had to make eye movements in the direction of their phone, their performance was more accurate, but slower, indicating that while the mobile phone was an attractive distractor, participants tried to avoid looking directly at it.

Together, we found no evidence that heavy and light media multitaskers vary in their ability to prevent distraction in laboratory tasks. Nevertheless, looking into self-reports, it seems that heavy media multitaskers do experience more problems related to distraction in everyday situations. Additionally, we found evidence that the mere presence of one's mobile phone might also be distracting.

To explain these findings, I proposed a novel theoretical framework for media-related multitasking. Specifically, media multitasking might occur when an individual switches from an exploitation-related mode of processing (i.e., trying to perform the task at hand, e.g., writing a thesis summary, well) to an exploration-related mode of processing (i.e., searching for alternative activities, e.g., checking one's social network). For competent multitaskers, this act of switching might occur because it helps to optimize their performance across tasks; these people have good awareness of the current payoff of the task at hand and the possible payoff of the alternative task. However, for distracted multitaskers, switching might occur d to their bias towards explorations or because they cannot stay engaged with the current task. Perhaps this framework would help the field to move forward: Instead of searching for domains of cognition which differentiate heavy from light multitaskers, we should start investigating the function of media multitasking behavior. In particular, one's ability to keep track of the payoff of the current and the alternative tasks might play a pivotal role to determine whether someone would be a good or distracted multitasker.

Samenvatting

Recente media-technologische ontwikkelingen hebben geresulteerd in de beschikbaarheid van velerlei betaalbare en krachtige media instrumenten. Gezien de alomtegenwoordigheid van deze instrumenten en gegeven de plasticiteit van ons brein, is het mogelijk dat frequent media gebruik effecten heeft op zowel cognitief als psychologisch gebied. Hierbij is het goed te beseffen dat deze effecten mogelijkerwijs zullen verschillen tussen individuen. Bij mensen die goed kunnen multitasken ("goede multitaskers") zou het gebruik van media instrumenten wel eens tot een meer efficiënte taakuitvoering kunnen leiden. Terwijl multimedia gebruik door mensen met cognitieve controle problemen ("afleidbare multitaskers") wel eens contra productief zou kunnen werken bij de uitvoering van hun taken.

In het kader van de discussie omtrent de effecten van de media technologie in het algemeen, en meer specifieke aspecten zoals media multitasking en het parallel verwerken van meerdere informatiestromen in het bijzonder, staan in dit proefschrift drie onderzoeksvragen centraal: Wat wordt verstaan onder media multitasking gedrag? Welke cognitieve- en gedragsvariabelen onderscheiden "zware" van "lichte" media multitaskers? En in welke mate beïnvloedt de aanwezigheid van media apparatuur het vermogen om informatie te verwerken.

Welke media activiteiten worden tijdens multitasking door mensen gecombineerd? In hoofdstuk 2 werd met gebruikmaking van netwerk analyses gekeken naar de antwoorden die mensen geven op de veel gebruikte "media gebruik" vragenlijst (MUQ). De MUQ meet hoe vaak mensen de ene media activiteit combineren met een andere media activiteit. De analyses lieten zien dat er bij media multitasking een klein aantal prominente media combinaties centraal staan, te weten combinaties van "texting", "browsing", luisteren naar muziek, en toegang tot sociale media. Deze combinaties kwamen tot op zekere hoogte overeen met wat bekend staat als "adaptieve combinaties van multitasking." Kenmerkend voor deze adaptieve combinaties is dat elk van deze media binnenkomt via een ander sensorisch kanaal, waarbij de informatiestroom bestaat uit informatie die later nog teruggevonden kan worden zodat de ontvanger verlies van informatie kan schakelen van het ene medium naar het andere.

Welke aspecten van cognitie onderscheiden "zware" van "lichte" media multitaskers? In de hoofdstukken 3 en 4 onderzochten wij correlaten van media multitasking, waarbij cognitief functioneren werd getoetst aan de hand van taakprestaties op cognitieve gedragstaken.

Uit de resultaten blijkt dat in cognitief opzicht “zware” en “lichte” media multitaskers niet verschilden voor wat betreft hun vermogen om distractie tegen te gaan. Onze bevindingen (o.a. die van een meta-analyse) laten, anders dan recentelijk in de literatuur gesuggereerd, zien dat “zware” media multitaskers niet overgevoelig zijn voor distractie die veroorzaakt wordt door stimuli in hun directe omgeving. Daarnaast vonden we ook geen verschil in de mate van afleidbaarheid door irrelevante informatie in het geheugen, en was er ook geen verschil in het vermogen om snel tussen 2 taken te switchen, of in de frequentie waarmee proefpersonen tijdens een cognitieve taak afdwaalden qua gedachten.

In hoofdstuk 5 onderzochten we correlaten van media multitasking gedrag via een reeks mini meta-analyses, waarin studies naar het dagelijks cognitieve functioneren met behulp van zelfrapportage vragenlijsten, werden geïncludeerd. De resultaten van de meta-analyses lieten zien dat “zware” media multitaskers meer problemen met gedragsregulatie en metacognitie rapporteerden. Verder rapporteerden ze meer (ernstige) ADHD-, depressie-, en angst symptomen, tesamen met verhoogde impulsiviteit en sensatiezoekend gedrag.

In hoeverre beïnvloedt de aanwezigheid van media instrumenten ons vermogen om informatie te verwerken? In hoofdstuk 6 onderzochten we de mogelijke gevolgen van de simpele aanwezigheid van een media instrument, iemands eigen mobiele telefoon, tijdens een antisaccade experiment. Het bleek dat het simpele feit van de aanwezigheid van iemands mobiele telefoon gepaard ging met een verminderde taakprestatie. Verder bleek dat de aanwezigheid van een mobiele telefoon wellicht een ruimtelijke voorkeur/bias teweegbrengt. Bij trials waarin de participanten oogbewegingen in de richting van hun telefoon moesten maken, bleek hun taakprestatie accuraat maar langzaam te zijn. Het is voorstelbaar dat de telefoon een dusdanig aantrekkelijke afleider vormde voor de participanten dat ze probeerden te vermijden om er direct naar te kijken.

Samenvattend, tijdens onze laboratoriumtaken bleken “zware” en “lichte” media multitaskers niet van elkaar te verschillen voor wat betreft hun vermogen om distractie/afleiding te negeren. Niettemin, suggereerden onze zelfrapportage resultaten dat in het dagelijks leven “zware” media multitaskers meer afleidbaarheidsproblemen ondervinden dan “lichte” media multitaskers. Bovendien, bleek dat enkel de aanwezigheid van iemands mobiele telefoon al van invloed kan zijn op taak prestatie en de verdeling van iemands aandacht.

Ter verklaring van onze bevindingen, en om tevens tot een beter begrip van het concept media-gerelateerde multitasking te komen, suggereer ik een nieuw theoretisch model. Dit model gaat uit van de gedachte dat media multitasking plaats vindt wanneer een individu omschakelt van een "exploitatie-gerelateerde" wijze van verwerken (trachten één hoofdtaak goed uit te voeren: bijv. het schrijven van een samenvatting) naar een "exploratie-gerelateerde" wijze van verwerken (het verkennen van alternatieve taken c.q. bezigheden: bijv. het checken van sociale netwerken). Voor competente multitaskers zal deze omschakeling mogelijk plaatsvinden wanneer er naar verwachting sprake zal zijn van een positief effect voor de uitvoering van meerdere taken tegelijkertijd: ze zijn zich bewust dat zowel de hoofdtaak als de parallelle taken zullen profiteren van hun aanpak. Echter, het is voorstelbaar dat afleidbare multitaskers bijna per definitie omschakelen naar een "exploratie-gerelateerde" aanpak vanwege hun inherente neiging tot exploratie of vanwege een fundamenteel onvermogen om zich te richten op slechts één taak. Wellicht dat bovenstaand model een nieuw licht zal werpen op de cognitieve aspecten van media multitasking: In plaats van zoeken naar de cognitieve verschillen tussen "zware" en "lichte" multitaskers, zou het onderzoeken vooral gericht moeten worden op de primaire functie van media multitasking. Met name het vermogen om het voordeel af te wegen van het uitvoeren van één taak versus het voordeel van het uitvoeren van meerdere taken vice versa, zou wel eens een belangrijke factor kunnen zijn bij het bepalen van of iemand een goede multitasker dan wel een afleidbare multitasker is.

Intisari

Perkembangan teknologi media terkini telah menyediakan kita gawai yang canggih, namun terjangkau. Mengingat keberadaan gawai-gawai canggih tersebut dan kemampuan otak kita untuk beradaptasi, aktivitas kita yang berhubungan dengan media mungkin memengaruhi terhadap ranah kognitif dan psikologis. Jika diamati secara kritis, konsekuensi ini dapat bervariasi antara satu orang ke orang lainnya. Misalnya, untuk orang dengan kemampuan multitasking yang baik (misal, *multitasker* kompeten), perangkat media akan membantu mereka menyelesaikan tugasnya dengan lebih efisien. Namun, untuk orang dengan masalah kontrol kognitif (misal, *multitasker* terdistraksi), perangkat media dapat mengganggu mereka saat menyelesaikan tugas. Tesis ini bertujuan menjawab tiga pertanyaan mengenai dampak teknologi media secara umum dan media multitasking, mengkonsumsi beberapa sumber informasi sekaligus, secara khusus: Apa yang mendasari perilaku media multitasking, domain kognisi dan perilaku apa saja yang membedakan *multitasker* berat dan ringan, dan sejauh mana kehadiran perangkat media memengaruhi kemampuan kita untuk memproses informasi?

Aktivitas media apa saja yang dilakukan seseorang dalam multitasking? Pada Bab 2, kami mereproduksi respon dari kuesioner penggunaan media (MUQ) yang umum digunakan dalam penelitian, ke dalam jaringan (networks). MUQ menanyakan seberapa sering seseorang menggabungkan satu aktivitas media dengan aktivitas media lainnya. Analisis jaringan menunjukkan bahwa media multitasking merujuk pada kumpulan kombinasi media yang menonjol, seperti Mengirim pesan, Jelajah web, Mendengarkan musik, dan Mengakses media sosial. Kombinasi yang menonjol ini menguatkan apa yang disebut sebagai kombinasi adaptif multitasking: Kombinasi perilaku tersebut biasanya dicirikan oleh kombinasi media yang setiap medianya diterima (oleh otak) melalui modalitas sensorik yang berbeda dan mengandung informasi yang tetap tersedia untuk dapat diakses di kemudian waktu (misalnya, pesan yang diterima melalui media sosial), sehingga memungkinkan pengguna untuk dapat dengan mudah beralih dari satu media ke media lainnya tanpa kehilangan informasi apa pun.

Domain kognisi mana yang membedakan antara media *multitasker* berat dan ringan? Pada Bab 3 dan 4, kami merangkum korelasi antara media multitasking dengan berbagai domain kognisi yang dinilai dengan mengukur kinerja. Hasilnya, kami tidak menemukan bukti bahwa ada perbedaan antara media *multitasker* berat dan ringan dalam fungsi kognitif yang berkaitan dengan kemampuan untuk mencegah gangguan (distraction). Penelitian dan meta-analisis yang kami lakukan menunjukkan bahwa, berbeda dengan hasil yang dikemukakan oleh berbagai penelitian dan ulasan terbaru, media *multitasker* berat tidak mudah terusik oleh gangguan yang ada di lingkungan mereka, atau ganggu dari memori mereka, atau gangguan ketika beralih dari satu tugas ke tugas lainnya, atau gangguan yang disebabkan oleh pikiran yang mengembara (melamun).

Pada Bab 5, kami mengamati korelasi antara perilaku media multitasking dengan pengukuran lapor-diri terkait fungsi kognitif dalam kehidupan sehari-hari melalui serangkaian meta-analisis mini. Artinya, kami mencari literatur penelitian yang melaporkan korelasi antara media multitasking dengan laporan diri mengenai fungsi harian, lalu kami mengategorikan temuan berdasarkan tema yang sama. Kami menemukan bahwa media *multitasker* berat melaporkan lebih banyak masalah yang berkaitan dengan regulasi perilaku dan metakognisi, lebih banyak gejala yang berkaitan dengan ADHD (Attention Deficit Hyperactive Disorder), depresi, kecemasan, dan tingkat impulsifitas dan mencari-sensasi yang lebih tinggi.

Sejauh mana kehadiran gawai memengaruhi kemampuan kita untuk memproses informasi? Pada Bab 6, kami memeriksa efek potensial dari keberadaan gawai, khususnya, gawai milik pribadi, tanpa adanya interaksi dengan perangkat tersebut dalam eksperimen antisaccade. Kami menemukan bahwa hanya dengan keberadaan gawai saja sudah berkaitan dengan kinerja yang lebih buruk dalam tugas yang diberikan di eksperimen tersebut. Selain itu, kami menemukan bahwa gawai dapat memicu spatial bias. Dalam uji coba, ketika partisipan harus membuat gerakan mata ke arah gawainya, kinerja mereka lebih akurat, tetapi secara perlahan, hasil menunjukkan bahwa meskipun gawai adalah pengalih perhatian yang menarik, para partisipan mencoba untuk tidak melihat langsung ke arah gawai.

Secara keseluruhan, kami tidak menemukan bukti bahwa media *multitasker* berat dan ringan berbeda kemampuannya untuk mencegah gangguan dalam menyelesaikan tugas-tugas di laboratorium. Meski demikian, jika melihat hasil lapor-diri, tampaknya media *multitasker* berat memang mengalami lebih banyak masalah berkaitan dengan gangguan dalam kehidupan sehari-hari mereka. Selain itu, kami menemukan bukti bahwa keberadaan gawai semata dapat menjadi pengganggu.

Untuk menjelaskan temuan-temuan tersebut, saya mengusulkan kerangka teori baru untuk multitasking terkait media. Secara khusus, media multitasking dapat terjadi ketika seseorang beralih dari cara pemrosesan terkait-eksploitasi (yaitu, mencoba melakukan tugas yang dihadapi, misalnya, menulis ringkasan tesis dengan baik) ke cara pemrosesan terkait-eksplorasi (yaitu, mencari kegiatan alternatif, misalnya, memeriksa media sosial). Untuk *multitasker* kompeten, peralihan ini mungkin terjadi karena dapat membantu mengoptimalkan kinerjanya secara keseluruhan; orang-orang ini memiliki kesadaran yang baik mengenai nilai dari tugas yang sedang dikerjakan dan kemungkinan hasil dari tugas alternatif. Namun, untuk *multitasker* terdistraksi, peralihan ini mungkin terjadi akibat bias terhadap eksplorasi atau karena mereka tidak dapat tetap fokus pada tugas yang sedang dikerjakan. Kerangka kerja ini diharapkan mampu membantu studi mengenai multitasking di masa yang akan datang: Alih-alih mencari domain kognisi yang membedakan antara *multitasker* berat dan ringan, kita harus mulai menyelidiki manfaat perilaku media multitasking. Secara khusus, kemampuan seseorang untuk menyadari nilai dari tugas utama dan tugas alternatif yang mungkin memainkan peran penting untuk menentukan apakah seseorang akan menjadi *multitasker* yang kompeten atau yang mudah terdistraksi.

Acknowledgments

Acknowledgments

You! You have reached the acknowledgments section of this thesis. Perhaps you have read (parts) of the thesis? Thank you. Perhaps this page was the first one you look for? Also, thank you! The book you are holding right now should exemplify my best works, so far. I hope you enjoyed reading it.

The training period to become a scientist is a long one. In my case, it took about 11 years. I had spent the last four of those 11 for this PhD project, and I am grateful to have met some amazing people who have been there in my ups and downs. In Indonesia (or somewhere in Asia), we say that it takes a village to raise a child. The following pages are a tribute to my villagers.

The first part belongs to the people who oversee(saw) my works in the village. Mark, thank you for the detailed and sometimes overwhelming amount of feedback you gave. I do learn a lot from you, no matter I sometimes hate the process, and I love you like a brother. I hope both of us have learned much in this process. Ritske, thank you for giving me the opportunity to do a PhD here, and for your nice comments (the one I remembered the most, from when I did my masters was “Not everything has to be difficult”). Susanne, thank you for giving me one of the first opportunities to do a collaborative project. Janneke, thanks for your patience in helping me organizing and re-organizing the meta-analytic results. Sebastiaan, thanks for teaching me about eye tracking and pupillometry, and for programming an application that I can actually use once I return to Indonesia to continue doing research. Marieke, thanks for your patience and our discussions on mind-wandering. I also would like to thank the members of the assessment committee, the PhD examining committee, and the contributors for the symposium: Anthony Wagner, Casper Albers, Dick de Waard, Hilde Voorveld, Kevin Madore, Jesper Aagaard, Niels Taatgen, and Susanne Baumgartner.

At the end of my working days, I return to a hut that belongs to me and my significant other. No matter how difficult my day is, Astin is there to listen and to share her stories with me. You are always here for me, figuratively and these days physically, and I cannot be happier after you decided to also do your PhD in the Netherlands.

At working days, I shared my working hut with two amazing people. Nadine and Tineke have provided both emotional and social supports in most days. You are quick in telling me to do things that I say do not particularly enjoy but would enjoy nonetheless (socializing, trying something new). You are also quick in correcting me whenever I did something wrong. I hope that I do not become too reliant on you. I hope you will still be figuratively there, in years to come. And thanks for organizing the party!

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Before I moved to the Netherlands, I came from another village. I remember my first academic advisor, Lyly Puspa (now I am somewhat one, too; this academic advising thing is difficult!) from my Bachelor days. Clara Ajisuksmo, Neila Ramdhani, and Johana Hadiyono also convinced me to pursue a career in science. I think it kinda worked. Neila, especially, encouraged me to study abroad and accommodated my first opportunity to do so. Thank you. Johana, thank you especially for introducing me to Astin. Also, thank you, my parents, Zanny Nagasena and Melania Chandra for your trust. We had not been this physically far before, and it must have been as difficult, if not more difficult for you to be apart from your only child for so long. Lastly, my PhD project had become a reality thanks to the scholarship I received from the Indonesia Endowment Fund for Education (LPDP). Without it, I would not even be able to afford to eat (and to have a roof over my head). Thank you, LPDP and Indonesian taxpayers!

Tomorrow, I will partly move to another village. I am excited to find future opportunities in my collaboration project with Jeremy, and to continue working at the teaching department of this university. The journey has not ended yet, but the part that has been over had contributed greatly to my personal growth. Forward!

Biography

Wisnu Wiradhany was born in Jakarta, Indonesia on October 5, 1987. He finished his BSc in Psychology at Atma Jaya Catholic University of Indonesia, Jakarta in 2010. In 2011, he enrolled in the MA program in Psychology at Universitas Gadjah Mada, Yogyakarta, which he finished in 2014. He moved to the Netherlands for the first time in 2013, upon receiving an Erasmus Mundus Scholarship to partake in an exchange program with University of Groningen. In 2015, he started his PhD project on media multitasking at the Department of Experimental Psychology, Faculty of Behavioural and Social Science and the Research School of Behavioural Cognitive Neuroscience of the University of Groningen. This project was fully funded by the Indonesia Endowment Fund for Education, Ministry of Finance, Republic of Indonesia. He is currently working in the Teaching Unit of the Psychology Department at the University of Groningen.