Uncovering the Structure of Media Multitasking and Attention Problems Using Network Analytic Techniques

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Abstract

Media multitasking has become nearly ubiquitous in the developed world. Higher self-reported media multitasking has consistently been shown to relate to self-reported attention problems, including symptoms of attention deficit/hyperactivity disorder (ADHD), but the magnitude of this relationship is small and heterogeneous across studies. These findings have motivated calls for increased specificity in media multitasking research, moving beyond aggregated summaries of multitasking behavior in favor of an approach that considers how specific combinations of media behaviors relate to cognitive outcomes of interest. Herein, we take a data-driven (Jack et al., 2018), computational approach to uncover the network structure of media multitasking behaviors in a sample of 2542 young adults in the United States. Results indicate that those with greater severity of ADHD symptoms tend to have more densely connected multitasking networks overall, as well as differing patterns of node centrality within the network. These results provide increased understanding of how individual differences in media multitasking habits relate to attention and cognition, and point to the promise of network-based analyses developing a fuller understanding within this topic domain.

Keywords: Media Multitasking, Attention, ADHD, Network Analysis

Media multitasking has become the de facto norm for media consumption in the developed world (Deloitte, 2019; Rideout et al., 2010). The average adult spends more than 11 hours per day listening to, watching, reading, or generally interacting with media (Nielsen, 2018), multitasking up to 96% of this time (Deloitte, 2019), and switching between media tasks multiple times per minute (Brasel & Gips, 2011; Yeykelis et al., 2014). Media multitasking is often shown to correlate with attention problems in everyday life (Uncapher & Wagner, 2018; van der Schuur et al., 2015; Wiradhany & Koerts, 2019), and with symptoms of cognitive disorders like attention deficit-hyperactivity disorder (ADHD; Magen, 2017; Uncapher et al., 2016). At the same time, individual differences in media multitasking habits seem to have very little influence on lab-based measures of attention (Wiradhany & Nieuwenstein, 2017). More frequent media multitaskers seem to underperform less frequent media multitaskers in attention tasks (see e.g., Gorman & Green, 2016; Ophir et al., 2009; Ralph & Smilek, 2017, 2017; Uncapher et al., 2016), but this is not always the case (Alzahabi & Becker, 2013; Lui & Wong, 2012; Minear et al., 2013).

These conflicting findings have prompted calls for increased research into how individual differences in media multitasking habits relate to attention and cognition (Beyens et al., 2018; Rothbart & Posner, 2015; Uncapher et al., 2017; Uncapher & Wagner, 2018). At present, this research is overwhelmingly reliant on a single measure: the Media Multitasking Index (MMI; Ophir et al., 2009). The MMI aggregates a large array of self-reported media use and multitasking variables into a single value, disregarding potentially important information regarding the specific combinations of media tasks a person engages in during their day to day lives (Baumgartner et al., 2017; Segijn et al., 2018; Wiradhany & Baumgartner, 2019).

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Media multitasking, however, encompasses a rich assortment of unique behaviors, each with their own inputs, outputs, and motivations, and each having their own influences on cognition (Fisher & Keene, 2020; Wang et al., 2015).

In recent years, researchers have begun to apply tools from network science in order to identify and analyze aspects of human behavior that are not well-characterized by uni-dimensional summary scores (see e.g., Borsboom et al., 2021; Borsboom & Cramer, 2013). In this approach, variables of interest in a dataset are represented as nodes in a network, with linkages between variables (e.g. conditional associations) represented as edges. In line with this approach, we herein analyze the MMI as a network, in which individual media tasks (e.g., watching television) are treated as nodes, and edges correspond to the frequency with which a person reports multitasking between each task (e.g., watching television while using mobile apps; Wiradhany & Baumgartner, 2019), weighted by the frequency with which a person reports engaging in each task in a given week. This MMI network has been shown to vary across populations in ways not captured by the aggregated MMI (Wiradhany & Baumgartner, 2019), but the relationship between the structure of the media multitasking network and attention problems is currently unknown.

Herein, we present results from a data-driven (Jack et al., 2018) effort to uncover the network structure of media multitasking behaviors in a sample of more than 2500 young adults, and to understand how variations in the topology of this network relate to attention problems, and to other individual differences. Results show that higher overall connectivity in the media multitasking network is associated both with greater ADHD symptoms and with greater self-reported failures of attention in everyday life. In addition to global connectivity, results indicate that attention problems are associated with variations in the connectivity of individual nodes in the multitasking network. These results provide increased understanding of how individual differences in media multitasking habits relate to attention and cognition, and suggest potential targets for interventions designed to ascertain the causal influence of media multitasking behaviors on attention-related cognitive function.

Media Use and Attention

The relationship between media use and attention problems has been an active topic of investigation for at least the last forty years (see e.g., Anderson et al., 1977; Tower et al., 1979). Many studies in this area report a positive association between media use and attention problems, with observed effects extending to a wide variety of domains (Landhuis et al., 2007; Swing et al., 2010; Zimmerman & Christakis, 2007). Other studies, though, suggest that there is no meaningful relationship between media use and attention problems after controlling for potential confounds (Obel et al., 2004; Stevens, 2006). These conflicting results are underscored by contradictory meta-analyses finding that media use is (Nikkelen et al., 2014; Zimmerman & Christakis, 2007) or is not (Ferguson, 2011, 2015) associated with suboptimal attention-related outcomes.

In many ways, the trajectory of research investigating media multitasking and attention has followed that of general media use. Some work presents convincing evidence that more frequent media multitaskers underperform less frequent media multitaskers in attention-demanding tasks (Cain & Mitroff, 2011; Moisala et al., 2016; Ophir et al., 2009; Uncapher et al., 2017), but other work shows no differences in performance between the two groups (Cardoso-Leite et al., 2016; Gorman & Green, 2016; Wiradhany et al., 2019; Wiradhany & Koerts, 2019; Wiradhany & Nieuwenstein, 2017), or even that more frequent media multitaskers perform *better* in certain aspects of attentional control (Alzahabi & Becker, 2013; Lui & Wong, 2012; Minear et al., 2013). Although self-report measures consistently suggest a positive relationship between media multitasking and attention problems (Baumgartner et al., 2014; Magen, 2017; Ralph et al., 2014), a meta-analysis suggests that these relationships are quite small and heterogeneous across studies, and that they don't account for a large proportion of the possible landscape of media multitasking behaviors (Wiradhany & Koerts, 2019).

These ambiguous findings have prompted calls for larger, more well-powered studies (Ralph & Smilek, 2017; Wiradhany & Nieuwenstein, 2017) of media multitasking, as well as for greater conceptual specificity in this domain (Beyens et al., 2018; Uncapher et al., 2017; Uncapher & Wagner, 2018). Media multitasking can take an almost infinite number of forms, depending on the particular media behaviors that are combined. Some media behaviors can be more efficiently combined than others, depending on the input, output, and processing systems that these behaviors rely on (Fisher & Keene, 2020; Wang et al., 2015). Multitasking behaviors also range widely in their motivational influences, and in the extent to which users have control over their multitasking behavior (Kononova et al., 2016; Ralph et al., 2018). In this sense, one could anticipate that different task combinations will be chosen with more frequency by those with attention issues than others, and that certain combinations of tasks may facilitate more or less efficient modes of attentional processing—potentially with long-term consequences.

Media Multitasking as a Network

Despite the general acknowledgment that multitasking behavior is not well captured by summary measures (e.g., Beyens et al., 2018; Uncapher & Wagner, 2018; Wiradhany & Baumgartner, 2019; Wiradhany & Koerts, 2019), the vast majority of work investigating individual differences in media multitasking relies on the Media Multitasking Index (MMI), calculated from the Media Use Questionnaire developed by Ophir, Nass, and Wagner (2009), a single summary measure of a large assortment of media multitasking behaviors. In the MMI, a participant estimates the amount of time each week he or she spends engaging in each of a number of different media tasks (such as talking on the phone or playing video games). The participant is then shown each media task again, and asked to rate how often he or she concurrently engages in each of the other media tasks while using the primary medium. A person's total MMI rating is then calculated as a weighted sum of all media multitasking pairs. This can be summarized in the equation:

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

Where m_i is the extent to which a person multitasks between two media, h_i is the amount of time that a person spends using the primary medium in a given week, and h_{total} is the person's total self-reported weekly media use.

Recently, Wiradhany and Baumgartner (2019) introduced a novel analytic approach to analyzing the Media Use Questionnaire that considers media multitasking as a directed network of interrelated behaviors. In this approach, each media task is treated as a node, and the frequency with which a person multitasks from that task (the *primary task)* to each other (*secondary*) task in the questionnaire is treated as a directed edge from the primary task to the secondary task. This results in a network with a number of nodes equal to the number of media tasks queried in the questionnaire and with $n_{tasks} \times (n_{tasks} - 1)$ edges. This approach affords researchers with much richer data regarding how individual pairs or clusters of multitasking behavior relate to outcomes of interest.

Although the results proffered by Wiradhany and Baumgartner (2019) were largely exploratory, they provide key insights into how network science may be used to better understand individual variation in media multitasking, and how it relates to attention problems.

Those with more severe attention problems may find themselves engaging in less efficient task combinations than those whose attention problems are less severe. As an example, someone may media multitask when typing an essay in a word processing program by listening to music in the background (tasks that use separate modalities and that can be efficiently parallelized, Cassidy & MacDonald, 2009). Someone may also media multitask when playing video games by attempting to watch online videos (tasks that use the same modality and usually cannot be efficiently done in parallel). Critically, these differences would be largely unobservable in the summary MMI, especially if these individuals spend the same amount of time each week performing each task combination. Treating media multitasking as a network of interrelated behaviors allows for analyses that consider how particular combinations of multitasking behaviors relate to attention problems. As such, a network perspective is likely to provide novel insight as to how individual differences in media multitasking behaviors relate to attention problems in everyday life and to the severity of ADHD symptoms.

Methods[1]

Participants

A sample of 2542 young adults was gathered from a large university in the western United States (M_{age} = 19.81, 67.20% female). Participants received extra credit for their participation and all measures were approved by the university's Institutional Review Board. We applied minimal filtering to the data to ensure data quality, excluding participants with more than 10% missing data, or who fell outside of ten standard deviations away from the mean in their reported weekly use of any particular medium. In addition, 17 participants were excluded who reported a weekly media use total of 0 hours. This resulted in a final N of 2303.

Measures

Media Multitasking. Participants completed a slightly modified version of the Media Multitasking Index (MMI; Ophir et al., 2009). The MMI produces a measure of how often an individual multitasks between any of a list of media tasks, weighted by the proportion of their total media use in a given week that is accounted for by the tasks. The exact list of media behaviors that are included in the MMI varies slightly from study to study (Baumgartner et al., 2014). In this study, the MMI consisted of the twelve items included in Ophir and Nass (2009)—print, television, music, non-music audio (e.g. podcasts or radio shows), video games, phone calls, text messaging, other messaging (e.g. WeChat, Facebook Messenger), email, web surfing, computer video (e.g. YouTube), and other computer apps (e.g. Word)—along with an additional item assessing use of other mobile apps (e.g., SnapChat, Instagram). For each of these thirteen items, participants were asked: a) to estimate the number of hours that they used that medium per week, and b) to report the frequency (from 1 - *almost never*, to 4 - *almost always*) with which they multitask with each of the other 12 media while using the primary medium. Participants reported an average of 94.54 hours (SD = 66.19) of media use per week across the 13 media tasks included in this study. The summary MMI was then calculated using the equation above (M = 4.00, SD = 1.84).

[1] Data and analysis code can be found in the supplemental material for this manuscript hosted on the Open Science Framework: https://osf.io/zutj5/?view_only=f8e7b8b8371a4813a1ec2ce067002130

To provide additional information regarding how participants' multitasking preferences relate to attention problems, we also included the polychronic-monochronic tendency scale (PMTS, Lindquist & Kaufman-Scarborough, 2007), a scale designed to examine individual differences in multitasking in general. In the PMTS, a participant responds on a 1 (*strongly disagree*) to 7 (*strongly agree*) scale as to how often they engage in multitasking in their day-to-day lives, and how competent they believe themselves to be when multitasking (M = 3.44, SD = 1.27).

Attention Problems. Attention problems were indexed in three ways. First, participants were asked to report whether they had ever received a diagnosis of ADHD (n = 127 reported). Second, participants filled out the Adult ADHD self-report scale (ASRS; Kessler et al., 2005, 2007). The ASRS is an 18-item scale used to aid diagnosis of ADHD in adult populations. The scale consists of 9 items related to symptoms of inattention (e.g., making careless mistakes, difficulty concentrating) and 9 items related to hyperactivity/impulsivity (e.g. feeling restless or fidgety, difficulty controlling behavior). For each item, the participant is asked to respond on a scale from 1-5 indicating how well they believe each item describes how they have felt and acted over the last six months. The mean of all items is considered as an index of ADHD symptom severity (M = 2.80, SD = 0.61).

Finally, given that attention problems in everyday life may or may not actually correspond with clinical ADHD symptoms, we also included the attention and cognitive errors scale (ARCES; Cheyne et al., 2006), a scale designed to assess everyday frustrations that result from lapses in sustained attention that are not necessarily indications of a clinical deficit. In the ARCES, participants respond on a scale from 1 (never) to 5 (very often) as to how often they experience certain attention failures in their daily lives (M = 2.70, SD = 0.71).

Data Analysis

All data were analyzed using the Python programming language (version 3.8.1). Data manipulation and cleaning were conducted using *pandas* 1.0.3. (McKinney, 2010) and *numpy* 1.18.1. (Walt et al., 2011). Network construction and analysis was conducted using *networkx* 2.4. (Hagberg et al., 2008). Networks were plotted using the Fruchterman-Reingold algorithm, which places nodes that are more central in the network near the center, and pushes less central nodes to the periphery. Statistical testing was conducted using *statsmodels* 0.11.0. (Seabold & Perktold, 2010), and data visualization was conducted using *altair* 4.1.0. (VanderPlas et al., 2018), and *seaborn* 0.11.2 (Waskom, 2021)

Network Construction

In order to create the media multitasking network, we first created a node for each of the 13 media tasks included in the media use questionnaire. As previous work showed little difference between "incoming edges" (when the media task is secondary) and "outgoing edges" (when the media task is primary; Wiradhany & Baumgartner, 2019), we combined incoming and outgoing edges into an undirected graph using a slightly modified version of the MMI equation:

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

Wherein ω_{ij} denotes the weight of the (undirected) edge between two media nodes, m_{ij} denotes the amount of time a participant reports multitasking with task j during task i, h_i denotes the amount of time the participant reports engaging in task i during a typical week. Likewise, m_{ji} denotes the amount of time the participant reports multitasking with task i during task j, h_j denotes the amount of time the participant reports engaging in task j during a typical week, and h_{total} denotes the total amount of time the participant reports using media in a typical week. This approach produces a network with

$$\frac{n_{tasks} \times \left(n_{tasks} - 1\right)}{2}$$

undirected, weighted edges (see Figure 1). Given that 13 media tasks were included in the version of the MUQ implemented in this study, the final network for each participant contained 78 edges. Edges in the network had an average weight of .31 (SD = .37).

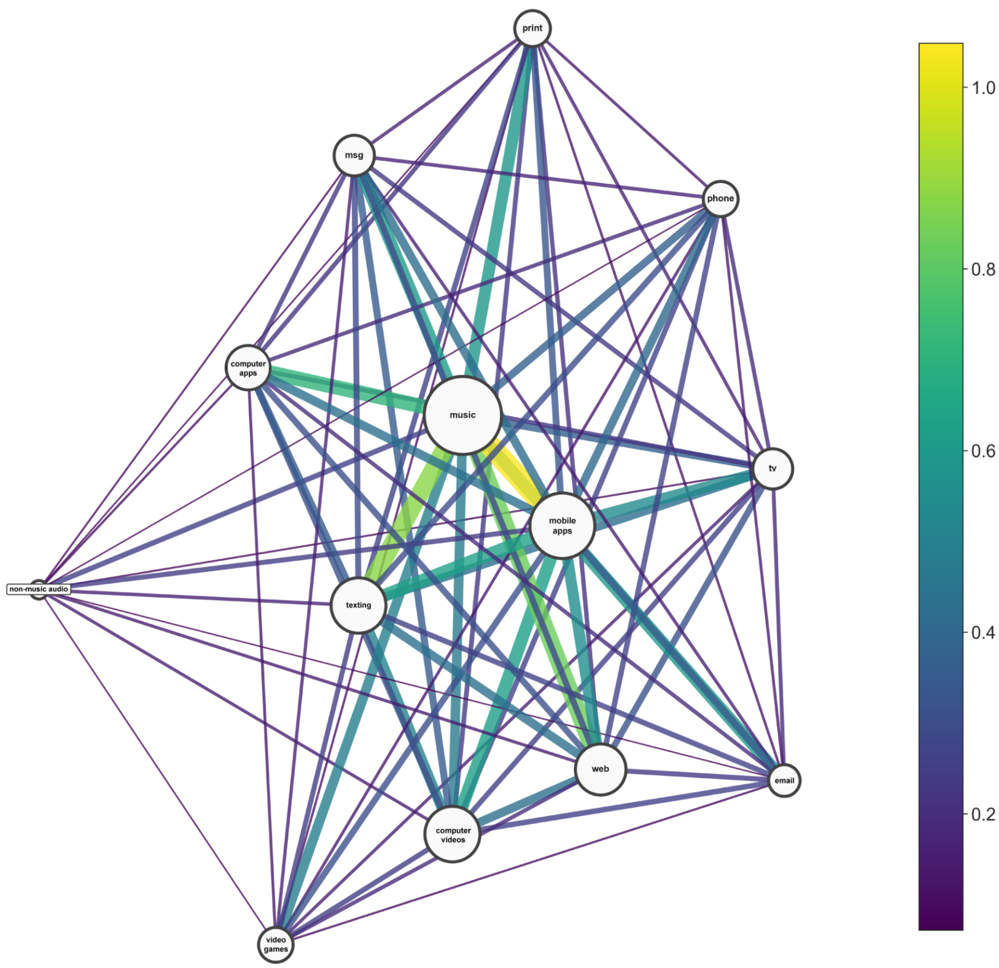

Figure 1: Full media multitasking network. Each media task in the media use questionnaire was treated as a node in the network. Edges denote the amount of time that participants reported multitasking between two tasks weighted by the proportion of time that the participants reported engaging in the two tasks in a typical week. Node size is proportional to the amount of time that participants reported engaging in the task in a typical week.

Results

Media Multitasking and Attention Problems

In order to ascertain the influence of media multitasking on attention problems, we first correlated each participant's summary MMI score with their mean ASRS and ARCES scores (see Figure 4). These correlations were both significant (ASRS: $r(2301) = .20$, $p < .001$; ARCES: $r(2301) = .24$, $p < .001$). Higher scores on the MMI were associated with higher scores on both the ASRS and the ARCES. These results are largely in accordance with findings from a recent meta-analysis, which reported a similar relationship between media multitasking as measured by the MMI and problems with attention regulation (Fisher's $z = .16$, Wiradhany & Koerts, 2019).

As the MMI contains information both on multitasking intensity (m) and media use frequency (h), we next sought to analyze the relationship between each of these factors and attention problems to ascertain which of the two facets of media multitasking behavior were more strongly related to problems in attention. Media use frequency was weakly correlated with both ASRS ($r(2301) = .10$, $p < .001$), and ARCES ($r(2301) = .09$, $p < .001$). In comparison, multitasking intensity was associated about twice as strongly with both the ASRS ($r(2301) = .18$, $p < .001$), and ARCES ($r(2301) = .23$, $p < .001$) as was total reported media use, nearing the association observed for the aggregated MMI scores. Polychronicity (PMTS score) was also found to be weakly associated with attention problems (ASRS: $r(2301) = .11$, $p < .001$, ARCES: $r(2301) = .10$, $p < .001$).

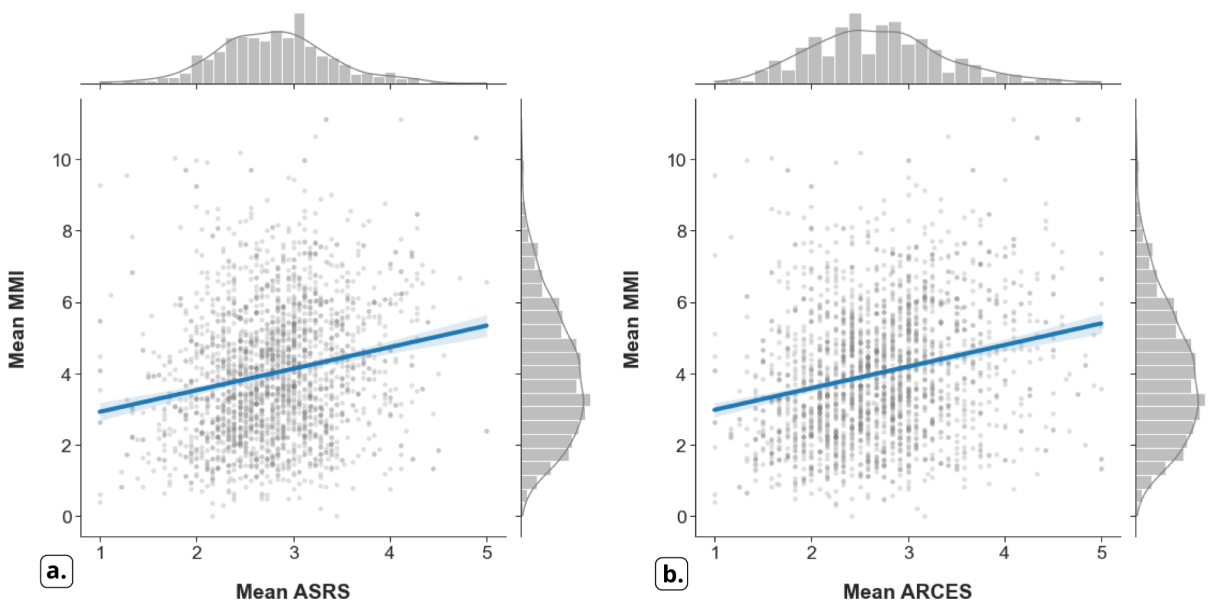

Figure 2: Relationship between summary MMI and a) ASRS: $r(2301) = .20$, $p < .001$; b) ARCES: $r(2301) = .24$, $p < .001$

The Multitasking Network

Next, we sought to parse apart the collection of different media multitasking behaviors included in the MMI to consider media multitasking behaviors in the form of a network. The *centrality* of a node in a network is an indicator of the relative importance of the node within the overall structure of the network

(Newman, 2010). Herein, we used *degree centrality (Dc)* — the sum of the weight from each edge connecting to a given node (Barrat et al., 2004) to ascertain which nodes in the multitasking network were most central. This analysis revealed music (Dc_i = 7.21), mobile apps (Dc_i = 5.89), and texting (Dc_i = 4.74) to be the three most central nodes in the multitasking network across all participants. Least central were non-music audio (Dc_i = 1.59), and print media (Dc_i = 2.67). Given that the MMI produces a network in which every node is connected to every other node, changes in the degree centrality of any node will by definition change the degree centrality of all other nodes, potentially masking relative degree differences between individual nodes across participants—especially when their multitasking networks greatly differ in average degree. As such, we conducted our analyses on both the raw MMI network, and on a mean-normalized network. Mean normalization was conducted by subtracting the average degree of the multitasking network for each participant from the degree centrality of each node within that participant's network.

As an initial examination of how the topology of the media multitasking network varies across subjects, we investigated the extent to which degree centrality varied based on participant sex and polychronicity (See *Figure 3a*). All nodes in the multitasking network were of higher degree in the high-polychronicity group apart from *Web, Computer Videos, Computer Apps, Messaging,* and *Print*. The greatest magnitude of difference between groups was observed for *Mobile Apps, Computer Videos,* and *Television*. When considering differences in relative degree, only the *Mobile Apps* node was of higher degree in the high-polychronicity group, and *Print* was of lower degree. Results indicate that *Mobile Apps, Texting, Web Browsing, Computer Apps, Messaging, Phone,* and *Email* were more central in the multitasking network for females than they were for males. For males, *Non-Music Audio, Video Games,* and *Computer Videos* were more central than they were for females (See *Figure 3b*). These differences remain largely consistent when considering relative degree differences between networks.

Multitasking Networks and Attention Problems

The above results suggest that considering media multitasking as a network can provide information as to how multitasking habits vary across groups in a manner that goes beyond the traditional summary MMI measure. Next, we examined how individual differences in the topology of the media multitasking network relate to variation in self-reported attention problems, as measured by the ASRS and ARCES. First, we investigated how the *average degree* of all nodes in the multitasking network relates to attention problems. Networks with a higher average degree are more densely connected than those with a lower degree. We expected that individuals who have more densely connected networks would score higher on measures of attention problems. This was shown to be the case. The average weighted degree of a person's media multitasking network was associated with the severity of their ADHD symptoms ($r(2301) = .20$, $p < .001$) and with attention failures in everyday life ($r(2301) = .24$, $p < .001$).

Next, we aimed to investigate whether the multitasking networks of those with high severity of ADHD symptoms would show different patterns of node centrality compared to those with low symptom severity. Results show that degree centrality was positively associated with ADHD symptom severity for 9 of the 13 nodes in the media multitasking network after false-discovery rate (FDR) correction (Benjamini & Hochberg, 1995; see Figure 4). In contrast, when considering differences in relative degree, centrality was positively associated with ADHD symptom severity after FDR correction only for the *Music* and *Mobile Apps* nodes. Degree centrality for the *Non-Music Audio* and *Print* nodes was negatively associated with ADHD symptom severity.

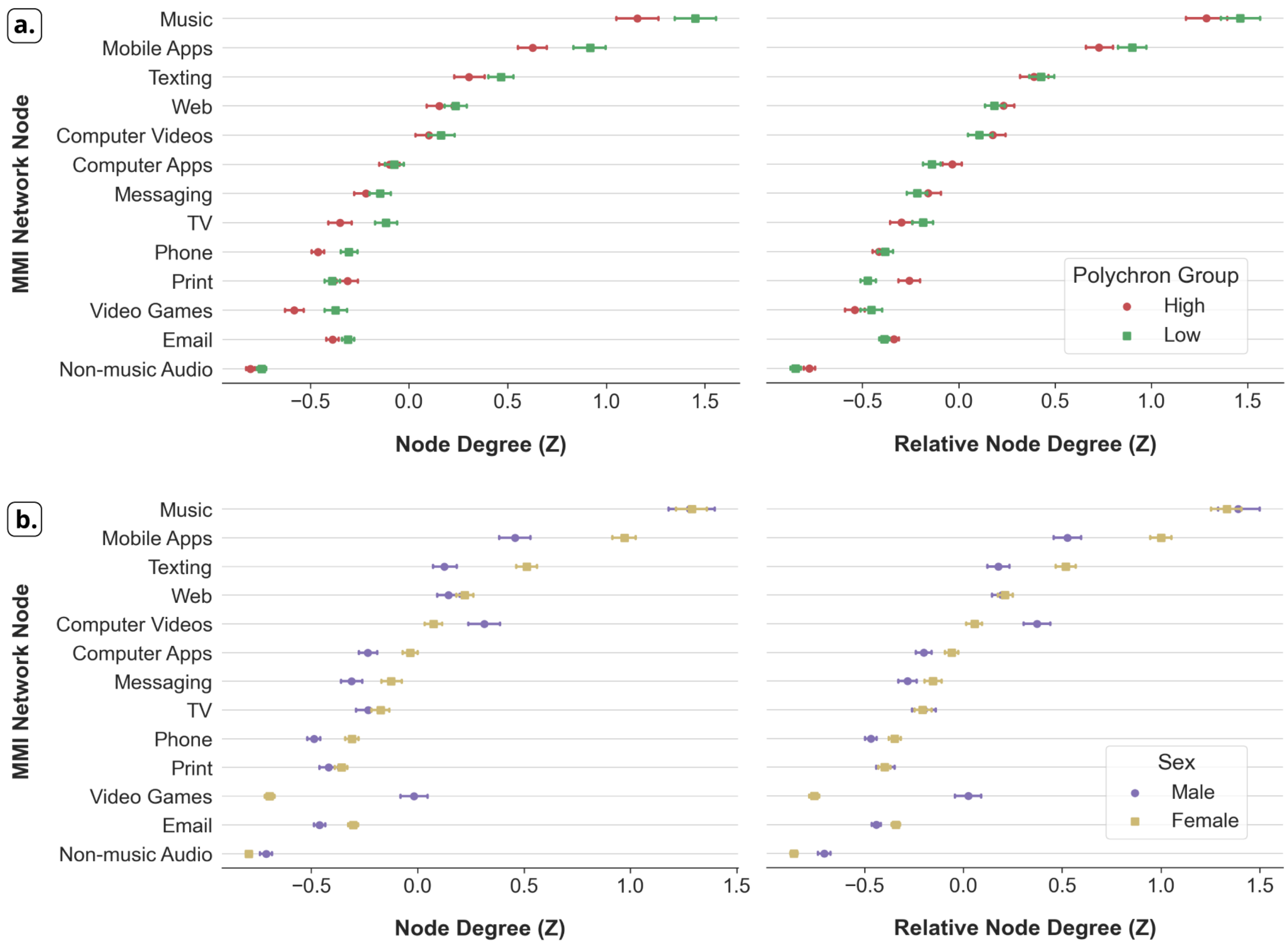

Figure 3: Degree centrality in the media multitasking network by: a) polychronicity and b) sex. Error bars represent bootstrapped 95% confidence intervals. High- and low-polychronicity groups were created via a tripartite split, retaining the upper and lower third of polychronicity scores

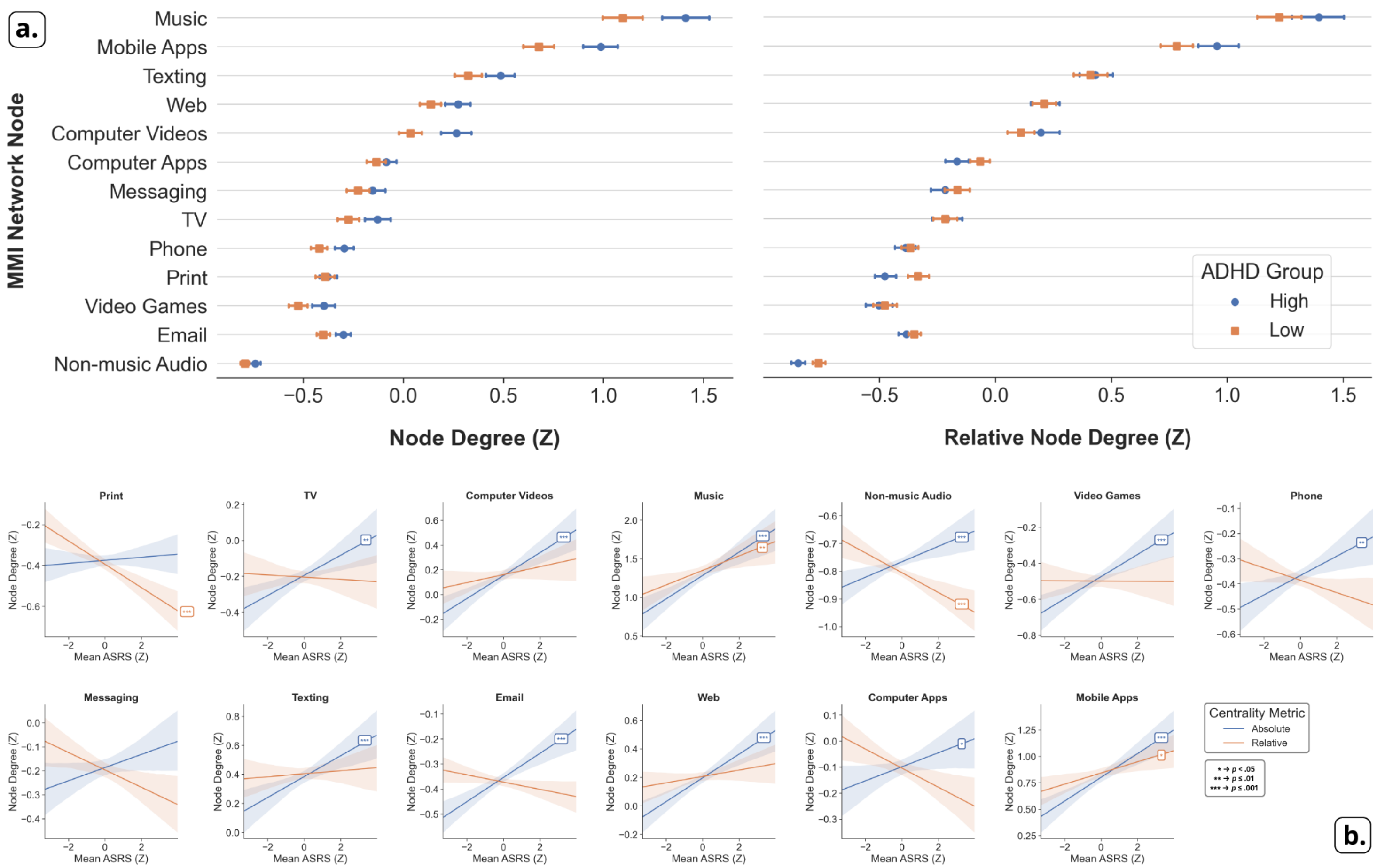

Figure 4: a) Degree centrality of each node in the media multitasking network for those with high ADHD symptom severity and those with low ADHD symptom severity. Error bars represent bootstrapped 95% confidence intervals. High- and low-ADHD groups were created via a tripartite split, retaining the upper and lower third of ASRS scores. Nearly all nodes in the multitasking network were of higher degree in the high-ADHD group. When considering relative degree differences, only *Music* and *Mobile Apps* were of higher degree in the high-ADHD group. The *Non-Music Audio*, *Phone*, *Computer Apps*, and *Email* nodes had lower degree in the high-ADHD group. b) Correlations between ADHD symptom severity and degree centrality. Degree centrality was positively associated with ADHD symptom severity for 9 of the 13 nodes. Relative degree centrality was positively associated with ADHD symptom severity for the *Music*, and *Mobile Apps* nodes, and was negatively associated with ADHD symptom severity for the *Print* and *Non-Music Audio*. Error bands represent bootstrapped 95% confidence intervals.

Discussion

Previous work has demonstrated that increased media multitasking is associated with greater self-reported attention problems, but also that the relationship is small, heterogeneous across studies, and largely unrelated to objective measures of attention. The bulk of this work uses the Media Multitasking Index (MMI; Ophir et al., 2009), which aggregates a large number of media multitasking behaviors into a single summary score, discarding information about individual multitasking behaviors. Recent work suggests that considering media multitasking as a network of interrelated behaviors rather than as a singular construct may provide increased clarity as to the relationship between media multitasking behaviors and attention (Wiradhany & Baumgartner, 2019).

In this study, we have presented exploratory results from a large study (N = 2303) designed to increase clarity as to how individual multitasking behaviors as measured by the MMI relate to attention problems in everyday life and to the severity of ADHD symptoms. We used the MMI to generate a network wherein individual media use behaviors (such as talking on the phone or watching television) are considered as nodes, and the frequency with which a person multitasks between any two behaviors is used as the weight of the edge linking the two. We investigated how variation in the topology of this network relates to individual differences such as polychronicity and sex, but also how these variations relate to ADHD symptom severity.

In keeping with previous work, our results indicate that increased media multitasking is associated with higher incidence of attention failures in everyday life and also with greater severity of ADHD symptoms. Increased media use was also associated with attention problems, albeit much more weakly. Critically, examining the MMI as a network reveals that the relationship between media multitasking and attention problems varies across the different media considered in the MMI. Node degree was positively associated with ADHD symptom severity for 9 of the 13 media behaviors included in the MMI, suggesting that those with greater attention problems have a more densely connected multitasking network overall. When considering relative degree differences between nodes, degree centrality was positively associated with ADHD symptom severity for only two of the 13 media behaviors (*Music* and *Mobile Apps*). Relative centrality of the *Print* and *Non-Music Audio* nodes was negatively associated with ADHD symptom severity.

A potential explanation for these findings can be found in clinical work suggesting that a primary symptom of ADHD is *under*-stimulation in everyday life (Nigg, 2006). As such, easily accessible media tasks such as listening to music and checking mobile apps while doing other activities may serve to increase entertainment and alleviate under-stimulation—especially if the other task is boring or uninteresting—highlighting the potentially adaptive nature of certain forms of media multitasking for those with attention problems. Previous work has suggested that the often fast-paced, stimulating nature of certain media multitasking behaviors may also facilitate under-arousal during periods of non-multitasking (Beyens et al., 2018), and could over time lead to greater severity of attention problems. Although the correlational data presented herein do not provide an answer as to the causal ordering of these phenomena, our results provide guidance as to which media multitasking behaviors may be more important to consider in longitudinal or experimental efforts to answer these questions.

The work presented here also comes with a few notable limitations. First and foremost, the Media Multitasking Questionnaire used to create the multitasking networks is a self-report measure. Recent work shows that self-reports of media use are only somewhat related to more objective measures such as device logs (Parry et al., 2021). Although the correspondence between self-reported media multitasking and more objective measures of multitasking behaviors is unknown, extant evidence suggests that self reports of certain media multitasking behaviors, such as the number of switches that occur within a given time period, are highly inaccurate (Brasel & Gips, 2011; Yeykelis et al., 2014). Future efforts should work to determine how multitasking networks generated from more objective measures of media use relate to attention problems, as well as other variables of interest. An additional limitation arises from the fact that the sample of participants included in this study was gathered from a single site at a large research university in the United States. Existing work suggests that the topology of the media multitasking network may vary across different countries or age groups (Wiradhany & Baumgartner, 2019). As such, future work should aim to establish the generalizability of the findings reported in this manuscript across different populations.

Conclusion

In the work presented herein, we leveraged a novel analytic approach that generates a network from the media behaviors assessed in the MMI in order to investigate the relationship between media multitasking and attention problems in a large sample of young adults. Our results indicate that increased media multitasking is associated with attention problems in everyday life and with symptoms of ADHD. Furthermore, we showed that certain combinations of media behaviors are more associated with attention problems than others—information that is lost when only considering the MMI as a single, summary measure. Results also suggest that multitasking combinations involving mobile apps and music are most strongly associated with attention problems whereas those involving print, non-music audio, and messaging were least strongly associated. These results serve to further clarify observed linkages between media multitasking and individual variation in attention, and highlight promising avenues for future research that goes beyond aggregate measures of multitasking in favor of a richer understanding of the landscape of media multitasking behaviors.

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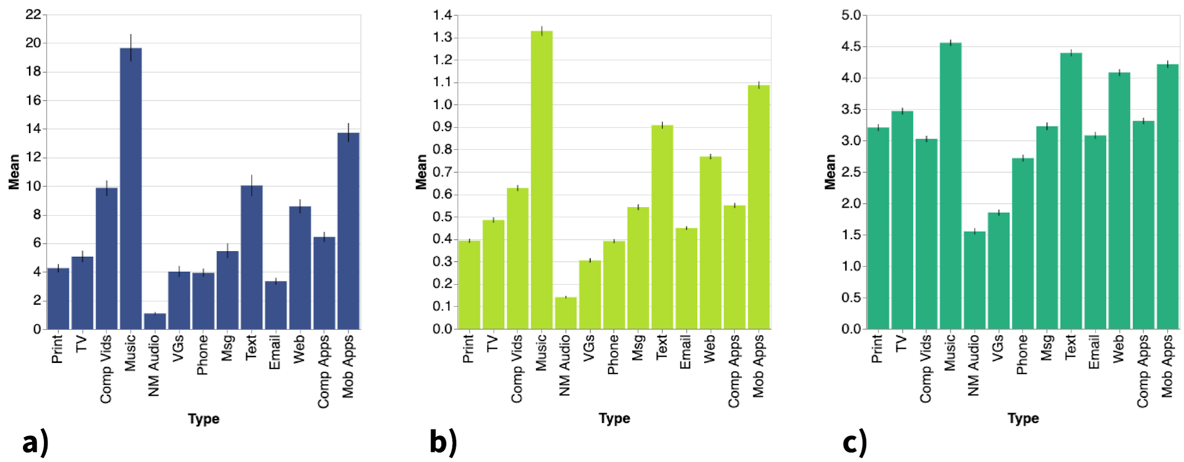
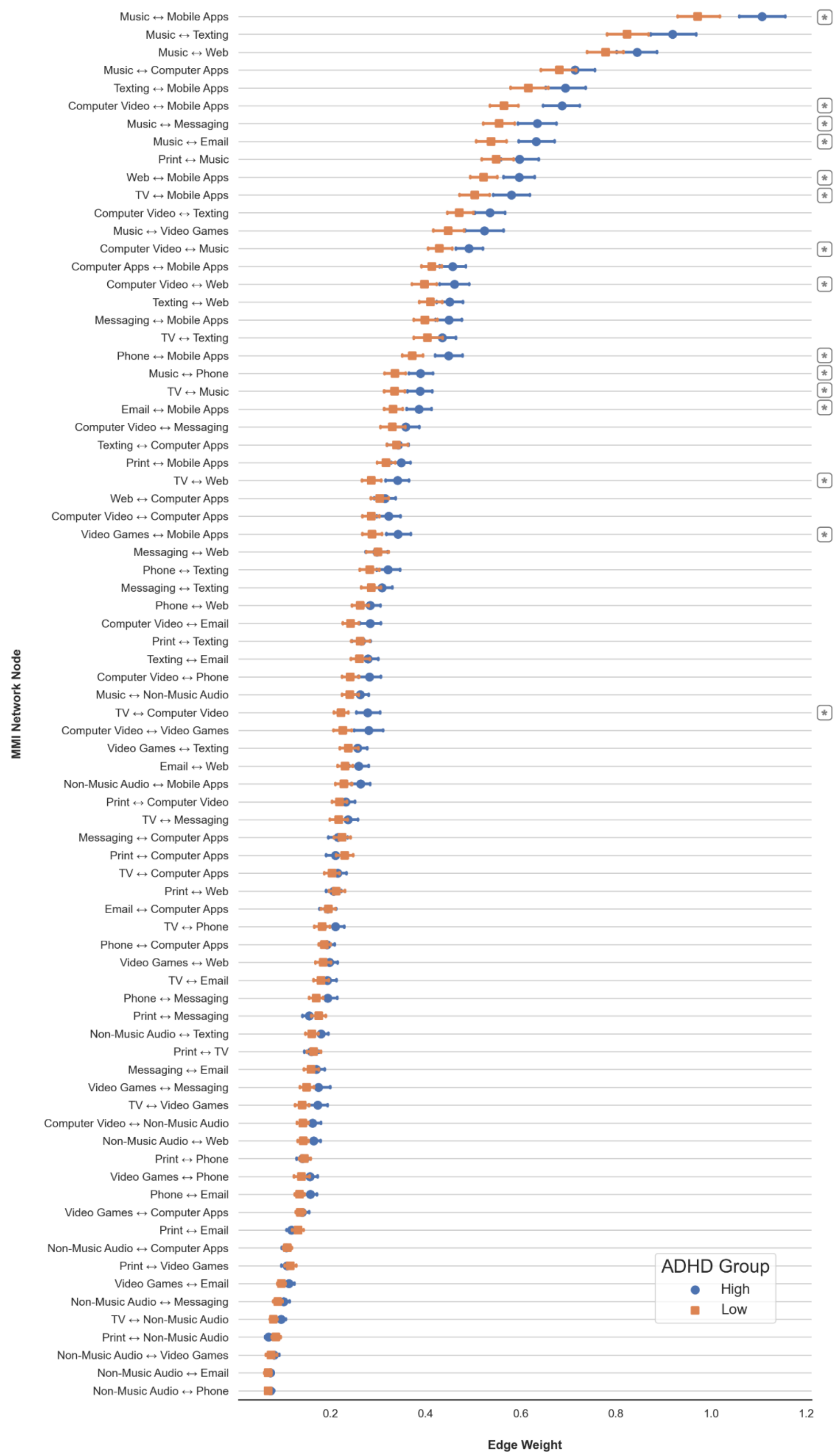
Supplementary Figures



Supplementary Figure 1: Summary statistics for each media task considered in this study. Error bars represent bootstrapped 95% confidence intervals. a) Raw media use per week; b) weighted MMI broken down by media task; c) unweighted responses to the MMI broken down by media task.



Supplementary Figure 2: Edge weight for each edge in the media multitasking network for those with high- and low- ADHD symptom severity. Error bars represent bootstrapped 95% confidence intervals. Asterisks denote edges that significantly differ in weight between the high- and low-ADHD group ($p < .001$). High- and low-ADHD groups were created via a tripartite split, retaining the upper and lower third of ASRS scores.