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## Santa Barbara

## Using Video Games to Modulate Functional Connectivity and Behavioral Performance in ADHD

A dissertation submitted in partial satisfaction of the requirements for the degree

Doctor of Philosophy in Communication

by

Jacob T. Fisher

Committee in charge:

Professor René Weber, Chair

**Professor Scott Grafton** 

Professor Scott Reid

September 2020

The dissertation of Jacob T. Fisher is approved.
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René Weber, Committee Chair

September 2020

# Using Video Games to Modulate Functional Connectivity and Behavioral Performance in ADHD

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by

Jacob T. Fisher

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It is difficult to formulate the words to sufficiently thank those who have directly advised me during my graduate career. Justin Keene, my advisor for my Master's thesis, is the one who got me into this mess. Although I was not planning on pursuing a Ph.D., he convinced me to quit my day job and start doing research full time. His training in research methods and psychophysiological data collection helped lay the foundation for my research in the Media Neuroscience Lab, and I am deeply grateful for his investment in me as a scholar, and his support as a friend. I do not think that the right words exist to thank René Weber, my Ph.D. advisor (although there may be a few German ones). René took a risk in bringing me into the lab and taking me under his wing. I had no training in brain imaging,

very little statistical knowledge, and a handful of harebrained ideas. His diligent advising positioned me to embark on this project, and his guidance along the way has made it into what it is today. I know that when this project is "in our rearview mirror" we will continue to collaborate well into the future. I could not have had a better guide.

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Thank you to all of these individuals and to the many more who I have not named.

This project would not exist without you.

Jacob Lisher

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Fisher, J.T., & Weber, R. (2020). Innovative health interventions at the intersection of neuroimaging and multimedia design. In Kim, J. & Song, H. (Eds.) *Technology and Health: Promoting Attitude and Behavior Change*. San Diego, CA: Elsevier.

Fisher, J.T., Huskey, R., Keene, J.R., & Weber (2020). The life of a model: Commentary on "How the LC4MP became the DHCCST". In Weber, R., & Floyd, K., (Eds.) *Handbook of Communication Science and Biology*. New York, NY: Routledge.

Fisher, J.T., & Keene, J.R. (2020). Attention, working memory, and media multitasking. In Weber, R., & Floyd, K., (Eds.) *Handbook of Communication Science and Biology*. New York, NY: Routledge.

Weber, R., & Fisher, J.T. (2020). Advancing the synchronization theory of flow experiences.

- In Weber, R., & Floyd, K., (Eds.) *Handbook of Communication Science and Biology*. New York, NY: Routledge.
- Fisher, J.T., Lonergan, C., Hopp, F.R., & Weber (in press). Media entertainment, flow experiences, and the synchronization of audiences. In Vorderer, P, & Klimmt, C., (Eds.) *Oxford Handbook of Entertainment Theory*. Oxford, UK: Oxford University Press.
- Hopp, F.R., Fisher, J.T., Cornell, D., Huskey, R., & Weber, R. (2020). The extended moral foundations dictionary (eMFD): Development and applications of a crowd-sourced approach to extracting moral intuitions from text at scale. *Behavior Research Methods*. Published online ahead of print.
- Hopp, F.R., Fisher, J.T., & Weber, R. (2020) Integrating news framing, dynamic-transactional paradigms, and computational modeling: An examination of the dynamic relationship between news frames and real-world events. *Journal of Communication*. 70(3), 335-355.
- Weber, R., Behr, K.M., Fisher, J.T., Lonergan, C., & Quebral, C. (2020). Video game violence & interactivity: effect or equivalence? *Journal of Communication*. 70(2), 219-244.
- Dienlin, T., Johannes, N., Bowman, N.D., Masur, P.K., Engesser, S., Kümpel, A.S., Lukito, J., Bier, L.M., Zhang, R., Johnson, B.K., Huskey, R., Fisher, J.T. ... De Vreese, C. (2020). An agenda for open science in communication. *Journal of Communication*. Published online ahead of print.
- Fisher, J.T., Hopp, F.R., Weber, R. (2019). Modality-dependent effects of perceptual load in multimedia processing. Journal of Media & Communication. 7(4), 149-165.
- Hopp. F.R., Schaffer, J., Fisher, J.T., Cornell, D., & Weber, R. (2019). iCoRe: The GDELT interface for the advancement of communication research. *Computational Communication Research*. 1(1), 13-44.
- Fisher, J.T., Keene, J.R., Huskey, R., & Weber, R. (2018). The limited capacity model of motivated mediated message processing: taking stock of the past. *Annals of the International Communication Association*. 42(4), 270-290.
- Fisher, J.T., Huskey, R., Keene, J.R., & Weber, R. (2018). The limited capacity model of motivated mediated message processing: looking to the future. *Annals of the International Communication Association*. 42(4), 291-315.
- Weber, R., Fisher, J.T., Hopp, F.R., & Lonergan, C. (2018). Taking messages into the magnet: method-theory synergy in communication neuroscience. *Communication Monographs*. 85(1). 81-102.

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Studies in Functional Magnetic Resonance Imaging Theory and Methods with professors René Weber, Scott Grafton, Michael B. Miller, and Gregory Ashby

#### **ABSTRACT**

Using Video Games to Modulate Functional Connectivity and

Behavioral Performance in ADHD

by

#### Jacob T. Fisher

Attention-deficit/hyperactivity disorder (ADHD) is a highly prevalent cognitive disorder with detrimental personal, social, vocational, and academic outcomes. Research paradigms at the intersection of media design and neuroimaging enable researchers to build understanding regarding the neural and cognitive mechanisms involved in ADHD during naturalistic tasks, and to create more effective clinical interventions. Extant work suggests ADHD-related cognitive performance differences are magnified under cognitive load, and minimized under perceptual load, but the neural mechanisms that undergird these effects have yet to be examined. In three studies—two behavioral and one brain imaging—we show that cognitive load and perceptual load differentially influence both task performance and functional connectivity in an ADHD-specific fashion. Cognitive load was found to result in reduced performance, greater reaction time variability (RTV), and reduced global brain network efficiency in individuals with ADHD. In contrast, perceptual load led to greater performance and reduced RTV in ADHD relative to non-ADHD individuals. Furthermore, results indicate that perceptual load eliminates differences in global brain network efficiency between ADHD and non-ADHD groups.

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#### Foreword

"Tell me to what you pay attention and I will tell you who you are."

## José Ortega y Gasset

I have always been fascinated with attention. The project described in this report represents an integration of many years of thinking and research into how and why the design of digital environments influences our attention, and how we can use this information in order to design tools and messages that are better for those whose attention is different from the norm—and in doing so create technologies that are better for all of us. Upon completion of my undergraduate career at Texas Tech University, I became an academic counselor at the TECHniques Center, a unique program providing supplemental academic support for students with learning disabilities, ADHD, and Autism Spectrum disorders. In this role, it became clear to me that the digital tools that we use to work, learn, and live our daily lives are not equally accessible to those with cognitive and learning differences, creating disparities in outcomes, and leading to frustration and disappointment among my students.

Having never quite planned to be a media scholar, I began to investigate how we might use principles of media psychology and user interface design to improve our digital lives, and to increase our knowledge of attention disorders like ADHD. Eventually, I decided to pursue these questions full time, joining the Cognition and Emotion Lab in the College of Media and Communication at Texas Tech, wherein I conducted my first project looking at how those with ADHD and without ADHD allocate attention differently during online learning — a project that later became my master's thesis. After my master's, I had the opportunity to join the Media Neuroscience Lab at the University of California Santa Barbara. In my research training at UCSB, I came across a multitude of theoretical

approaches that honed my thinking in relation to attention and media design, including the Load Theory of Selective Attention and Cognitive Control (Lavie, 2006), the Limited Capacity Model of Motivated Mediated Message Processing (LC4MP; Lang, 2000; 2006), the Synchronization Theory of Flow (Weber et al., 2009), the Cognitive Theory of Multimedia Learning (Mayer, 2013), and several more. I also greatly benefited from my training in neuroscience and brain imaging from Drs. René Weber, Scott Grafton, Michael Miller, Barry Giesbrecht, Gregory Ashby, and others, as well as my training in network science as a member of the NSF IGERT program in Network Science and Big Data.

In my first project at UCSB, I began to integrate predictions from these theories with my budding understanding of cognitive neuroscience to design a study investigating how those with ADHD respond to cognitive load (how much a particular task requires maintaining information in mind and protecting it from interference), and perceptual load (how difficult a task is to see, hear, or otherwise sense). I used a stimulus developed in the Media Neuroscience lab called *Asteroid Impact*, which I continued to assist in developing throughout my graduate training. In this experiment, we found that adding cognitive load within the game seemed to more detrimentally impact performance in those with severe ADHD than it did in those without symptoms, but that adding perceptual load actually *improved* the performance of those with ADHD. Strikingly, this effect was also observable along the continuum of ADHD symptoms. The more severe one's symptoms, the stronger the effects. Encouraged, we further refined the stimulus and conducted a series of additional studies, eventually culminating in the first study reported herein.

Buoyed by the results from this first series of studies, my advisor, René Weber, and I applied for a small grant from the Academic Senate at UCSB to conduct a brain imaging

study investigating the neural underpinnings of the ADHD-contingent influence of cognitive and perceptual load. Having received the funds, along with a generous seed grant from the Theodore Fett Foundation, we began collecting the data for the second study of this project in the fall of 2018. This collection went slowly, due to the difficulty of recruiting special populations for brain imaging research and the busy-ness of all of our academic lives.

Finally, we ran our last participant in the summer of 2019, and began our plans for analyzing the data using a network neuroscience approach. In these analyses, it became clear that cognitive and perceptual load produced differing brain network topologies in those with severe ADHD symptoms compared to those with mild or nonexistent symptoms of ADHD. Most notably, those with ADHD exhibited much-reduced *efficiency* in brain network topology compared to those without ADHD, but these differences disappeared under perceptual load.

Although these findings were encouraging, a gap remained in our understanding. In all of our studies so far in this area, we used ADHD symptom severity as a proxy for actual ADHD diagnosis, a practice that (although widely used), is not without its critics. As such, we began to build collaborations with local healthcare providers and with Student Health Services at UCSB to design a study in which we used an actual ADHD diagnosis to delineate between groups rather than self-reported symptom severity. Right around the time we planned to launch the study, the world fell into the throes of the COVID-19 pandemic, precluding any efforts to collect in-person data, especially within a clinical setting. Undeterred, I began to rebuild *Asteroid Impact* from the ground up so that it could be run in a browser rather than being restricted to a local machine, allowing us to collect data in a more ecologically valid setting — participants' own homes. After hundreds of hours of

development, we tested and launched our third study in late May, 2020. In this study (study 3 reported herein), we used a pre-screener to only recruit those who had been clinically diagnosed with ADHD (along with a control sample). Results indicate that the same effects we observed in study 1 are also observable across diagnostic lines, and in a non-student sample.

The results of these three studies are encouraging for two reasons. First, these results further highlight the utility of video games for conducting neuroscience research (Mathiak & Weber, 2006). A recent upwelling of research within communication and the cognitive and social neurosciences has begun to realize the potential of naturalistic stimuli for understanding the "brain in the real world." The work presented here leverages the unique status of video games as both highly engaging and highly controllable, enabling researchers to test precise questions while collecting rich, time-locked neural behavioral, and content-analytic data. Second, these results suggest that by designing a digital environment in a certain way, performance and neural efficiency gaps between ADHD and non-ADHD groups could potentially be minimized or even eliminated. For media and human-computer interaction scholars, these results point to a number of future research opportunities at the intersection of digital media design and neuroscience seeking to develop tools that can improve the lives of those with cognitive disorders and that can help all of us direct our attention in more effective ways.

#### Introduction

Attention deficit/hyperactivity disorder (ADHD) is a highly prevalent cognitive processing disorder conferring long-term, debilitating symptoms of inattention, hyperactivity, and impulsivity (Barkley, 1997). Individuals with ADHD experience suboptimal outcomes in many areas, including reduced educational and vocational achievement (Biederman et al., 2004; Loe & Feldman, 2007), higher rates of drug and alcohol abuse (Biederman et al., 1998; Lee et al., 2011), lower self-esteem (Harpin et al., 2016) and diminished overall quality of life (Danckaerts et al., 2010). The prevalence of ADHD in the United States has increased by more than 60 percent in the last twenty years, underscoring the critical importance of research to better understand the causes of ADHD and to improve diagnosis and treatment strategies (Chung et al., 2019; Xu et al., 2018).

Naturalistic (e.g., smoothly evolving in time and perceptually engaging; Finn et al., 2019; Green & Bavelier, 2012; Mathiak & Weber, 2006; Salmi et al., 2019; Vanderwal et al., 2017; Weber et al., 2018) tasks reveal rich information about how individual brain responses relate to behavior (Anguera et al., 2013; Eickhoff et al., 2020; Mishra, Sagar, et al., 2016; Vanderwal et al., 2017, 2019). Naturalistic paradigms afford less experimental control than traditional cognitive neuroscience paradigms (Nastase, Goldstein, & Hasson, 2020), but the use of video games can provide a "happy medium" — a rich, engaging environment that can nonetheless be directly "modded" (Elson & Quandt, 2016; Mathiak & Weber, 2006) to incorporate controlled manipulations (Klasen et al., 2012; Mathiak & Weber, 2006). In this sense, video games are uniquely suited for bridging the gap between traditional cognitive neuroscience approaches to studying ADHD and comparatively more "real-world" paradigms.

Those with ADHD have been shown to be more susceptible than those without ADHD to the detrimental influence of increasing cognitive load on task performance (Roberts et al., 2012), but intriguingly this pattern seems to be reversed for perceptual load (Forster et al., 2014). Extant work suggests that global brain network efficiency is associated with increased performance in cognitive tasks (e.g. working memory or reasoning tasks; Bassett et al., 2009; Hearne et al., 2017), but not perceptual tasks (such as tone discrimination; Weiss et al., 2011). Those with ADHD have been shown to exhibit decreased global brain network efficiency at rest (Konrad & Eickhoff, 2010, Lin et al., 2014, Wang et al., 2009), but little is known about functional connectivity patterns in the ADHD brain during a task, or how these patterns relate to task performance.

To investigate these questions, we conducted three experiments using a custom-developed arcade-style video game called *Asteroid Impact*. The primary goal in *Asteroid Impact* is to quickly collect crystals and perform cued button presses while avoiding asteroids that bounce around the screen (See Figure 1). In study 1, we collected behavioral data (n = 230) while participants played *Asteroid Impact* in a lab setting. In study 2, we collected fMRI data from 36 individuals (18 with severe ADHD symptoms and 18 with mild to absent symptoms), and examined differences in brain network efficiency between ADHD and non-ADHD groups. In study 3, we collected behavioral data (n = 100) while participants played *Asteroid Impact* at home on their personal computers.

#### Results

As a first step toward testing the influence of cognitive and perceptual load on task performance in ADHD, we conducted a study wherein we recruited 230 individuals from the participant pool at the University of California Santa Barbara. *Asteroid Impact* enables

targeted manipulation of both cognitive and perceptual load within a naturalistic environment that adapts to the performance of the player, reducing inter-individual variability that results from varying skill. Participants played seven rounds of the game: a practice round followed by two rounds with added cognitive load, two rounds with added perceptual load, and two baseline rounds. Other than the practice round, all rounds were presented in random order. Performance in the game was measured as the number of crystals collected within each 30-second window of gameplay divided by the number of asteroid collisions (see *Methods*). We assessed ADHD symptom severity using the Adult ADHD Self-Report Scale v1.1 (Kessler et al., 2005). Since ADHD seems to be best described in terms of both categorical and continuous factors (Elton et al., 2014; Silk et al., 2019), we conducted analyses both with commonly-used ADHD cutoffs and with the full underlying distribution of ADHD symptom

severity values.

Results from study 1 indicate that cognitive and perceptual load impact attentional

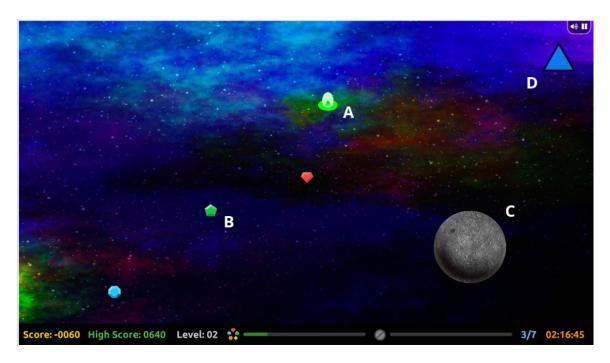


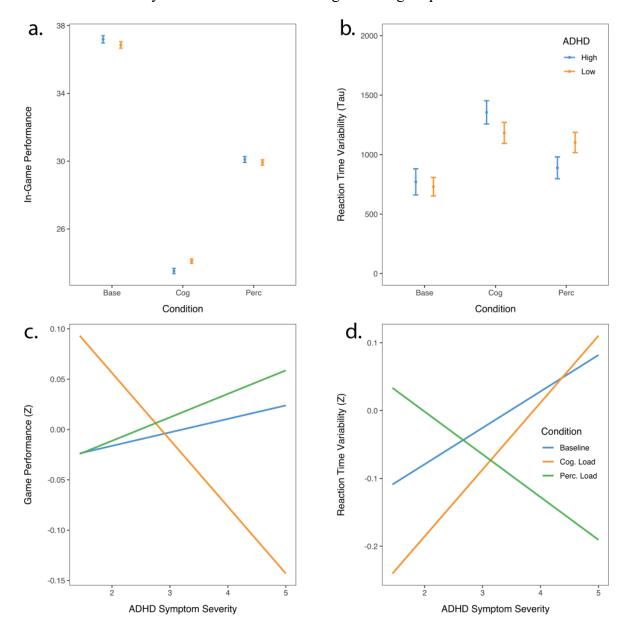
Figure 1: Schematic of Asteroid Impact gameplay. The primary goal of the game is to navigate a "spaceship" (A) around the screen to collect as many crystals (B) as possible before time runs out, while concurrently avoiding asteroids (C) and responding to intermittent speeded reaction time probes (D). Asteroid Impact adapts to the skill level of the player by increasing the quantity, size, and speed of asteroids, ensuring that all participants play at a difficulty level that is approximately equal to their skill. This serves to minimize differences in performance between players as a result of skill.

performance in a manner contingent on ADHD symptoms (F(1,228) = 56.45, p < .001, see Figure 2a). Under cognitive load, those with high ADHD symptom severity underperformed in the video game task compared to those with mild or nonexistent ADHD symptoms ( $M_{hi} = 23.62$ ,  $M_{lo} = 24.13$ ). The opposite pattern was observed for both the perceptual load condition ( $M_{hi} = 30.86$ ,  $M_{lo} = 29.81$ ), and the baseline condition, in which those with severe ADHD symptoms outperformed those with mild to no symptoms ( $M_{hi} = 37.79$ ,  $M_{lo} = 36.93$ ). Under high perceptual load, those with severe ADHD symptoms also exhibited lower RTV—an indicator of reduced attentional lapses during game play ( $M_{hi} = 547.58$ ,  $M_{lo} = 603.75$ ). As an

additional test of the relationship between ADHD symptoms and the influence of cognitive and perceptual load on performance, we also conducted analyses in which we treated ADHD symptom severity as a continuum. This analysis revealed that as ADHD symptom severity increased, the relative influence of both cognitive and perceptual load also increased (See Figure 2). This interaction was significant both for performance ( $\beta = -.04$ , p = .001), and for reaction time variability ( $\beta = -.08$ , p = .036).

In the second study, we sought to elucidate a candidate neural mechanism for the ADHD-specific influence of cognitive and perceptual load we observed in study 1. Of primary interest was global brain network *efficiency*—the inverse of the average shortest path length between nodes in the functional connectivity network—as previous studies have shown that those with ADHD exhibit lower global efficiency both at rest and during certain cognitive tasks (Konrad & Eickhoff, 2010; Lin et al., 2014; Wang et al., 2009). A group of 36 individuals (18 with severe ADHD symptoms and 18 with mild or no ADHD symptoms) played nine rounds of *Asteroid Impact* (three baseline, three cognitive load, three perceptual load) while undergoing functional magnetic resonance imaging (fMRI). Nodes in the

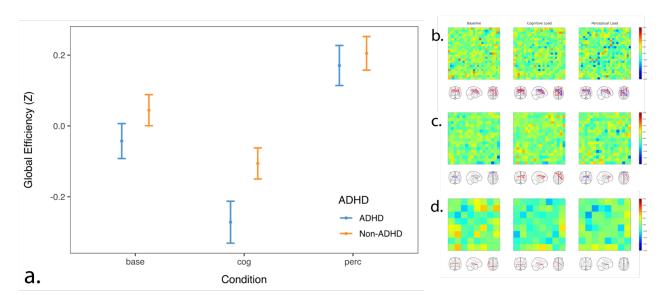
functional connectivity network were created using a 264-region parcellation atlas from



**Figure 2:** Influence of cognitive and perceptual load during game play on: a, c) game performance (collecting crystals and avoiding asteroids), and b, d) reaction time variability, as measured using the variance in the exponential portion of the reaction time distribution, tau. Bottom row depicts performance at baseline and under cognitive and perceptual load as a function of continuous ADHD symptom severity

Power et al. (2011), and edge weights were assigned using the correlation of the mean neural time series within each of the 264 regions.

Results show that under cognitive load, those in the ADHD group had lower global efficiency in functional connectivity networks (M = .195, SD = .014) than the non-ADHD group (M = .198, SD = .010), but that there was no difference in global efficiency between ADHD and non-ADHD groups during the perceptual load condition (see Figure 3a). Furthermore, increased global efficiency was associated with higher in-game performance ( $\beta$  = .025, p < .001), suggesting that decreased performance during cognitive load in those with ADHD may be at least partially attributable to a decrease in network efficiency in the brain. These efficiency differences that we observed between ADHD and non-ADHD groups seem to be driven by varying patterns of connectivity in attention-related brain networks, including the frontoparietal control network, the salience network, and the ventral attention network



**Figure 3**: a) Global efficiency (normalized) under baseline, cognitive load, and perceptual load conditions. During cognitive load, those with ADHD exhibited much lower efficiency values than those without ADHD, but these differences were not observed during perceptual load; b) connectivity differences between ADHD and non ADHD in the: b) frontoparietal network; c) salience network; and d) ventral attention network.

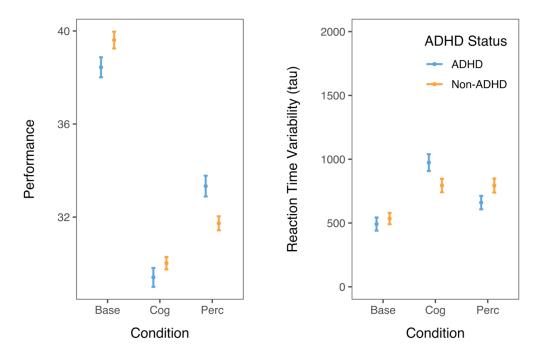
(see Figure 3b-d).

In the third study, (N = 100) we extended the findings of studies 1 and 2 using a non-

student sample and using clinical diagnosis to delineate between ADHD and non-ADHD groups rather than self-reported symptom severity. The relationship between ADHD diagnosis, self-reported symptom severity, and neural/behavioral performance indicators is at present still somewhat of an open question. As such, this study was designed to elucidate the extent to which ADHD-related individual differences in performance in response to cognitive and perceptual load would follow a categorical or dimensional structure. To do so, we developed an online version of Asteroid Impact, allowing participants to complete the study in a more ecologically valid setting—on their personal computers in their own homes. We again observed an ADHD-specific influence of both cognitive and perceptual load (see Figure 3). As in study 1, we observed an interaction between load condition and ADHD (F(1,98) = 16.81, p < .001) such that those with ADHD slightly underperformed compared to those without ADHD during cognitive load ( $M_{ADHD} = 29.40$ ,  $M_{N-ADHD} = 30.01$ ), and clearly outperformed those without ADHD during perceptual load ( $M_{ADHD} = 33.33$ ,  $M_{N-ADHD} =$ 31.73). Replicating study 1, those with ADHD also exhibited lower RTV than those without ADHD during perceptual load ( $M_{ADHD} = 660.04$ ,  $M_{N-ADHD} = 793.45$ ). The opposite pattern was observed during cognitive load, in which those with ADHD exhibited higher RTV than those without ADHD ( $M_{ADHD} = 973.43, M_{N-ADHD} = 793.76$ ).

#### **Discussion**

In the present study, we provide evidence that performance in a naturalistic task is contingent on both cognitive and perceptual load. Cognitive load had a detrimental impact on performance, reaction time variability, and brain network efficiency in both ADHD and non-ADHD groups. Cognitive load also widened the gap in performance between non-ADHD and ADHD groups, with the ADHD group performing worse under cognitive load than the non-ADHD group. In contrast, perceptual load resulted in enhanced performance, reduced reaction time variability, and greater brain network efficiency in ADHD relative to the non-ADHD group. Our results provide evidence for the task-dependent nature of ADHD-related neural and behavioral differences and highlight the usefulness of video game "mods" to incorporate controlled manipulations into a naturalistic task. These results reveal rich



**Figure 4:** Influence of cognitive and perceptual load in study 3 during game play on: a) game performance (collecting crystals and avoiding asteroids), and b) reaction time variability, as measured using the variance in the exponential portion of the reaction time distribution, tau.

information regarding when and why ADHD individuals may perform less optimally than those without ADHD, and how performance in ADHD may be improved by modifying the design of a digital environment.

## Cognitive Load Magnifies Behavioral and Neural Indicators of ADHD Symptoms

Previous studies have focused on the distraction-magnifying influence of cognitive load in attention-demanding tasks (Kelley & Lavie, 2011; Konstantinou et al., 2014), and have suggested that differential susceptibility to cognitive load (e.g. via reduced working memory capacity) may be linked to suboptimal cognitive performance in those with ADHD (Roberts et al., 2012). In the present study, we demonstrate that increased cognitive load has a detrimental influence on task performance and reaction time variability in both ADHD and non-ADHD individuals, but that those with ADHD are comparatively more affected. We show that this relationship is observable both in categorical and continuous treatments of ADHD. Under cognitive load, those with ADHD performed worse in the video game task, had higher reaction time variability, and had lower brain network efficiency than those without ADHD.

Although lower performance in ADHD has previously been observed in highly controlled cognitive tasks (such as dual choice or flanker tasks; Adamo et al., 2014; Roberts et al., 2012), this study is the first to show an ADHD-specific influence of cognitive load in comparatively more "real-world" task performance, and to link differences in performance under cognitive load to variation in functional connectivity networks in the brain.

These results can be interpreted in light of recurrent observations that those with ADHD exhibit decreased efficiency in resting state and task-evoked brain networks (Konrad & Eickhoff, 2010; Lin et al., 2014; Wang et al., 2009), as well as aberrant modulation of

default mode and frontoparietal attention networks (Castellanos et al., 2008; Uddin et al., 2008). These modulations have also been linked to trial-to-trial variation in attentional lapses (Prado et al., 2011). Increased global efficiency in functional brain networks has been linked with greater performance in cognitive tasks (Bassett et al., 2009; Hearne et al., 2017). As such, reconfiguration of global brain networks in those with ADHD in response to increasing cognitive load could be expected to result in less efficient network topologies—and to result in decreased performance in the task.

Connecting aberrant patterns of functional connectivity with symptom domains is a fundamental question within ADHD research (Castellanos & Proal, 2012). Our observation that those with ADHD perform worse and have lower brain network efficiency under cognitive load suggests that linking naturalistic task performance with indices of brain network topology could provide informative neurobiological signatures distinguishing clinically-relevant features of ADHD and predicting both symptoms and responsivity to treatment in these individuals (Cai et al., 2018, 2019).

## Perceptual Load Minimizes ADHD-Related Performance Deficits and Behavioral Variability

A growing body of research demonstrates that perceptual load may be beneficial to cognitive performance in ADHD when compared to non-ADHD groups (Forster et al., 2014; Söderlund et al., 2007). It has remained unclear, though, whether the benefits of increased perceptual load for those with ADHD are limited to basic, highly-controlled cognitive tasks, or whether they are observable in more "real-world" task performance. Here, we demonstrate that perceptual load has a positive influence on both performance and reaction time variability in those with ADHD. Whereas those with ADHD underperformed those without

ADHD under cognitive load, they *outperformed* those without ADHD under perceptual load. Our results also provide evidence that intra-individual reaction time variability—a consistently-observed ADHD phenotype (Kofler et al., 2013; Tamm et al., 2012)—is modulated by perceptual load. Individuals with ADHD were found to be more variable than those without ADHD during cognitive load but were less variable under perceptual load.

These findings augment recent work suggesting that perceptual load may act to eliminate variability in ADHD attributable to cognitive control deficits (Forster et al., 2014). The Load Theory of Selective Attention and Cognitive Control (Lavie et al., 2004) suggests that perceptual load shifts the balance of attentional selection mechanisms away from executive control and toward more bottom-up filtering and selection. It follows then, that the addition of perceptual load may enable those with ADHD to leverage relative strengths in sensory integration and perception abilities (Panagiotidi et al., 2017; Rosas et al., 2010) while minimizing their reliance on cognitive control mechanisms. Indeed, ADHD is associated with increased local efficiency in brain networks (Lin et al., 2014), a topological signature associated with increased performance in perceptual discrimination tasks (Weiss et al, 2011). Further supporting this conclusion is recent work showing that the addition of conflicting dialogue (increasing cognitive load) within a naturalistic, multi-talker conversation desynchronizes brain activity between individuals with ADHD, but that introducing white noise (perceptual load) does not (Salmi et al., 2019).

Neurobiologically-informed video games have recently been introduced as potential interventions for improving ADHD symptoms (see e.g., Mishra, Sagar, et al., 2016; Ziegler et al., 2019), highlighting neural signatures of distractor suppression and interference resolution as useful targets for intervention. Related work shows that those who habitually play action

video games seem to exhibit increased attention, cognitive control, and working memory abilities compared to their peers (Cardoso-Leite et al., 2016; Green & Bavelier, 2003; Latham et al., 2013; Spence & Feng, 2010). In contrast, sustained engagement in other media is associated with *decreased* performance in these same domains. Those who frequently engage in *media multitasking* (concurrently doing two or more media tasks) exhibit reduced cognitive control, and have higher self-reported symptoms of ADHD (Beyens et al., 2018; Nikkelen et al., 2014; Ra et al., 2018; Uncapher et al., 2016, 2017). These findings highlight the necessity of developing better understanding regarding how individual differences in media habits influence (and are influenced by) cognitive individual differences (Fisher & Keene, 2019).

#### **Conclusions**

In three experiments, we showed that ADHD-specific variation in task performance and functional connectivity is modulated by both cognitive load and perceptual load.

Cognitive load disproportionately degrades performance, reaction time variability, and brain network efficiency in ADHD whereas perceptual load has largely opposite effects — minimizing observable differences between ADHD and non-ADHD. These results demonstrate that performance and neural efficiency gaps between ADHD and non-ADHD groups can be minimized or even eliminated when task parameters are changed. This work aligns with a growing collection of evidence showing that changes in cognition and attention during task performance are reflected in changes in brain network topology and dynamics (Gonzalez-Castillo et al., 2015; Kucyi et al., 2017; Rosenberg et al., 2020), and that these patterns of variations can reveal information about underlying clinical conditions that is largely inaccessible using other methods (Finn et al., 2018; Guo et al., 2015; Salmi et al.,

2019). Taken together, our findings highlight a number of future research opportunities at the intersection of neuroscience and media design that can contribute to greater understanding of complex disorders like ADHD and to targeted interventions to improve cognitive performance.

#### Methods

#### **General Overview**

All research was conducted in accordance with the University of California Santa Barbara Human Subjects Committee (IRB Protocol No. 23-20-0286 & 24-19-0051). In each of the three studies, we used Asteroid Impact, an open-source video game stimulus. In this first two experiments, participants played Asteroid Impact in a lab environment, and in the third, participants played a browser-based version on their personal computer. The primary goal in Asteroid Impact is to navigate a spaceship around the screen with the mouse, collecting valuable crystals while avoiding asteroids (see Figure 4). Previous work has shown that cognitive resource availability tends to be high during boredom (ability >> difficulty) and frustration (ability << difficulty), and low whenever difficulty and ability are approximately matched (Harris et al., 2017; Huskey et al., 2018). As such, we designed the game to adapt its difficulty level (the speed, quantity, and size of asteroids) to player performance over time, ensuring that all participants are challenged at a level that meets (but does not exceed) their abilities. Asteroid Impact has been previously shown to be motivating and engaging, and to be usable within both a behavioral and fMRI setting (Huskey, Craighead, et al., 2018; Huskey, Wilcox, et al., 2018).

In each of the three experiments, participants played three different variations of the

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<sup>&</sup>lt;sup>1</sup> https://github.com/medianeuroscience/asteroid\_impact

game: a baseline condition, a cognitive load condition, and a perceptual load condition. These conditions were identical across the three experiments. Participants also completed a speeded reaction time task during gameplay, in which they were asked to press the "X" key on a keyboard when they saw a blue square appear on screen, and to press "Y" when they saw a purple triangle. This task was designed to index the speed and variability in participants' response times during each condition. In each experiment, the speeded reaction time task was rewarded with in-game points. The triangle was worth 10 points (the equivalent of one crystal), and the square was worth 1000 points. In all experiments reported herein, we only consider reaction time data from low-reward probes, as reward is known to modulate both the speed and variability of response times in ADHD (Tamm et al., 2012; Uebel et al., 2010).

Manipulating Cognitive Load. Cognitive load was introduced into the game using a variant of an n-back rule maintenance task. The n-back is a widely used experimental paradigm in the fields of neuroscience and cognitive psychology in which individuals must perform a particular action—typically pressing a button—whenever a given stimulus matches a stimulus that occurred a certain number of trials in the past (Owen et al., 2005). This manipulation has been shown to elicit activation in working memory related brain regions and to be perceived as cognitively difficult (Eriksson et al., 2015; Veltman et al., 2003). In the version of the n-back employed in this study, participants were told that "some of the crystals are sabotaged" and that collecting two crystals of the same color in a row would result in a loss of 1000 in-game points (the equivalent of ten crystals). This required participants to maintain the identity of the most recently collected crystal in working memory while collecting the next crystal. A manipulation check included in study 3 revealed that the

cognitive load condition was more cognitively difficult than the other two conditions (see Supplemental Figure 1).

Manipulating Perceptual Load. The study of perceptual load has a rather long and contentious history within visual perception and cognitive neuroscience research (Fitousi & Wenger, 2011), but a recurring finding is that increased perceptual load can improve performance in visual perception tasks in people with ADHD (Forster et al., 2014; Forster & Lavie, 2007, 2009). Perceptual load has been manipulated in several ways, including increasing the number of items that need to be identified at any given time, increasing the difficulty of item identification (through blurring, distortion, rotation, etc.), increasing auditory or visual background noise, and reducing contrast between the foreground and the background (Elliott & Giesbrecht, 2010; Torralbo & Beck, 2008). In this study, we manipulated perceptual load by adding an overlay to the gameplay environment that reduces the opacity of foreground elements (asteroids and crystals) by 75% relative to the background. A manipulation check conducted in study 3 revealed that participants found the perceptual load condition more difficult to see than the other conditions (see Supplemental Figure 1).

**Measuring Performance.** As the primary goal in *Asteroid Impact* is to collect crystals while avoiding asteroids, we measured in-game performance as the number of crystals collected within a thirty-second window divided by one plus the number of asteroid collisions within the same window. Mean performance did not significantly vary between Study 1 and Study 3 ( $M_{SI} = 30.4$ ,  $M_{S3} = 31.2$ ), but was significantly lower in the fMRI study ( $M_{S2} = 18.61$ ). High intra-subject variability in response times is an etiologically important characteristic in ADHD (Kofler et al., 2013; Tamm et al., 2012), likely reflecting more

frequent lapses in attention. Reaction time variability was measured by fitting an ex-Gaussian distribution to each participant's reaction times within each round and taking the standard deviation of reaction times falling within the exponential portion of the distribution (tau; Tamm et al., 2012). Overall reaction time variability was higher in study 3 (M = 1241.96) than in study 1 (M = 962.26) or study 2 (M = 987.92), potentially due to the online nature of the study.

### Study 1

**Participants.** Participants in Study 1 were recruited from the subject pool of the Communication department at the University of California Santa Barbara. All participants provide written informed consent and earned course credit for their participation. In total, 230 participants completed the study (159 female, 69 male, 2 chose not to answer,  $M_{age}$  = 19.58). Two participants reported having taken medication for ADHD within the 12-hour period before the study, and as such were excluded from the analyses reported herein.

Experimental Design. Participants were invited into a computer lab with ten cubicles, each containing a Dell computer with a 16" x 9" monitor. Each participant was given a consent form outlining the purpose of the study and describing the Asteroid Impact task. After the participants finished reading and signing the consent forms, a researcher read a short prompt reiterating the goal of the game along with its controls. After this, participants put on headphones to minimize distraction, and began playing the game. Participants completed seven rounds of gameplay in total — a practice round and two rounds in each condition. All rounds following the practice round were presented in randomized order. After all levels were completed, participants completed the questionnaire items and were dismissed and thanked for their participation.

ADHD symptom severity was determined using the full version of the Adult ADHD Self-Report Scale (ASRS; Kessler et al., 2005). The ASRS has been shown to have 97.9% total classification accuracy (sensitivity 68.7%) for clinicians' ADHD diagnosis, a  $\kappa$  of .76, and a Chronbach's  $\alpha$  in between .63 and .72 in the general population of the United States (Hines et al., 2012; Kessler et al., 2007). ASRS scores range from 1 to 4. Participants who scored 3.2 or greater were considered as high symptom severity (N = 54), and those who scored 2.0 or lower were considered as low symptom severity (N = 48). In addition to the ASRS, participants completed a series of self-report questionnaires and provided basic demographic data. Data from these additional questionnaires are not reported herein.

Analyses. All analyses in Study 1 were conducted in R (R Core Team, 2013). Before analysis, data were minimally pre-processed, removing RTs that were greater than five standard deviations away from the mean within subjects and conditions. All main effects predictions were tested using linear mixed-effects models fit using the *lmer()* function from the *lme4* package in R. (Bates et al., 2015). Cognitive load, perceptual load, and ADHD status were treated as fixed effects, and were coded using effects coding. Random intercepts were included for each participant. All reported betas are standardized. As an additional check, ASRS scores were used as a continuous variable denoting severity of ADHD symptoms.

#### Study 2

Participants. Participants in this study were recruited from the subject pool at the University of California Santa Barbara and from the general community. A total of 36 participants were recruited, 18 participants with high ADHD symptom severity and 18 participants with low ADHD symptom severity. Participants were assigned to ADHD

1. Those whose ASRS scores were above (below) the high (low) ADHD cutoff were contacted by a researcher and invited to schedule a brain imaging appointment. Data from two participants were excluded due to equipment malfunction.

Scanning Parameters and Pre-Processing. All brain imaging data were collected on a 3T Siemens Magnetom Prisma located in the Brain Imaging Center at the University of California, Santa Barbara (TR = 400 ms, TE = 35 ms, flip angle =  $52^{\circ}$ , acquisition matrix =  $64 \times 64$ , in-plane resolution =  $3 \text{mm}^3$ ). Upon arriving in the Brain Imaging Center, participants provided informed consent, and filled out a metal-screening form. After this, participants spent approximately 10 minutes seated at a laptop practicing the video game task that they would be performing in the scanner. Upon completing the practice task, participants changed into scrubs and a researcher positioned them in the scanner, where they underwent a T1 structural scan followed by the video game task, a T2 structural scan, and a short gambling task which is not reported herein. Functional runs included three 600-volume repetitions within each condition (baseline, cognitive load, perceptual load).

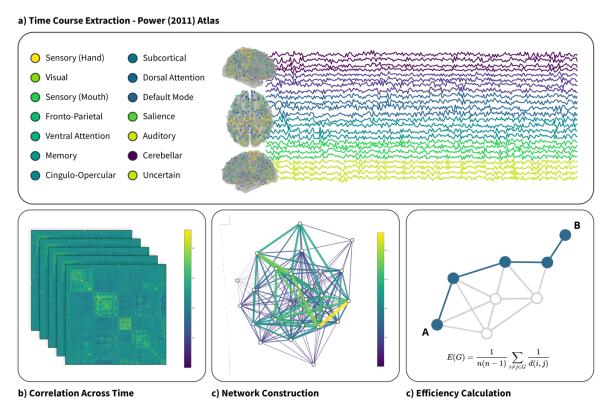
All brain imaging data were preprocessed with *fMRIprep*, a *Nipype* based tool (Esteban et al., 2019; Gorgolewski et al., 2011), and with *xcpEngine*, a supplemental pipeline for denoising data used in functional connectivity analyses (Ciric et al., 2017, 2018; Lydon-Staley et al., 2019). Each T1w volume was corrected for intensity non-uniformity using N4 bias field correction from the ANTs registration suite (Avants et al., 2011), and then skull-stripped using the OASIS template provided by ANTs. Brain surfaces were reconstructed using FreeSurfer (Dale et al., 1999), and spatially normalized to the ICBM 152 nonlinear asymmetrical template (version 2009c) using ANTs. Brain tissue segmentation was

performed using FSL FAST (Jenkinson et al., 2012). Functional data were slice time corrected using the 3dTShift function from the AFNI software package (Cox, 1996; Gold et al., 1998) and motion corrected using FSL MCFLIRT. Following this, functional data were co-registered to the T1w anatomical image using boundary-based registration with six degrees of freedom (Greve & Fischl, 2009). Motion correcting transformations, BOLD to T1w transformation, and registration of the T1w to the MNI template were conducted using ANTs. ICA-based AROMA was used to generate aggressive noise regressors and to create output files that are non-aggressively denoised. Further pre-processing conducted in xcpEngine included denoising time series data based on the ICA-AROMA and global signal, and white matter confounds generated by fMRIPrep, and conducting temporal band-pass filtering (0.01 < f < 0.15 Hz) to reduce the influence of low-frequency drift and high-frequency physiological noise.

**Network Creation and Analysis.** After preprocessing, each run was divided into 8 non-overlapping segments of 75 TRs, and the mean signal was extracted from the prewhitened timeseries in each of 264 regions of interest (ROIs) as defined in Power et. al (2011). Edges were constructed pairwise between each node with edge weights assigned as the correlation between the timeseries extracted from each pair of regions, resulting in  $264 \times 264$  matrix of Pearson's R values (see Figure 5). Network efficiency was calculated within each chunk as the inverse of the average shortest path distance between each pair of nodes in the whole-brain network (M = .19, SD = .012). Following previous studies (e.g., Chan et al., 2014; Finc et al., 2017; Lydon-Staley et al., 2019), we only considered positively-weighted edges, setting all negative edges to zero. Efficiency scores between ADHD and non-ADHD groups in each condition were compared using a linear mixed-effects

model fit using the *lmer()* function from the *lme4* package in R. (Bates et al., 2015).

## Study 3



**Figure 5**: Conceptual depiction of brain network extraction and analysis. a) Time series data is averaged within a 5mm sphere surrounding each of 264 regions of interest (ROIs) as defined in the Power et al. (2011) atlas. This atlas is divided into 14 subnetworks as defined by task-based functional connectivity. b) Pairwise correlation is calculated between each of the 264 ROIs, resulting in a 264 x 264 correlation matrix. c) edge weights in the network are assigned as the *Pearson's R* value between each node; d) Network efficiency is calculated as the inverse of the mean of all pairwise shortest paths.

**Participants.** Participants in Study 3 were recruited using an online sample from the online service Prolific Academic.<sup>2</sup> In total, 825 participants completed the pre-screener for the study, for which they earned \$5. Participants who self-reported an ADHD diagnosis were invited to complete the second half of the study, along with a matched group of those who reported: a) having never been diagnosed with ADHD, and b) having very few symptoms of

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<sup>&</sup>lt;sup>2</sup> https://www.prolific.co

ADHD. 100 participants completed the second half of the study (50 ADHD, 50 Non-ADHD, 37 female, 67 male,  $M_{age} = 29.14$ ). All participants provided informed consent and earned an additional \$5 for their participation.

Experimental Design. Participants played a browser-based (WebGL) version of Asteroid Impact created using Unity game design software.<sup>3</sup> This implementation ensures minimal lag in reporting reaction times and other in-game events due to internet speeds and ping times, as all game logging is performed on participants' local machine, and then uploaded at the end of each round to a server located at the University of California Santa Barbara. Participants were required to complete the game on a personal computer with a screen at least 11" in size, and that has a mouse pointer rather than a touchscreen interface. Participants completed seven rounds of gameplay in total—a one-minute practice round and two three-minute rounds in each condition. All rounds following the practice round were presented in randomized order. After each round, participants were presented with three survey items indexing the level of cognitive load, perceptual load, and enjoyment that they experienced in the previous round. After all levels were completed, participants were thanked for their submission and dismissed from the study.

Analysis. As in study 1, all analyses were conducted in R (R Core Team, 2013), and all data were subjected to minimal pre-processing. All main effects predictions were tested using linear mixed-effects models fit using *lmer()* (Bates et al., 2015). Cognitive load, perceptual load, and ADHD diagnosis were treated as fixed effects, and were coded using effects coding. Random intercepts were included for each participant. All reported betas are standardized.

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<sup>&</sup>lt;sup>3</sup> https://unity.com/

## References

- Anguera, J. A., Boccanfuso, J., Rintoul, J. L., Al-Hashimi, O., Faraji, F., Janowich, J., Kong, E., Larraburo, Y., Rolle, C., Johnston, E., & Gazzaley, A. (2013). Video game training enhances cognitive control in older adults. *Nature*, *501*(7465), 97–101. https://doi.org/10.1038/nature12486
- Avants, B. B., Tustison, N. J., Song, G., Cook, P. A., Klein, A., & Gee, J. C. (2011). A reproducible evaluation of ANTs similarity metric performance in brain image registration. *NeuroImage*, *54*(3), 2033–2044. https://doi.org/10.1016/j.neuroimage.2010.09.025
- Barkley, R. A. (1997). Behavioral inhibition, sustained attention, and executive functions: Constructing a unifying theory of ADHD. *Psychological Bulletin*, *121*(1), 65–94.
- Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, 67(1), 1–48. https://doi.org/10.18637/jss.v067.i01
- Biederman, J., Monuteaux, M. C., Doyle, A. E., Seidman, L. J., Wilens, T. E., Ferrero, F., Morgan, C. L., & Faraone, S. V. (2004). Impact of executive function deficits and attention-deficit/hyperactivity disorder (ADHD) on academic outcomes in children. Journal of Consulting and Clinical Psychology, 72(5), 757–766. https://doi.org/10.1037/0022-006X.72.5.757
- Biederman, J., Wilens, T. E., Mick, E., Faraone, S. V., & Spencer, T. (1998). Does attention-deficit hyperactivity disorder impact the developmental course of drug and alcohol abuse and dependence? *Biological Psychiatry*, *44*(4), 269–273. https://doi.org/10.1016/S0006-3223(97)00406-X

- Cai, W., Chen, T., Szegletes, L., Supekar, K., & Menon, V. (2018). Aberrant time-varying cross-network interactions in children with Attention-Deficit/Hyperactivity Disorder and its relation to attention deficits. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, 3(3), 263–273.
- Cai, W., Griffiths, K., Korgaonkar, M., Williams, L., & Menon, V. (2019). Task-evoked effective connectivity in salience and central executive networks predicts cognitive control ability and inattention symptoms in children with adhd. *Biological Psychiatry*, 85(10), S234–S235. https://doi.org/10.1016/j.biopsych.2019.03.593
- Castellanos, F. X., & Proal, E. (2012). Large-scale brain systems in ADHD: Beyond the prefrontal–striatal model. *Trends in Cognitive Sciences*, *16*(1), 17–26. https://doi.org/10.1016/j.tics.2011.11.007
- Chan, M. Y., Park, D. C., Savalia, N. K., Petersen, S. E., & Wig, G. S. (2014). Decreased segregation of brain systems across the healthy adult lifespan. *Proceedings of the National Academy of Sciences*, *111*(46), E4997–E5006. https://doi.org/10.1073/pnas.1415122111
- Chung, W., Jiang, S.-F., Paksarian, D., Nikolaidis, A., Castellanos, F. X., Merikangas, K. R., & Milham, M. P. (2019). Trends in the prevalence and incidence of attention-deficit/hyperactivity disorder among adults and children of different racial and ethnic groups. *JAMA Network Open*, 2(11), e1914344–e1914344.
  https://doi.org/10.1001/jamanetworkopen.2019.14344
- Ciric, R., Rosen, A. F. G., Erus, G., Cieslak, M., Adebimpe, A., Cook, P. A., Bassett, D. S., Davatzikos, C., Wolf, D. H., & Satterthwaite, T. D. (2018). Mitigating head motion artifact in functional connectivity MRI. *Nature Protocols*, *13*(12), 2801–2826.

- https://doi.org/10.1038/s41596-018-0065-y
- Ciric, R., Wolf, D. H., Power, J. D., Roalf, D. R., Baum, G. L., Ruparel, K., Shinohara, R. T.,
  Elliott, M. A., Eickhoff, S. B., Davatzikos, C., Gur, R. C., Gur, R. E., Bassett, D. S.,
  & Satterthwaite, T. D. (2017). Benchmarking of participant-level confound regression
  strategies for the control of motion artifact in studies of functional connectivity.
  NeuroImage, 154, 174–187. https://doi.org/10.1016/j.neuroimage.2017.03.020
- Cox, R. W. (1996). AFNI: Software for analysis and visualization of functional magnetic resonance neuroimages. *Computers and Biomedical Research*, 29(3), 162–173. https://doi.org/10.1006/cbmr.1996.0014
- Dale, A. M., Fischl, B., & Sereno, M. I. (1999). Cortical surface-based analysis: I. segmentation and surface reconstruction. *NeuroImage*, *9*(2), 179–194. https://doi.org/10.1006/nimg.1998.0395
- Danckaerts, M., Sonuga-Barke, E. J. S., Banaschewski, T., Buitelaar, J., Döpfner, M., Hollis,
  C., Santosh, P., Rothenberger, A., Sergeant, J., Steinhausen, H.-C., Taylor, E., Zuddas,
  A., & Coghill, D. (2010). The quality of life of children with attention
  deficit/hyperactivity disorder: A systematic review. *European Child & Adolescent*Psychiatry, 19(2), 83–105. https://doi.org/10.1007/s00787-009-0046-3
- Eickhoff, S. B., Milham, M., & Vanderwal, T. (2020). Towards clinical applications of movie fMRI. *NeuroImage*, 116860. https://doi.org/10.1016/j.neuroimage.2020.116860
- Elliott, J. C., & Giesbrecht, B. (2010). Perceptual load modulates the processing of distractors presented at task-irrelevant locations during the attentional blink.

  \*Attention, Perception, & Psychophysics, 72(8), 2106–2114.

  https://doi.org/10.3758/BF03196687

- Elson, M., & Quandt, T. (2016). Digital games in laboratory experiments: Controlling a complex stimulus through modding. *Psychology of Popular Media Culture*, *5*(1), 52–65. http://dx.doi.org/10.1037/ppm0000033
- Elton, A., Alcauter, S., & Gao, W. (2014). Network connectivity abnormality profile supports a categorical-dimensional hybrid model of ADHD. *Human Brain Mapping*, *35*(9), 4531–4543. https://doi.org/10.1002/hbm.22492
- Eriksson, J., Vogel, E. K., Lansner, A., Bergström, F., & Nyberg, L. (2015). Neurocognitive architecture of working memory. *Neuron*, *88*(1), 33–46. https://doi.org/10.1016/j.neuron.2015.09.020
- Esteban, O., Markiewicz, C. J., Blair, R. W., Moodie, C. A., Isik, A. I., Erramuzpe, A., Kent, J. D., Goncalves, M., DuPre, E., Snyder, M., Oya, H., Ghosh, S. S., Wright, J., Durnez, J., Poldrack, R. A., & Gorgolewski, K. J. (2019). fMRIPrep: A robust preprocessing pipeline for functional MRI. *Nature Methods*, *16*(1), 111. https://doi.org/10.1038/s41592-018-0235-4
- Finc, K., Bonna, K., Lewandowska, M., Wolak, T., Nikadon, J., Dreszer, J., Duch, W., & Kühn, S. (2017). Transition of the functional brain network related to increasing cognitive demands. *Human Brain Mapping*, *38*(7), 3659–3674. https://doi.org/10.1002/hbm.23621
- Finn, E. S., Corlett, P. R., Chen, G., Bandettini, P. A., & Constable, R. T. (2018). Trait paranoia shapes inter-subject synchrony in brain activity during an ambiguous social narrative. *Nature Communications*, *9*(1), 1–13. https://doi.org/10.1038/s41467-018-04387-2
- Finn, E. S., Glerean, E., Khojandi, A. Y., Nielson, D., Molfese, P. J., Handwerker, D. A., &

- Bandettini, P. (2019). Idiosynchrony: From shared responses to individual differences during naturalistic neuroimaging. *NeuroImage*, *215*(116828). https://doi.org/10.31234/osf.io/yeu89
- Fitousi, D., & Wenger, M. J. (2011). Processing capacity under perceptual and cognitive load:

  A closer look at load theory. *Journal of Experimental Psychology: Human Perception*and Performance, 37(3), 781–798. https://doi.org/10.1037/a0020675
- Forster, S., & Lavie, N. (2007). High perceptual load makes everybody equal: Eliminating individual differences in distractibility with load. *Psychological Science*, *18*(5), 377–381. https://doi.org/10.1111/j.1467-9280.2007.01908.x
- Forster, S., & Lavie, N. (2009). Harnessing the wandering mind: The role of perceptual load. *Cognition*, 111(3), 345–355. https://doi.org/10.1016/j.cognition.2009.02.006
- Forster, S., Robertson, D. J., Jennings, A., Asherson, P., & Lavie, N. (2014). Plugging the attention deficit: Perceptual load counters increased distraction in ADHD.

  \*Neuropsychology\*, 28(1), 91–97. https://doi.org/10.1037/neu0000020
- Gold, S., Christian, B., Arndt, S., Zeien, G., Cizadlo, T., Johnson, D. L., Flaum, M., & Andreasen, N. C. (1998). Functional MRI statistical software packages: A comparative analysis. *Human Brain Mapping*, *6*(2), 73–84. https://doi.org/10.1002/(SICI)1097-0193(1998)6:2<73::AID-HBM1>3.0.CO;2-H
- Gonzalez-Castillo, J., Hoy, C. W., Handwerker, D. A., Robinson, M. E., Buchanan, L. C., Saad, Z. S., & Bandettini, P. A. (2015). Tracking ongoing cognition in individuals using brief, whole-brain functional connectivity patterns. *Proceedings of the National Academy of Sciences*, 112(28), 8762–8767. https://doi.org/10.1073/pnas.1501242112
- Gorgolewski, K., Burns, C. D., Madison, C., Clark, D., Halchenko, Y. O., Waskom, M. L., &

- Ghosh, S. S. (2011). Nipype: A flexible, lightweight and extensible neuroimaging data processing framework in python. *Frontiers in Neuroinformatics*, 5. https://doi.org/10.3389/fninf.2011.00013
- Green, C. S., & Bavelier, D. (2012). Learning, attentional control, and action video games.

  \*Current Biology, 22(6), R197–R206. https://doi.org/10.1016/j.cub.2012.02.012
- Greve, D. N., & Fischl, B. (2009). Accurate and robust brain image alignment using boundary-based registration. *NeuroImage*, 48(1), 63–72. https://doi.org/10.1016/j.neuroimage.2009.06.060
- Guo, C. C., Nguyen, V. T., Hyett, M. P., Parker, G. B., & Breakspear, M. J. (2015). Out-of-sync: Disrupted neural activity in emotional circuitry during film viewing in melancholic depression. *Scientific Reports*, 5(1), 1–12.
  https://doi.org/10.1038/srep11605
- Harpin, V., Mazzone, L., Raynaud, J. P., Kahle, J., & Hodgkins, P. (2016). Long-term outcomes of ADHD: A systematic review of self-esteem and social function. *Journal of Attention Disorders*, 20(4), 295–305. https://doi.org/10.1177/1087054713486516
- Hines, J. L., King, T. S., & Curry, W. J. (2012). The adult ADHD self-report scale for screening for adult attention deficit–hyperactivity disorder (ADHD). *The Journal of the American Board of Family Medicine*, 25(6), 847–853. https://doi.org/10.3122/jabfm.2012.06.120065
- Huskey, R., Craighead, B., Miller, M. B., & Weber, R. (2018). Does intrinsic reward motivate cognitive control? A naturalistic-fMRI study based on the synchronization theory of flow. *Cognitive, Affective, & Behavioral Neuroscience*, 18(5), 902–924. https://doi.org/10.3758/s13415-018-0612-6

- Huskey, R., Wilcox, S., & Weber, R. (2018). Network neuroscience reveals distinct neuromarkers of flow during media use. *Journal of Communication*, 68(5), 872–895.
- Jenkinson, M., Beckmann, C. F., Behrens, T. E. J., Woolrich, M. W., & Smith, S. M. (2012).
  FSL. NeuroImage, 62(2), 782–790. https://doi.org/10.1016/j.neuroimage.2011.09.015
- Kelley, T. A., & Lavie, N. (2011). Working memory load modulates distractor competition in primary visual cortex. *Cerebral Cortex*, 21(3), 659–665. https://doi.org/10.1093/cercor/bhq139
- Kessler, R. C., Adler, L. A., Gruber, M. J., Sarawate, C. A., Spencer, T., & Van Brunt, D. L. (2007). Validity of the World Health Organization Adult ADHD Self-Report Scale (ASRS) Screener in a representative sample of health plan members. *International Journal of Methods in Psychiatric Research*, 16(2), 52–65.
  https://doi.org/10.1002/mpr.208
- Kessler, R. C., Adler, L., Ames, M., Demler, O., Faraone, S., Hiripi, E., Howes, M. J., Jin, R., Secnik, K., Spencer, T., Ustun, T. B., & Walters, E. E. (2005). The World Health
  Organization adult ADHD self-report scale (ASRS): A short screening scale for use in the general population. *Psychological Medicine*, 35(2), 245–256.
  https://doi.org/10.1017/S0033291704002892
- Klasen, M., Weber, R., Kircher, T. T. J., Mathiak, K. A., & Mathiak, K. (2012). Neural contributions to flow experience during video game playing. *Social Cognitive and Affective Neuroscience*, 7(4), 485–495. https://doi.org/10.1093/scan/nsr021
- Kofler, M. J., Rapport, M. D., Sarver, D. E., Raiker, J. S., Orban, S. A., Friedman, L. M., & Kolomeyer, E. G. (2013). Reaction time variability in ADHD: A meta-analytic review of 319 studies. *Clinical Psychology Review*, *33*(6), 795–811.

- https://doi.org/10.1016/j.cpr.2013.06.001
- Konrad, K., & Eickhoff, S. B. (2010). Is the ADHD brain wired differently? A review on structural and functional connectivity in attention deficit hyperactivity disorder.

  \*Human Brain Mapping\*, 31(6), 904–916. https://doi.org/10.1002/hbm.21058
- Konstantinou, N., Beal, E., King, J.-R., & Lavie, N. (2014). Working memory load and distraction: Dissociable effects of visual maintenance and cognitive control. *Attention, Perception, & Psychophysics*, 76(7), 1985–1997. https://doi.org/10.3758/s13414-014-0742-z
- Kucyi, A., Hove, M. J., Esterman, M., Hutchison, R. M., & Valera, E. M. (2017). Dynamic brain network correlates of spontaneous fluctuations in attention. *Cerebral Cortex*, 27(3), 1831–1840. https://doi.org/10.1093/cercor/bhw029
- Lavie, N., Hirst, A., de Fockert, J. W., & Viding, E. (2004). Load theory of selective attention and cognitive control. *Journal of Experimental Psychology: General*, *133*(3), 339–354. https://doi.org/10.1037/0096-3445.133.3.339
- Lee, S. S., Humphreys, K. L., Flory, K., Liu, R., & Glass, K. (2011). Prospective association of childhood attention-deficit/hyperactivity disorder (ADHD) and substance use and abuse/dependence: A meta-analytic review. *Clinical Psychology Review*, *31*(3), 328–341. https://doi.org/10.1016/j.cpr.2011.01.006
- Lin, P., Sun, J., Yu, G., Wu, Y., Yang, Y., Liang, M., & Liu, X. (2014). Global and local brain network reorganization in attention-deficit/hyperactivity disorder. *Brain Imaging and Behavior*, 8(4), 558–569. https://doi.org/10.1007/s11682-013-9279-3
- Loe, I. M., & Feldman, H. M. (2007). Academic and educational outcomes of children with ADHD. *Journal of Pediatric Psychology*, 32(6), 643–654.

- https://doi.org/10.1093/jpepsy/jsl054
- Lydon-Staley, D. M., Ciric, R., Satterthwaite, T. D., & Bassett, D. S. (2019). Evaluation of confound regression strategies for the mitigation of micromovement artifact in studies of dynamic resting-state functional connectivity and multilayer network modularity.

  Network Neuroscience, 3(2), 427–454. https://doi.org/10.1162/netn a 00071
- Mathiak, K., & Weber, R. (2006). Toward brain correlates of natural behavior: FMRI during violent video games. *Human Brain Mapping*, *27*(12), 948–956. https://doi.org/10.1002/hbm.20234
- Mishra, J., Anguera, J. A., & Gazzaley, A. (2016). Video games for neuro-cognitive optimization. *Neuron*, 90(2), 214–218. https://doi.org/10.1016/j.neuron.2016.04.010
- Mishra, J., Sagar, R., Joseph, A. A., Gazzaley, A., & Merzenich, M. M. (2016). Training sensory signal-to-noise resolution in children with ADHD in a global mental health setting. *Translational Psychiatry*, 6(4), e781–e781. https://doi.org/10.1038/tp.2016.45
- Owen, A. M., McMillan, K. M., Laird, A. R., & Bullmore, E. (2005). N-back working memory paradigm: A meta-analysis of normative functional neuroimaging studies. *Human Brain Mapping*, 25(1), 46–59. https://doi.org/10.1002/hbm.20131
- Power, J. D., Cohen, A. L., Nelson, S. M., Wig, G. S., Barnes, K. A., Church, J. A., Vogel, A.
  C., Laumann, T. O., Miezin, F. M., Schlaggar, B. L., & Petersen, S. E. (2011).
  Functional network organization of the human brain. *Neuron*, 72(4), 665–678.
  https://doi.org/10.1016/j.neuron.2011.09.006
- R Core Team. (2013). *R: a language and environment for statistical computing*. R Foundation for Statistical Computing. http://www.R-project.org/
- Roberts, W., Milich, R., & Fillmore, M. T. (2012). Constraints on information processing

- capacity in adults with ADHD. *Neuropsychology*, *26*(6), 695–703. https://doi.org/10.1037/a0030296
- Rosenberg, M. D., Scheinost, D., Greene, A. S., Avery, E. W., Kwon, Y. H., Finn, E. S., Ramani, R., Qiu, M., Constable, R. T., & Chun, M. M. (2020). Functional connectivity predicts changes in attention over minutes, days, and months.

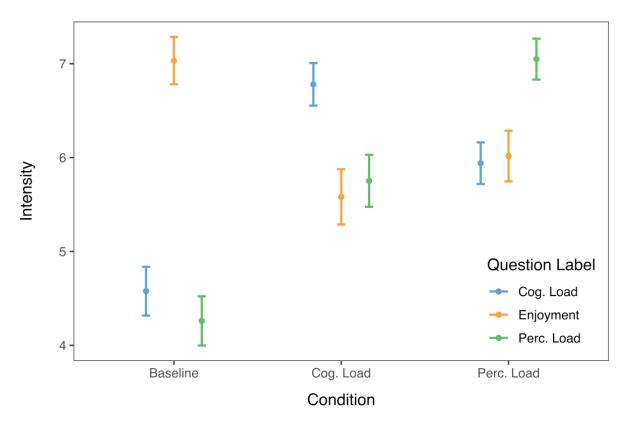
  \*Proceedings of the National Academy of Sciences. https://doi.org/10.1101/700476
- Salmi, J., Metwaly, M., Tohka, J., Alho, K., Leppämäki, S., Tani, P., Koski, A., Vanderwal, T., & Laine, M. (2019). ADHD desynchronizes brain activity during watching a distracted multi-talker conversation. *NeuroImage*, 116352.
  https://doi.org/10.1016/j.neuroimage.2019.116352
- Silk, T. J., Malpas, C. B., Beare, R., Efron, D., Anderson, V., Hazell, P., Jongeling, B., Nicholson, J. M., & Sciberras, E. (2019). A network analysis approach to ADHD symptoms: More than the sum of its parts. *PLOS ONE*, *14*(1), e0211053.
- Söderlund, G., Sikström, S., & Smart, A. (2007). Listen to the noise: Noise is beneficial for cognitive performance in ADHD. *Journal of Child Psychology and Psychiatry*, 48(8), 840–847. https://doi.org/10.1111/j.1469-7610.2007.01749.x
- Tamm, L., Narad, M. E., Antonini, T. N., O'Brien, K. M., Hawk, L. W., & Epstein, J. N. (2012). Reaction time variability in ADHD: A review. *Neurotherapeutics*, *9*(3), 500–508. https://doi.org/10.1007/s13311-012-0138-5
- Torralbo, A., & Beck, D. M. (2008). Perceptual-load-induced selection as a result of local competitive interactions in visual cortex. *Psychological Science*, *19*(10), 1045–1050. https://doi.org/10.1111/j.1467-9280.2008.02197.x
- Uebel, H., Albrecht, B., Asherson, P., Börger, N. A., Butler, L., Chen, W., Christiansen, H.,

- Heise, A., Kuntsi, J., Schäfer, U., Andreou, P., Manor, I., Marco, R., Miranda, A., Mulligan, A., Oades, R. D., Meere, J. V. D., Faraone, S. V., Rothenberger, A., & Banaschewski, T. (2010). Performance variability, impulsivity errors and the impact of incentives as gender-independent endophenotypes for ADHD. *Journal of Child Psychology and Psychiatry*, *51*(2), 210–218. https://doi.org/10.1111/j.1469-7610.2009.02139.x
- Vanderwal, T., Eilbott, J., & Castellanos, F. X. (2019). Movies in the magnet: Naturalistic paradigms in developmental functional neuroimaging. *Developmental Cognitive Neuroscience*, *36*, 100600. https://doi.org/10.1016/j.dcn.2018.10.004
- Vanderwal, T., Eilbott, J., Finn, E. S., Craddock, R. C., Turnbull, A., & Castellanos, F. X. (2017). Individual differences in functional connectivity during naturalistic viewing conditions. *NeuroImage*, 157, 521–530. https://doi.org/10.1016/j.neuroimage.2017.06.027
- Veltman, D. J., Rombouts, S. A. R. B., & Dolan, R. J. (2003). Maintenance versus manipulation in verbal working memory revisited: An fMRI study. *NeuroImage*, 18(2), 247–256. https://doi.org/10.1016/S1053-8119(02)00049-6
- Wang, L., Zhu, C., He, Y., Zang, Y., Cao, Q., Zhang, H., Zhong, Q., & Wang, Y. (2009).
  Altered small-world brain functional networks in children with attention-deficit/hyperactivity disorder. *Human Brain Mapping*, 30(2), 638–649.
  https://doi.org/10.1002/hbm.20530
- Weber, R., Alicea, B., Huskey, R., & Mathiak, K. (2018). Network dynamics of attention during a naturalistic behavioral paradigm. *Frontiers in Human Neuroscience*, 12(182), 1–14. https://doi.org/10.3389/fnhum.2018.00182

- Weber, R., Tamborini, R., Westcott-Baker, A., & Kantor, B. (2009). Theorizing flow and media enjoyment as cognitive synchronization of attentional and reward networks.

  \*Communication Theory, 19(4), 397–422. <a href="https://doi.org/10.1111/j.1468-2885.2009.01352.x">https://doi.org/10.1111/j.1468-2885.2009.01352.x</a>
- Weiss, S. A., Bassett, D. S., Rubinstein, D., Holroyd, T., Apud, J., Dickinson, D., & Coppola, R. (2011). Functional brain network characterization and adaptivity during task practice in healthy volunteers and people with schizophrenia. *Frontiers in Human Neuroscience*, 5. <a href="https://doi.org/10.3389/fnhum.2011.00081">https://doi.org/10.3389/fnhum.2011.00081</a>
- Xu, G., Strathearn, L., Liu, B., Yang, B., & Bao, W. (2018). Twenty-year trends in diagnosed attention-deficit/hyperactivity disorder among us children and adolescents, 1997-2016. *JAMA Network Open*, 1(4), e181471.
  https://doi.org/10.1001/jamanetworkopen.2018.1471
- Ziegler, D. A., Simon, A. J., Gallen, C. L., Skinner, S., Janowich, J. R., Volponi, J. J., Rolle, C. E., Mishra, J., Kornfield, J., Anguera, J. A., & Gazzaley, A. (2019). Closed-loop digital meditation improves sustained attention in young adults. *Nature Human Behaviour*, 1. https://doi.org/10.1038/s41562-019-0611-9

## **Supplemental Figures**



**Figure S1:** Manipulation check responses from study 3. Error bars represent 95% confidence intervals. Participants reported the highest level of enjoyment in the baseline condition, the highest level of cognitive difficulty in the cognitive load condition, and the highest level of perceptual difficulty in the perceptual load condition.