THE EFFECTS OF SMARTPHONE SCREEN TIME ON BEHAVIORAL VARIABILITY

By

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This thesis is dedicated to my beautiful wife, Lucia. Thank you for encouraging me to pursue my dreams. Your patience through the endless late nights is beyond admirable.

Ecclesiastes 4:9-10.

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ABSTRACT

Individuals diagnosed with conditions such as attention-deficit/hyperactivity disorder (ADHD), autism spectrum disorder (ASD), and depressive disorders tend to display levels of variable behavior disparate from their peers. Previous research has shown that variable behavior can be enhanced or reduced through reinforcement; however, the factors contributing to behavioral variability are poorly understood. Screen time has been hypothesized as a factor that may influence behavioral variability. The present study aimed to explore the possible relationship between smartphone screen time, behavioral variability, and self-reported ADHD, ASD, and depressive symptoms. To explore this relationship, participants attended a session where they reported their screen time use through a smartphone app. Next, participants completed a computer-based behavioral variability task, during which they drew rectangles on the screen. Points were given only for rectangles that were sufficiently different from those previously made (i.e., variable responding). Finally, participants completed the Beck Depression Inventory (BDI-II), Autism Spectrum Quotient-10 (AQ-10), and Adult ADHD Self-Report Scale (ASRS-v1.1). We found weak correlations between scores on the AQ-10 and ASRS-v1.1 and between the ASRS-v1.1 and the BDI-II. There were also moderate correlations between different measures of behavioral variability and between objective and subjective screen time scores, showing consistency in these assessments. However, no systematic relation between screen time and behavioral variability was observed.

Keywords: variability, screen time, autism, ADHD, depression, smartphone

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CHAPTER I: INTRODUCTION

Variability in behavior is adaptive for numerous reasons. Reacting to different, unique situations adaptively can facilitate both survival and learning. The degree to which an organism behaves variably can have important implications for its physical and psychological health. Numerous factors contribute to an increase or decrease in behavioral variability in humans. Social, cultural, biological, and psychological factors all play a part in shaping behavioral variability. While many factors may play a vital role, research on what can affect behavioral variability remains ongoing. For example, a relatively new aspect of human society is the advent of screen-based technology. The use of screen-based devices is often referred to as screen time. Since introducing these new electronics, researchers have sought to understand what consequences might stem from their use. One connection worth investigating is the potential relationship between screen time and behavioral variability.

Behavioral Variability

Adapting and changing to specific external influences is evolutionarily beneficial and increases an organism's chances of surviving and thriving in its environment (Darwin, 1859). For example, animals that forage for food in various locations are more likely to find it than those that repeatedly look in the same location (Wright et al., 2010). In addition, as organisms learn, behavioral flexibility can be a protective factor in overcoming crises and fostering resiliency (Orkibi, 2021). Historically, behavioral variability has been crucial to versatility and human development (Temple & Stojanowski, 2019). This ability to adapt and to be flexible allows for a nearly limitless

number of responses to circumstances (Hadders-Algra, 2010). Although there are certain situations where variability is not preferred (e.g., when performing inappropriate behaviors such as disrobing or acting in a manic, socially unacceptable manner), variability is generally considered a beneficial or adaptive quality of behavior. Thus, variability in behavior can be regarded as fundamental in learning new skills, problem-solving, and encouraging creativity (Neuringer, 2004).

Beginning in the late 20th century, variability was viewed less as a facet of behavior that can be disregarded and more as a vital dimension of behavior that can be changed and studied (Page & Neuringer, 1985). In studying behavioral variability, it has been found that restricted behavioral variability is a characteristic of many different pathologies. For example, part of diagnosing intellectual developmental disorders is examining an individual's adaptive functioning, which is their ability to perform age-appropriate life skills (American Psychiatric Association, 2022). A component of determining a person's adaptive functioning is their ability to vary their behavior when needed (American Association on Intellectual and Developmental Disabilities, 2022; Sparrow et al., 2016). As variability is essential to adaptive functioning, it is critical to understand how variable behavior can be controlled and taught.

There is some debate on how to define variability in the literature. Some argue that behavioral variability can be viewed as an operant, meaning that it is part of an organism's behavior that can be controlled by antecedents and consequences (Page & Neuringer, 1985). In other words, organisms learn whether and how much to vary their behavior in particular situations. In addition, many researchers posit that variability does

not refer to purely random behavioral change but can be viewed as a continuum encompassing a wide range of response variability (Neuringer, 2002). A series of responses might be repetitive, varied, or somewhere between the two ends of the spectrum. In addition, some contend that variable responses can be generally characterized as random, novel, or creative (Neuringer, 2002). Indeed, genuinely spontaneous responses are probabilistic and unpredictable (Brugger, 1997). Novel responses are generally viewed as not having been emitted or observed before, whereas creative responses have an additional artistic or functional aspect (Neuringer, 2002). For this study, variability will be broadly defined as the degree of change in an organism's behavior.

Control of Variable Behavior

To fully conceptualize behavioral variability, it is crucial to understand the methods used to control it. Some of these methods rely on consequences. From a behavioral perspective, consequences are the stimuli or actions following a behavior (Collier-Meek et al., 2017). Consequences may increase or decrease the likelihood of a specific behavior occurring if similar circumstances exist (Cooper et al., 2019). Specifically, consequences that increase the probability of a behavior are referred to as reinforcers, whereas consequences that decrease the chances of a behavior are defined as punishers (Cooper et al., 2019). Many studies have shown that behavioral variability can be reliably controlled using reinforcement (for a review, see Neuringer & Jensen, 2013).

One essential aspect of reinforcement that can increase or decrease behavioral variability is an organism's experience with schedules of reinforcement (Stokes, 1995).

For example, the behavioral variability observed may depend on the type of reinforcement schedule or history to which the organism is exposed or has previously been exposed (Antonitis, 1951). For example, continuous reinforcement schedules tend to produce lower behavioral variability, whereas intermittent schedules usually result in higher levels (Stokes, 1995). Additionally, response variability often increases when reinforcement is withheld (i.e., extinction; Antonitis, 1951). Furthermore, and most relevant to the present study, reinforcement schedules can promote new or varied behavior by establishing a criterion that must be met to receive reinforcement (e.g., Goetz et al., 1973; Page & Neuringer, 1985; Pryor et al., 1969).

Such reinforcement schedules designed to maintain behavioral variability have been investigated using various subjects, including human and non-human animals (e.g., Goetz & Baer, 1973; Page & Neuringer, 1985; Pryor et al., 1969; Ross & Neuringer, 2002). Broadly, these schedules involve differentially reinforcing specific responses based on novelty, recency, or frequency. For example, pigeons have been shown to peck variable sequences when a lag schedule, which reinforces non-recent responses, was implemented. According to a lag schedule, a response is only reinforced if it differs from a certain number of previous responses (Page & Neuringer, 1985). Additionally, college students have learned to draw rectangles of variable sizes and locations when frequency-based variability schedules are in place (Ross & Neuringer, 2002). In a relative frequency threshold contingency, a response is only reinforced if it has been made infrequently in the past (for more details, see Method). Other significant research has since been conducted to replicate and extend these findings (for reviews, see Neuringer, 2012,

2014). Experiments have involved pigeons (e.g., Doughty et al., 2013; Jensen & Neuringer, 2008; Stahlman & Leising, 2016), rats (e.g., Galizio & Odum, 2022; Neuringer, 1991; Wagner & Neuringer, 2006), humans (e.g., Doolan & Bizo, 2013; Hansson & Neuringer, 2018; Radley et al., 2018), and more (e.g., Belkaid et al., 2020; Manabe et al., 1997; Schusterman & Reichmuth, 2008). These experiments support the conclusion that reinforcing consequences can maintain variability, and the fact that consequences and different reinforcement schedules impact behavioral variability suggests that it is an operant dimension of behavior.

Antecedent stimuli and situations can also influence how variably an organism may behave. Controlling behavioral variability involves analyzing antecedents or environmental events that occur just before a behavior. These initial conditions can significantly impact the variability of behavior (e.g., Antonitis, 1951; Stokes, 1995; Goetz et al., 1973). For example, a discriminative stimulus is an antecedent (e.g., color, light, sound, context, etc.) that occurs before and exerts control over a behavior. A discriminative stimulus controls a behavior's occurrence because it is reliably reinforced when present and not reinforced when absent. Studies with rats, pigeons, and humans have found that behavioral variability can be controlled by discriminative stimuli that signal the reinforcement of either variability or repetition (Brodhead et al., 2016; Denney & Neuringer, 1998; Page & Neuringer, 1985). For example, Page and Neuringer (1985) arranged an experiment in which pigeons received food when they behaved either variably or repetitively, depending on the antecedent stimuli present. Pigeons learned to respond variably in one discriminative stimulus (e.g., red buttons on the wall) and to

behave repetitively in the presence of another (e.g., green buttons), based on which reinforcement schedule was in place in each context. These findings illustrate that antecedents, such as discriminative stimuli, can determine the degree of variability an organism exhibits, again supporting the notion that variability is an operant.

Additional studies have also investigated how specific individual differences may significantly impact behavioral variability (Neuringer & Huntley, 1992; Hunziker et al., 1996). For example, Neuringer and Huntley (1992) found that younger rats responded more variably than older rats, although older rats responded faster than younger rats. However, there was no significant difference in behavioral variability between male and female rats. Thus, this experiment demonstrated that age might be an essential factor in determining an individual's level of variability, while biological sex may not be. However, it may also suggest that age is nothing more than an extended or shorter reinforcement history for the organism. In addition, researchers have also examined the role of different behavioral traits (i.e., "shy" versus "bold," defined by behavioral patterns) on levels of variability in rats (Weiss & Neuringer, 2012).

Concerning humans, another individual difference that may influence behavioral variability is the presence or extent of a person's psychopathology. *The diagnostic statistical manual of mental disorders 5 - text revision* (*DSM 5-TR*) contains several disorders that reference repetitive motor movements and patterns and non-repetitive behavior as a critical criterion in their description (American Psychiatric Association, 2022). An inability to appropriately vary is an aspect of several distinct types of

psychopathologies, from social disorders to depressive and psychotic disorders (American Psychiatric Association, 2022).

Behavioral Variability and Psychopathology

Previous research has demonstrated that reinforcement can maintain variability (for a review, see Neuringer, 2002) and that the advantages of behavioral variability in acquiring new skills and promoting creativity are clear (e.g., Hansson & Neuringer, 2018; Weiss & Neuringer, 2012). Neurodivergent individuals (i.e., those whose neurology and/or behavior fall outside the bounds of typical societal norms) can sometimes struggle to behave variably, even when it would be beneficial to do so (American Psychiatric Association, 2022; Shah et al., 2022). Determining the relationship between behavioral variability and an individual's mental or neurodevelopmental disorder could be beneficial because it would allow practitioners to understand additional aspects of the disorder.

Autism spectrum disorder (ASD) is a neurodevelopmental disorder that involves stereotyped movement and inflexible behavior, among other symptoms (American Psychiatric Association, 2022). Some of these restricted, repetitive behaviors manifest as stereotypic behaviors that usually emerge around the age of four and may take the form of a limited selection of preferred tangible items, food preferences, stereotypic motor behaviors, or rigid routines, to name a few (Bancroft et al., 2016; Lalli et al., 1994; MacDonald et al., 2007). This behavioral inflexibility can be problematic, leading to social isolation and reduced learning opportunities (Rodriguez & Thompson, 2015). Progress has shown that intervention can increase and reinforce behavioral variability (Miller & Neuringer, 2000; Rodriguez & Thompson, 2015; Wolfe et al., 2014). Although

research is ongoing and direct control of behavioral variability is still being explored, several promising results teaching behavioral variability for individuals with ASD have been found.

In contrast to some of the more restricted and stereotyped behavior seen in many individuals with ASD, people diagnosed with attention-deficit/hyperactivity disorder (ADHD) are prone to display excessively variable behavior (American Psychiatric Association, 2022; DuPaul et al., 2001; Neuringer, 2009). These behaviors often occur when it is not socially acceptable, such as in the classroom during work tasks or parent-child interactions (American Psychiatric Association, 2022; DuPaul et al., 2001; Neuringer, 2009). The reason for the increased levels of behavioral variability compared to neurotypical individuals is unclear. Some have hypothesized that individuals diagnosed with ADHD have decreased brain activation in the temporal lobe that might influence behavioral variability (Rubia et al., 2007), and others point to an executive inhibition deficit as a possibility for the increase in behavioral variability (Neuringer, 2009; Nigg, 2001). Regardless, whereas reinforcement has been used to increase behavioral variability in individuals diagnosed with ASD, reinforcement could be used to moderate behavioral variability in those diagnosed with ADHD. However, limited research has been conducted on operant variability in individuals with ADHD (Hunziker et al., 1996; Saldana & Neuringer, 1998).

Abnormal levels of behavioral variability may also contribute to other psychological disorders. For example, a large part of the criteria for psychotic disorders is disorganized motor behavior, manifesting as stereotyped or repetitive movements

(American Psychiatric Association, 2022; Pishkin & Williams, 1983; Schultz & Searleman, 2002). Another psychological disorder related to low behavioral variability is major depressive disorder. Although there is not extensive literature regarding behavioral variability and depressive disorders, preliminary research suggests that depressed individuals show lower levels of behavioral variability than their neurotypical peers (Hopkinson & Neuringer, 2003). In diagnostic terms, this decline in variability might be related to the symptom known as psychomotor retardation; if less behavior is occurring, there are fewer opportunities to vary (American Psychiatric Association, 2022). Reducing behavioral rigidity and encouraging behavioral variability could be vital in improving outcomes for individuals with schizophrenia and other psychological disorders as well. Further research is needed to understand why some individuals behave more variably than others, and we should aim to investigate other factors that could influence behavioral variability.

Screen Time

Screen time is commonly understood as electronic screen use by individuals. The type of technology that is used in the definitions of screen use varies slightly depending on both the year and purpose of the study, but examples include televisions, phones, computers, tablets, and more (Jari et al., 2014; Jones et al., 2021; Keikha et al., 2020; Martin et al., 2021; Olson et al., 2022). For the present study, screen time will be defined as watching or engaging in content on a handheld or non-handheld device such as a personal computer (PC), cell phone, television (TV), or tablet.

During the 21st century, various problems have been found to correlate with the rise in screen time (Paulich et al., 2021). For example, a study examined the differences between youths aged 9-11 years who met the recommended guidelines for screen time and sleep (2 hours or less of screen time per day and 9-11 hours of sleep per night) and those who did not. Researchers discovered that the children who met those guidelines had a lower prevalence of problematic externalizing (e.g., aggression, delinquency) and internalizing (e.g., depression, anxiety) behaviors (Sampasa-Kanyinga et al., 2021). Subsequent research has found that screen time may negatively affect executive function (Portugal et al., 2021; Soares et al., 2021). Specifically, inhibitory control in the form of attention and orienting to distractors when involved in a visual media task was lower for children who engaged in a high amount of screen time than those who did not (Portugal et al., 2021). However, screen time may affect individuals differently depending on their distinct features, such as gender, age, and other internal and external factors. (e.g., various psychopathologies).

Screen Time and Psychopathology

Autism spectrum disorder (ASD), characterized by deficits in social skills and restricted interests, has been associated with increased screen time (American Psychiatric Association, 2022; Slobodin et al., 2019). In a meta-analysis of 16 studies that examined ASD and screen time among children and young adults ages 0-19 diagnosed with ASD and their neurotypical counterparts, it was found that children and young adults with ASD in these samples spent more time with screens than their neurotypical peers (Chonchaiya et al., 2011; Slobodin et al., 2019). Some research suggests that higher use of screen time

is a factor that may lead to an increased risk of social anxiety, which may have important implications for those with ASD (Westby, 2018). Although many hypotheses have been created that point to certain conclusions, the inferences that can be made are inconclusive, and causality between the different factors has not been definitively determined.

Another disorder that may have a relationship with screen time is ADHD. Although there is not a plethora of literature examining the effects of screen time on individuals with ADHD, some preliminary studies have investigated this relationship (Cavalli et al., 2021; Soares et al., 2022; Vaidyanathan et al., 2021). In a study of children 2-6 years old diagnosed with ADHD, researchers found that the severity of a child's ADHD was correlated to the amount of screen time to which they were exposed (Vaidyanathan et al., 2021). Specifically, children rated higher on an ADHD severity scale reported more daily screen time (Vaidyanathan et al., 2021). Although this relationship does not establish causation or directionality of the affiliation, it creates an interesting correlation to explore. Screen time may also be a potential environmental risk factor for developing and increasing ADHD diagnoses and symptomology (Soares et al., 2021). However, evidence of a relationship between screen time and ADHD is mixed. Some studies have suggested that screen time is not correlated with the development of early childhood ADHD diagnoses (Ferguson, 2011; Stevens & Mulsow, 2006).

Very little literature addresses the potential effects of screen time and depressive symptomology and disorders. Some evidence points to the idea that youth exposed to more screen time and less sleep are at a higher risk of developing depressive

symptomology than their peers (Liu et al., 2019; Wang et al., 2021). In addition, some research also suggests that there may be a connection between depressive and anxious symptoms and the duration of screen time (on TV, smartphones, and computers) spent each day of the week (Forte et al., 2021).

Another factor that may influence depressive symptoms is the form of screen time with which someone engages. Social media and mobile phones have been associated with more significant depressive symptoms than other forms of screen time, such as TV and video games (Liu et al., 2019; Ma et al., 2021). However, current research is divided on which media contribute to depressive symptoms, and other research has shown TV to be associated with more significant depressive symptoms. In contrast, computer and mobile devices were associated with less severe symptomology (Yu et al., 2019). In addition, prolonged TV viewing and total screen time in adolescence were risk factors for developing depressive symptoms in young adulthood (Grøntved et al., 2015). Given these mixed results, it is difficult to conclude the exact relation between screen time and depressive symptomology.

Screen Time and Behavioral Variability

It has been proposed that screen time may be a factor that influences behavioral variability or vice versa. Two seminal hypotheses exist to explain the potential relationship between screen time and variability. The stimulation hypothesis suggests that variability can be stimulated by viewing different behaviors on electronic devices. The reduction hypothesis posits that creativity becomes disrupted due to screen time and that

screen time can ultimately lead to decreased creativity (Calvert & Valkenburg, 2013). Both hypotheses have some research that may substantiate the claims.

Proponents of the stimulation hypothesis point to Albert Bandura's (1986) social learning theory in partial support of the idea that people can increase their creativity by observing others during their screen time activities. Several studies have supported this perspective. A longitudinal study following children ages 5-18 found that those who reported watching more informational media when they were five also reported more involvement in creative activities (such as art classes, music activities, and drama) as teenagers (14 to 18 years old). In addition, they also scored higher on divergent or creative thinking tasks such as the verbal ideational fluency test. Children who watched more violent, less informational, and educational media scored lower on creativity tasks and participated in fewer creative activities (Anderson et al., 2001). However, the research is correlational and has several limitations, such as relying on self-report and a non-diverse sample (e.g., 87% European American and from the Midwest area of the United States).

The reduction hypothesis states that consuming media decreases creativity because of displacement and exposure to visual storytelling (Calvert & Valkenburg, 2013). Displacement refers to the idea that more creative outlets such as reading and writing are being supplanted by less-creative past-times such as television and other media. One study examined this difference between the ability to generate creative responses in children aged 12 and 13. Children were given the same information in video, print, or audio format and were instructed to provide researchers with creative responses

to the information (Meline, 1976). Those given the information in video format produced fewer responses than those exposed to it through print and audio format (Meline, 1976). This research suggests that the medium by which information is conveyed may impact variability. However, the literature is mixed and correlational.

Purpose of the Current Study

The primary purpose of the present study was to further our understanding of the possible relationship between smartphone screen time and behavioral variability. We collected data on college students' screen time use and behavioral variability to investigate this connection and assess any potential correlation. If participants who engaged in more screen time also behaved more variably, then screen time and behavioral variability would be positively correlated, which may provide evidence supporting the hypothesis that screen time stimulates variable behavior or vice versa. Nonetheless, the stimulation theory and existing research suggest that this will depend on the type of screen time that the participants consume. Therefore, we asked participants about smartphone screen time and screen time on other devices.

Conversely, if participants with more screen time use behaved less variably, our results would show a negative correlation. These findings would provide evidence supporting the hypothesis that screen time displaces creative, or variable, behavior, or vice versa. If we were to observe no systematic relationship between variability and screen time, we would have learned more about one of the factors that do not significantly impact behavioral variability. However, further research would be required to draw this conclusion definitively.

Past studies on screen time have primarily utilized self-reports instead of objective measures to track the screen time of their participants. However, continual technological advances and increasing screen time have led to the development of more impartial methods. The current study involved the default screen time tracking methods included with iOS and Android smartphones to track the screen time activities of participants. For further information, however, we also asked participants to self-report estimates of their total screen time use across other devices.

Various methods have been used to assess behavioral variability and creativity, including different play activities like coloring activities (Bancroft et al., 2016), variable responses to social situations based on predetermined appropriate variable responses (Radley et al., 2018), verbal creativity tasks such as creating unique stories (Mottweiler & Taylor, 2014), guessing games (Zlotowski & Bakan, 1963), block-building (Goetz & Baer, 1973), button push tasks (Miller & Neuringer, 2000), and other tasks to experiment with variability. The current experiment utilized an established computer-based rectangle game to measure participant variability (Galizio et al., 2020; Ross & Neuringer, 2002). In this task, participants used the cursor on the screen to click and drag, creating rectangles of varying sizes and locations. We assessed variability as it occurred under different schedules of reinforcement (i.e., points). Some advantages of this task are that it can be easily administered on a computer, includes a discrete and objective response (a rectangle, categorized by size and location), and is more engaging for adult participants than other tasks involving simple responses (e.g., button pressing). In addition, it is a straightforward task that does not necessitate complex instructions for a participant to be

able to take part in the task. This simple nature allows participants to understand how to complete the task. In addition, it reduces the training time for the researchers who are administering the task. Furthermore, the task is relatively short, taking approximately 30 minutes for most participants to complete. One aim of the current study was to analyze the results of this task and its possible relationship with screen time.

As both behavioral variability and screen time have been linked with specific psychopathologies, a secondary purpose of the current study was to investigate individual differences in behavioral variability and screen time, especially related to symptoms of certain psychopathologies, including ASD, ADHD, and depression. In our study, we administered health screeners to detect ASD, ADHD, and depressive symptoms (Allison et al., 2012). Any relationships we discovered would add to the current literature on screen time and behavioral variability and enhance our understanding of these topics.

CHAPTER II: METHODS

Participants

Participants for the study were college students in introductory psychology courses recruited through the psychology department research pool, or Sona Systems® (see Appendix A). All students were at least 18 years old. Only students with a smartphone with the default screen time tracking app activated were eligible to participate. Participants gave informed consent before completing any surveys or tasks (see Appendix B). After completing the rest of the experimental tasks, participants completed a demographics survey through Qualtrics® to assess participant characteristics (see Appendix C). All research methods were developed to minimize possible emotional or psychological distress, so participants were debriefed immediately following their session (see Appendix D). Experimental procedures were conducted in line with the guidelines provided by the American Psychological Association and were approved by the Institutional Review Board (IRB) of Middle Tennessee State University (MTSU; Protocol Number: FY2023-36). All participants were assigned a participant identification number to maintain confidentiality.

A total of 63 participants began the study. One participant did not finish the experiment because they did not have their screen time tracking app activated before the study. Additionally, four participants experienced technical difficulties during the behavioral variability task, which resulted in their data not saving correctly, so these participants were excluded from data analysis. Following this exclusion, a total of 58 participants completed the entire study with usable data. Table 1 shows the participant

characteristics, based on the demographics survey, for all participants who completed the study with usable data. Furthermore, five outliers were identified and excluded (see Data Analysis for details). Fifty-three participants remained after this exclusion.

Setting

The participants took part in the study in a small on-campus computer lab room with minimal distractions. The participants completed the study on one of the room's computers. When multiple participants were tested in the same room, the start time was staggered, and each individual was seated at least two seats away from other participants.

Procedure

For this study, participants signed up through the SONA system using their university login credentials. Upon signing into the system, they selected the option to 'View Available Studies.' There was a brief description of the study so potential participants could decide if they wanted to participate. Then, they selected the study and signed up for a time slot. They were instructed to check the settings on their smartphone to ensure that the appropriate screen time tracking programs had been enabled for at least one week before their time slot, and they were told to bring their smartphone to the session (see Appendix A).

Participants completed an informed consent form when they arrived for their scheduled session (see Appendix B). This consent form included information about the purpose of the study, their privacy and right to discontinue the study at any time if they so choose, and the possible effects of the study. Then, participants were seated at a computer to complete several tasks: (1) a survey in which they reported their screen time, (2) a

behavioral variability task, and (3) several different psychopathology screeners. Each of these tasks is described in detail below. After completing all the tasks, participants completed a demographics survey (see Appendix C) and were debriefed by the researcher (see Appendix D). The entire study was expected to take up to 60 minutes. After completing the study, participants received course credit and were reminded to contact the researchers at any time if they had questions or concerns.

Materials and Design

Screen Time Assessment

In the first task, participants completed a Qualtrics® survey in which they reported their screen time use (see Appendix E). The survey began with questions related to general screen time use. Participants were asked to estimate their average daily screen time use in hours across all devices over the last week. They were also asked to indicate all the screen time devices they owned.

On the next page, participants were asked to find their researcher to help them. The researcher described the ScreenTime programs used to track their smartphone use and a general description of the program for either Android® users or iPhone® (iOS) users. The program for iOS users is the ScreenTime system, and for AndroidOS users, it is the Digital Wellbeing® system. These applications are included in the default operating system of the iPhone and Android phones and can track the time a person spends on their phone. Both systems operate similarly by measuring the time an individual interacts with their device after opening it. Following this information, the researcher instructed the participant to locate records of their screen time use on their phone. If needed, the

researcher helped the participant find the records. Participants entered their daily average smartphone screen time use over the past week, and the researcher verified that the information was entered correctly. The researcher only observed the specific amount of screen time used, not the particular applications and websites visited by the individuals.

Behavioral Variability Task

Next, individuals were given a computer-based behavioral variability task. This task involved participants using the mouse to click and drag on the screen to form rectangles. The participant was seated in front of a computer, and the researcher loaded the program, which displayed the instructions (see Appendix F). The researcher read the instructions aloud to the participant and asked whether the participant had any questions. The instructions included information that participants were about to play a game that involved creating rectangles. Then, they were informed that some rectangles would produce points, that participants would hear a tone when they earned a point, that the total number of points would be shown on the screen, and that the object of the game was to earn as many points as possible. The participant was then given a pair of headphones to hear the tones and told to press the "Start" button when ready.

The task details were similar to those of Galizio et al. (2020). Participants performed the task on a large white area in the center of the computer screen (see Appendix F). The white space did not include grid lines or any other spatial parameters to guide participants in the areas in which they could draw rectangles. Participants used the lab computer's mouse to create the rectangles by pushing the mouse's left button and making the desired rectangle. When the mouse's left button was pressed and dragged, the

shape of the rectangle appeared. Upon release of the button, the rectangle disappeared. A point delivery and tone followed some rectangles, and some rectangles had no programmed consequence. Between each trial of the task, there was a 1-s interval in which the computer screen became blank, and participants could not use the mouse.

The categorization of rectangles was based on both size and location for the task. Specifically, the dimensions scrutinized for the task were the size (area) of the rectangles and their specific location on the screen (represented by the center of the rectangles). For each of these dimensions, 16 different categories were created. For example, with the size dimension, a model random generator could make a large number of rectangles that fit within the confines of the screen. Then, the 16 different categories were defined so that each rectangle, from smallest to largest, had an equal occurrence in each category (see Galizio et al., 2020, and Ross & Neuringer, 2002, for details).

During the task, points were delivered for some rectangles according to a relative frequency threshold contingency, which requires behavioral variability. The relative frequency of each of the dimensions was calculated on each trial. Each time a participant drew a rectangle, the relative frequency for each category was determined. Then, these relative frequencies were compared to a fixed threshold value. The fixed threshold value was selected based on Galizio et al.'s (2020) procedure. The threshold value of 0.2 signified that for a point to be delivered, the rectangle drawn had to be in a category of the target dimension, size or location, in which 20% or less of the rectangles had already occurred. This value was selected because it is relatively lenient, which allows for greater individual differences in levels of behavioral variability.

Participants completed two conditions, or versions, of the same game. They completed 300 rectangles in each condition. In the first condition, one of the dimensions, size or location, was set as the target dimension. The first target dimension was counterbalanced across participants. The other dimension was established as the target dimension in the second condition. For example, if a participant's target dimensions were size in the first condition and location in the second, then that participant had to make rectangles that varied in terms of size to earn points for the first 300 rectangles and rectangles that varied in terms of location to earn points for the second 300 rectangles. In each condition, levels of variability were measured for both dimensions. If participants responded according to the contingencies, we would expect to see high levels of variability on the target dimension, but not the other dimension, during each phase.

Psychopathology Screeners

Next, participants completed three psychopathology screeners in a random order. All surveys were administered through Qualtrics® on a computer in the lab. These screeners are described below.

The Autism Spectrum Quotient-10 (AQ-10; see Appendix G) was administered to assess for possible symptoms of ASD. The AQ-10 is a well-validated screener (internal consistency for adults was 0.85 and for adolescents .89) that provides a quick measure of where an individual may be on the autism spectrum (Allison et al., 2012; Baron-Cohen et al., 2001). The screener contains ten brief statements. Each question of the AQ-10 focuses on behaviors that many individuals with ASD exhibit. The participants were given statements describing autistic behaviors and asked to rate their agreement with how much

they exhibit the behaviors. The level of agreement uses a four-point Likert scale, progressing from “Definitely Agree” to “Definitely Disagree,” with “Slightly Agree” and “Slightly Disagree” used to report moderate agreement or disagreement (Allison et al., 2012). It should be noted that although this questionnaire is designed to indicate whether an individual shows some of the symptoms of ASD, the AQ-10 is not an official diagnostic tool.

The Beck Depression Inventory-II (BDI-II; see Appendix H) is a highly validated (internal consistency of 0.93) and proven measure containing 21 items used as a self-report assessment to measure attitudes and symptoms of depression (Beck et al., 1961; Contreras et al., 2004). The inventory covers depressive symptoms such as pessimism, past failure, anhedonia (loss of pleasure), and guilty feelings. It asked participants which statement regarding the symptoms they feel describes their current state. Despite its widespread use as a screener, the BDI-II is not the single determiner of an individual’s potential depressive state. Instead, it is utilized in concert with other measures to make a diagnosis (Subica et al., 2014).

The Adult ADHD Self-Report Scale (ASRS-v1.1; see Appendix I) is a screener tool developed to help determine if a person has symptoms consistent with ADHD criteria outlined in the *DSM-5 TR* (Kessler et al., 2005). It was designed for adult use and was tested on a sample of adults aged 18-44. The ASRS-v1.1 has six brief statements that require the individual to indicate their agreement on a five-point Likert scale from “Never” to “Very Often” (Kessler et al., 2005). These statements indicate self-reported complete disagreement with the statement to complete agreement. The scale also contains

descriptors between the two polar ends that indicate moderate agreement. As a self-report tool, the ASRS-v1.1 is used to express if an individual has symptoms consistent with a diagnosis of ADHD and is not utilized as an official diagnostic tool. In addition, the National Institute for Health Research (NHS), which created the screener in tandem with researchers from Harvard Medical School, has tested the validity of the ASRS-v1.1 and has demonstrated that it is a well-validated screener (internal consistency for the total scores was 0.84, and the subset symptom scores were 0.83; Subica et al., 2014). Another group of psychiatrists has also demonstrated similar levels of internal validity (Adler et al., 2006).

Demographics Survey

Finally, participants were asked to report personal demographic information in a Qualtrics® survey (see Appendix C). Questions included: gender identity, age, race/ethnicity, level of education, parental education, and primary language. In addition, participants were asked whether they had ever received a diagnosis of a mental disorder, psychological condition, or educational disability of any kind. Finally, participants were asked to describe what they thought the study was about and how they believed they earned points in the variability task.

Data Analysis

The dependent measures for the screen time assessment included objective and subjective measures. The objective measure was the average number of hours of screen time per day recorded on the participant's smartphone over the last week. The researcher verified this value, and it should represent the participant's smartphone use objectively.

The subjective measure was the participant's self-reported estimate of their daily screen time use, in hours, across all devices. This self-reported value was analyzed separately because it is a more subjective measure than the verified number of smartphone hours.

The dependent measures for the behavioral variability task included the number of points earned and the U-value. The number of points earned is the total number of points delivered across both task conditions. More points would indicate more variable behavior according to the target dimension. U-value is another measure for the behavioral variability task, commonly utilized to evaluate an overall level of variability with a range of 0 to 1 (Page & Neuringer, 1985). A U-value of 0 demonstrates complete repetition (for this study, it would be that all rectangles made fell into the same category in the dimension), and a U-value of 1 indicates completely stochastic, variable/random responses (i.e., rectangles made in every possible category equally). U-value is determined using Equation 1,

$$U = -\sum_{i=1}^{n} \frac{Rf_i * log_2(Rf_i)}{log_2(n)}, \quad (1)$$

where Rf_i in the equation refers to the relative frequency that a response is emitted, and n is the number of response categories (for this study, we used 16). U-values were compared across conditions and dimensions using a 2 x 2 repeated-measures two-way analysis of variance (ANOVA), with a Šídák's multiple comparison test to examine interaction effects. This analysis was conducted using GraphPad Prism.

The dependent measures for the psychological screeners were the scores on each survey. For example, the Autism Spectrum Quotient 10 (AQ-10) has scores that allow a participant to be quickly screened on certain behavioral traits common with individuals with autism. For the screener, one point could be earned for each question, and a score of six or higher (with a maximum score of ten) may indicate the possible presence of adult autism (Allison et al., 2012). When tested in the general population, one study found that the average score was 2.69 (*SEM* = 0.02) for men and 2.25 (*SEM* = 0.02) for women (Lundin et al., 2019). Given that the sample in the current study may or may not contain individuals diagnosed with ASD, we would expect to observe similarly low scores on average.

The Beck Depression Inventory-II has scores that range from zero to 63. The scores on the inventory are divided into different groups. From zero to 13, a person is considered to be reporting minimal depressive symptoms; from 14 to 19 is considered mild; from 20 to 28 is regarded as moderate; and from 29 to 63 is deemed severe self-reported depression (Beck et al., 1961). In the general population, one study found an average score of 10.6 (*SD* = 10.9) for both men and women (Roelofs et al., 2013). Given this general population average and additional research conducted with college students, we would expect to see analogously low scores on average (Whisman & Richardson, 2015).

Finally, the Adult ADHD Self-Report Scale (ASRS-v1.1) has a different scoring procedure than the other self-report screeners. In the ASRS-v1.1, the screener consists of non-numerical values affixed to the items that range from ‘Never’ to ‘Very Often.’ If the

study participant checked ‘Sometimes,’ ‘Often,’ or ‘Very Often,’ these items were counted as a point toward their overall adult ADHD score. Three or fewer points indicate that your symptoms may not be consistent with adult ADHD, while four or more points suggest that the person may have symptoms consistent with adult ADHD (Kessler et al., 2005). In one study of ASRS-v1.1 in the general population, the average score for individuals aged 18-29 was 2.99 (SD = 4.10), with average scores decreasing as age increased (Adler et al., 2019). We would expect to see similar average scores in the current study, which included a similar age range.

Given that this study is a preliminary investigation of the potential relation between behavioral variability, screen time, and various psychological symptoms, the primary analytic technique used was correlation. To determine which correlation analytic technique would be the most appropriate, the data for all variables were assessed for normality using the Shapiro-Wilk test. The Shapiro-Wilk test was used because it is one of the most powerful tests for non-normal distributions and has one of the lowest Type I error rates (Öztuna et al., 2006; Shapiro, 2015; Shapiro & Wilk, 1965). Also, the Shapiro-Wilk test is used for studies that have relatively smaller samples (Shapiro & Wilk, 1965; Romão et al., 2010). Because the data were not normally distributed, a non-parametric statistic was used for the correlation analysis. Therefore, to measure the strength and direction of the association between the variables, we used Spearman’s ρ, which is a non-parametric statistic. Spearman’s ρ is determined using Equation 2,

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2 - 1)} \quad (2)$$

where d_i^2 is the difference between the two ranks of each. In addition, n is the number of observations for the study. Spearman's ρ assesses the monotonic relationship between the variables. The relationship may show that as one variable increases, the value of the other variable also increases. However, the monotonic relationship may also indicate that as the value of one variable increases, the other variable value decreases. A Spearman's ρ of 1 shows a perfect positive correlation between the variables (i.e., as one variable increases, so does the other), while a ρ of -1 shows a perfect negative correlation. Correlational analyses were conducted using R (version 421, 2023.06.0). The R code is available in Appendix J.

Upon analyzing the results, it became apparent that some data points may have been outliers. To be conservative, we conducted all analyses with the full data set (those who experienced technical difficulties and were unable to complete all of the parts of the study were excluded) and a second data set that removed participants who were deemed to be outliers. Four participants were excluded from the final 'Full Data' set due to technical difficulties in the behavioral variability task. Subsequently, we had n = 58 participants in the Full Data set. In the second data set, potential outliers were identified using the interquartile range of the data multiplied by three times (IQR*3). The interquartile range is a measure of the spread of the data or, in essence, a measure of statistical dispersion (Bock et al., 2000; Mishra et al., 2019). Each quartile represents a

fourth of the data, and the interquartile range signifies the difference between the 25th and 75th quartiles. This spread was extended to three times the interquartile range. Participants whose data fell outside this range for at least one dependent variable were excluded. Utilizing this approach, data for five participants were determined to be probable outliers on at least one dependent variable, so these participants were removed for the second analysis. This reduced the second data set to n = 53 participants.

A power analysis was conducted before beginning the experiment to ensure that our study was sufficiently powered to detect a significant correlation. A power analysis calculates the smallest sample size required for an experiment given a pre-decided significance level, effect size, and statistical power. An a priori power analysis was conducted using G*Power to estimate the necessary sample size. To detect a significant correlation with a moderate effect size ($\rho = 0.4$), assuming a two-tailed test, an alpha level of 0.05, and high power (>0.8), a sample size of 44 would be required. Since no previous research has investigated the relationship between behavioral variability and screen time, we proposed using a sample size of 50 for this study. Fifty-eight participants completed the study with usable data, and 53 remained after removing probable outliers.

CHAPTER III: RESULTS

Descriptive Statistics

Descriptive statistics for all dependent variables are shown in Table 2. Table 2 is divided into seven rows, each containing descriptive data (means and standard deviations) relating to one of the variables analyzed in the study. The first three rows have scores on each psychological screener done in the study, and the fourth row pertains to points earned in the behavioral variability task (due to the task involving the creation of rectangles, the behavioral variability task is referred to as the rectangle task in the table). The fifth row references the U-values for the target dimension in the first condition of the rectangle task, and the sixth and seventh rows contain objective and subjective screen time values in hours. Table 2 is divided into two different sections, one for the 'Full Data' set, which refers to the data that contains all 58 participants included in the study, and one for the 'IQR*3 Data' set, which is the data for 53 participants after eliminating probable outliers.

Behavioral Variability Task

Participants performed highly variably on the rectangle task, as evidenced by high U-values and points earned for most rectangles created (see Table 2 for descriptive statistics). Although participants' performance was highly variable in both conditions across both dimensions, size and location, they did show differential responding according to the contingencies in place. Specifically, as shown in Figure 1, U-values were generally higher for the target dimension in each condition. The results of the 2 x 2 repeated-measures two-way ANOVA showed no main effect of the condition [$F = 2.613$

(1,114); $p = 0.1088$] or dimension [$F = 0.2566$ (1,114); $p = 0.6135$]. There was a significant interaction between dimension and condition [$F = 31.17$ (1,114); $p < 0.0001$]. During Condition 1, U-values were significantly higher for the first target dimension than the alternative dimension ($p = 0.0009$). During Condition 2, U-values were significantly higher for the second target dimension than the alternative dimension ($p = 0.0136$).

Additionally, U-values for the first target dimension showed a significant decrease from Condition 1 to Condition 2 ($p = 0.0118$), and U-values for the second target dimension showed a significant increase across conditions ($p < 0.0001$). Together, these results indicate that the contingencies controlled levels of behavioral variability. Participants' rectangles varied more along whichever dimension was required to produce points, and their levels of variability adjusted when the contingencies changed across conditions. According to these results, the rectangle task successfully reinforced variable responding of specific dimensions, indicating strong experimental control.

Correlations

Several weak positive associations and two moderate positive associations were seen between the different psychopathology screeners, the behavioral variability task, and the screen time assessment. These associations were found within the 'Full Data' set and the 'IQR*3' data set. Furthermore, the probability or *p* scores for the two data sets are found in Appendix K. For the 'Full Data' set, the correlation values are found in Figure 2. This figure shows a correlogram, which includes a scatterplot for each pair of variables, a histogram for each variable, and the ρ value for correlation. One of these weak positive associations is between the ASRS-v1.1 and AQ-10 scores that participants received in the

study ($\rho = 0.33$). This finding suggests that there may be a weak-to-moderate positive association between those participants who tended to score highly in the ADHD screener and the ASD screener (Dancey & Reidy, 2007). This detection is consistent with previous findings that suggest that ADHD and ASD can often occur comorbidly (American Psychiatric Association, 2022). There was also a weak positive association between BDI-II scores and ASRS-v1.1- scores ($\rho = 0.27$). This association suggests that those who scored higher in the depression inventory also tended to score higher in the ADHD screener. The *DSM-5 TR* also indicates that some individuals diagnosed with depression may also be diagnosed with ADHD (American Psychiatric Association, 2022).

The results showed a moderate positive correlation ($\rho = 0.61$) between U-values and the number of points received in the rectangle task. This moderate correlation supports the validity of the behavioral variability task. Specifically, when participants behaved more variably (higher U-values), they scored more points, which is the purpose of the task. Another moderate positive correlation ($\rho = 0.57$) was found between objective and subjective screen time use. This association may suggest that participants can successfully estimate their screen time use.

Although the correlational values between the two data sets are relatively similar, one crucial distinction exists. Figure 3 shows a weak positive correlation ($\rho = 0.28$) between BDI-II scores and the scores received on the rectangle task. This may contradict some of the existing literature, which suggests that individuals who are depressed show lower levels of behavioral variability than their neurotypical peers (Hopkinson & Neuringer, 2003). However, additional research would need to be conducted as the weak

correlation indicates that as BDI-II scores increase (which would suggest a higher depressive score), rectangle task scores also tend to increase.

The correlogram of the 'IQR*3' data set shares similar values with the correlogram of the 'Full Data' set. The correlation between ASRS and AQ10 scores decreased slightly (from $\rho = 0.33$ to $\rho = 0.31$), and the correlation values between BDI and ASRS scores showed a modest increase (from $\rho = 0.27$ to $\rho = 0.31$). However, the modest correlations between the screen time measures and U-value and the rectangle task only showed negligible changes. An additional correlation that changed between data sets was the correlation between ASRS and rectangle task scores (from $\rho = 0.25$ to $\rho = 0.27$). However, although the correlation between the ASRS and rectangle task points had a weak correlational value ($\rho = 0.27$), its probability, or p-value, was trending towards significance ($p = .051$). Further research on these different tasks would be needed to understand this trend.

CHAPTER IV: DISCUSSION

The study aimed to examine the potential relationship between smartphone screen time, self-reported ADHD, ASD, depressive symptoms, and behavioral variability. For this research, we hypothesized that higher screen time would negatively correlate with variability and that scores on the ADHD, ASD, and depressive scales would either mediate or increase this negative correlation. We utilized the behavioral variability task previously tested by Galizio et al. (2020) to measure the behavioral variability of the participants. This task was performed similarly to the 2020 study in that the participants earned points for creating rectangles variably, and similarly high levels of variability were observed. However, levels of variability were not systematically correlated with screen time.

According to commonly established interpretation guidelines, the ASRS-v1.1 and the AQ-10 had a weak correlational relationship (Full Data: $\rho = 0.25$, IQR*3: $\rho = 0.31$) (Dancey & Reidy, 2007). This finding suggests that study participants tended to score similarly on the AQ-10 and the ASRS-v1.1. This correlation may indicate that people who score similarly regarding ADHD symptoms also score similarly concerning autism behavioral traits. The positive correlational value suggests a positive statistical relationship and that as scores on the ASRS-v1.1 increased, so did scores on the AQ-10. The strength of the value indicates that this was not an absolute relationship.

Furthermore, it is unclear whether the entirety of the screeners had items that correlated with each other or if certain items correlated more strongly than others. Additional analyses would need to be conducted to understand this relationship.

However, a few inferences can be made following this correlation. First, participants taking the ASRS-v1.1 and the AQ-10 may have scored similarly due to the content similarity within the items. For example, both screeners have questions related to each other, such as how a person conceptualizes a project. The ASRS-v1.1 asks how often the individual has "trouble wrapping up the final details of a project, once the challenging parts have been done." The AQ-10 asks participants to indicate how much they "usually concentrate more on the whole picture, rather than the small details" (Allison et al., 2012; Kessler et al., 2005). Second, both screeners have items that concern staying on task when performing a job. Furthermore, although these screeners cannot be used to diagnose individuals with either autism spectrum disorder or ADHD fully, this weak correlation suggests that individuals who take the aforementioned screeners may behave in ways that are similar to those with ADHD or autism spectrum disorder.

The ASRS-v1.1 also shares a weak positive correlation with the BDI-II (Full Data: $\rho = 0.37$, IQR*3: $\rho = 0.31$). The *DSM-5 TR* suggests that major depressive disorder occurs in a minority of individuals with ADHD but more often than in the general population (American Psychological Association, 2023). However, as the population of the participants in the study came from a general student population and not a clinical population, this is speculative. Similar to the ASRS-v1.1 and the AQ-10, the ASRS-v1.1 and the BDI-II share resemblances in the specific items within the screeners. The BDI-II contains items that share common behavioral traits with ADHD, such as a person's energy level, restlessness, indecisiveness, and concentration (Beck et al., 1961). The ASRS-v1.1 and BDI-II's weak positive correlation may also have been correlated because of the

population that was used for the study. Anxiety, indecisiveness, and an unfocused nature are typical for a significant minority of college students (Healthy Minds Study, 2020). This trend for many college students indicates that there may be a slightly higher-than-average score for college students on both the BDI-II and the ASRS-v1.1.

The study found a moderate positive correlational relationship between U-values in the rectangle task and the points earned in the rectangle task (Full Data: $\rho = 0.46$, IQR*3: $\rho = 0.59$). This correlation may suggest that U-values were related to the number of points earned in the study (i.e., the more points earned, the higher the U-value given to the participant). This positive correlational relationship may confirm that the task can assess behavioral variability. Past research has also demonstrated this relationship (Galizio et al., 2020). This relationship may also provide additional credence to the continued use of the rectangle task in future research. Although behavioral variability is still not completely understood, the internal validity of the point system and U-values for the participants appears valid.

An additional correlation that was noted was a moderate positive correlation between the subjective screen time and objective screen time scores (Full Data: $\rho = 0.54$, IQR*3: $\rho = 0.57$). This moderate correlation may suggest that participants could accurately predict their screen time usage. This finding differs from previous research suggesting that participants could not accurately report their screen time use (Hodes & Thomas, 2021; Ohme et al., 2021). However, it should be noted that in the present study, the description of the experiment may have impacted participants' estimation of their screen time. Because the study description explicitly stated that the research was related

to screen time, one of the inclusion criteria was that the participants had to have the screen time tracking app activated on their smartphone for at least a week before their sign-up time. It is likely that students had already checked their screen time usage before arriving at the study and were thus able to report their use on the subjective measure equivalent to the usage report provided by the objective measures. This behavior was observed in a few participants in the study, who arrived at the study room with the screen time applications already pulled up on their phones and with their screen time usage visible. Future research should examine whether participants can accurately report their screen time use without first consulting their apps.

A final correlation that was detected was between the ASRS and the rectangle task points. However, despite this correlation's weak relationship, its p-value ($p = .051$) is trending toward significance. This relationship is consistent with previous literature that suggests that organisms with symptoms consistent with an ADHD diagnosis often display more variable behavior than their neurotypical peers (American Psychiatric Association, 2022; DuPaul et al., 2001; Hunziker et al., 1997; Neuringer, 2009). Nonetheless, the full extent and directionality of the relationship between these two tasks and their implications would need further exploration.

Limitations of the Screen Time Assessment

Several crucial limitations need to be noted when considering this study. One example is the specific screen time measure used to capture the amount of smartphone screen time each participant had. Although the ScreenTime and Digital Wellbeing® applications possibly reduce the subjectivity of utilizing self-report measures that have

been used in several other studies to measure screen time (Chonchaiya et al., 2011; Jari et al., 2014; Jones et al., 2021; Keikha et al., 2020; Martin et al., 2021; Olson et al., 2022; Slobodin et al., 2019), due to the novel nature of the applications, their reliability and validity remain in question. Specifically, it remains to be seen how accurate the applications are at precisely monitoring the interactions between the owner of the smartphone and the smartphone itself. For example, in a study of adults in Denmark, researchers utilized an application called SDU DeviceTracker, created by the University of Southern Denmark (Kristensen et al., 2022). The researchers compared it to the Apple ScreenTime and ActionDash applications. These researchers found that regarding the ScreenTime application, the iOS application underestimated users' daily screen time and differed markedly from the Android application, ActionDash, which they used. They hypothesized that this indicates a risk of considerable error on an individual level.

However, the ScreenTime application has been used by other researchers, who suggest that there is some utility to the application and that the application can be used to study discrepancies between self-reported screen time and the data collected through the ScreenTime application (Ohme et al., 2021). Utilizing this method, they found that most of the self-reports of the screentime durations differed significantly from the time reported through the tool. However, the direction of this differentiation seems to depend considerably on the study. For example, two studies released in 2021 agreed that users could not report their screentime data accurately. However, one study (Ohme et al., 2021) stated that most participants underreported their screen time use. In contrast, another

study reported that participants over-reported their screen time use (Hodes & Thomas, 2021).

There were several limitations specific to the present study. Anecdotally, a few survey participants reported that they were confused about the wording of the screen time items. The participants were asked to estimate their daily average screen time in hours from the past week. Thus, they may have been confused about whether their estimate should be an estimate of their total usage weekly or throughout one day. Wording the questions more clearly in future research would address this potential concern. Another limitation of the study concerning the screen time assessments is the one-week activation of the screen time applications required for the study. This requirement necessarily limits the number of participants that could be included in the study. In addition, simply owning a smartphone limits the type of individuals who could be involved in the study. For example, individuals with a smartphone may have different screen time habits and usage.

Limitations of the Psychopathology Screeners

The psychopathology screeners used also have limitations. First, given the nature of ASD and how different each presentation can be, depending on the individual, it can be difficult to regard a short screener as being able to ascertain common autistic behaviors accurately. For example, in creating the screener, 90% of the adults who took the test, who were a part of the autism group, were diagnosed with Aspergers (Allison et al., 2012). This diagnosis is now outdated with the *Diagnostic Statistical Manual 5th Ed.* update (American Psychiatric Association, 2013). In addition, the specific nature of the

behaviors the adults exhibited, which the screener was created from, may limit its generalizability to other, different presentations of adult autism.

The Beck Depression Index (BDI-II) also has several crucial limitations. First, the BDI-II only measures how an individual feels for the past two weeks (Beck et al., 1961). This feature could be a potential drawback because it limits the ability to measure or understand a person's historical depressive states. For example, persistent depressive disorder, a disorder that is characterized by long-lasting depressive feelings, may be unrealized if a person were to take the BDI-II and not feel depressed or distraught for the past two weeks. An additional limitation is the discriminant validity of the BDI-II. Although Beck et al. (1961) can demonstrate the discriminant validity between depressives and nondepressives (i.e., people who have been diagnosed with depression and those who have not), it is less effective at discriminating between other disorders or symptoms such as anxiety (Richter et al., 1998). Essentially, this limits the ability of the BDI-II to accurately assess if a person has depression. Finally, additional researchers note the instability of scores over a single day (Richter et al., 1998). Participants instructed to take the BDI-II at different times during the day received different scores overall. Again, this may be due to the nature of the BDI-II and its focus on short-term, current issues.

The Adult ADHD Self-Report Scale (ASRS-v1.1), utilized in our study to measure ADHD symptoms, also has notable limitations. Primarily, the ASRS-v1.1 is limited due to its highly brief nature. Although Kessler et al. (2004) suggest that the short, 6-item version can function and assess the same ADHD symptomology as its 18-item counterpart, the screener may still have inefficacies. Furthermore, the ASRS-v1.1 is also

hindered by its relatively small sample size (compared to its original, longer predecessor). The ASRS-v1.1 was created using a subsample of 154 participants of its original 9083 participants, which may limit its generalizability.

Limitations of the Behavioral Variability Task

The behavioral variability task utilized in the current study has several limitations. The first limitation of the task lies in its content validity. It is unclear if a participant who scores highly on the behavioral variability task is more behaviorally variable globally (outside of the study). It is still uncertain whether the measure can generalize outside of a lab setting.

Furthermore, engagement of the task is another concern. The task is largely stagnant, and the participant is stationary and only produces a limited number of actions. This condition may have led to boredom and decreased motivation to fully engage in the task. Also, the value of the points was arbitrary and not tied to any specific goal or incentive. This point system may have made some participants indifferent to the number of points they achieved. The researcher set some basic social expectations at the start of the study by mentioning that the participants should attempt to get as many points as possible. However, whether this effectively promoted a modicum of internal motivation is unclear. It should also be noted that the only compensation for participating in the study was course credit, but their performance on the task had no impact on receiving it.

In addition, the variability requirements used in the study were fairly lenient. The study utilized a threshold value of 0.20. This value means that for a point to be delivered, the rectangle had to have been in a category of the target dimension (time or location)

where 20% or fewer of the rectangles had occurred. However, 20% is a fairly high percentage point for the variability requirement, and only relatively moderate levels of variability are required to produce points. Data may have differed if more stringent or more lenient requirements were utilized. As mentioned in previous research, another limitation of the task is the use of U-values to measure variability (Galizio et al., 2020). U-value cannot explain a participant's specific responses but rather measures variability on a general, global level.

Limitations of the Sociodemographic Features

The results of the demographics collected in the study (see Table 1) mirrored many of the demographics of Middle Tennessee State University (National Center for Education Statistics, 2021). For example, for the 'Full Data' set and the IQR*3 data, a majority of women were involved in the study. MTSU also has a majority of women, at 55% of the undergraduate student population. Although the study reflects the gender demographics of MTSU's student body, having nearly two-thirds of the study's participants identify as women may be a drawback. Women may perform differently on the rectangle task than other genders (Hines, 2010). Furthermore, there were not enough participants of different genders to understand if there were significant differences in data (see Table 1). Additional research and a more controlled, diverse sample may allow researchers to understand the possible gender differences in behavioral variability, screen time, and psychopathological traits.

The vast majority of the participants in the study consisted of students aged 18 to 24 years old (see Table 1). This restricted age group may be a limitation because some

researchers have shown differences in behavioral variability between younger and older adults (Myerson et al., 2007). Due to how homogenous the study was, exploring group differences by age was not feasible. This shortcoming in the study opens up the possibility that the data may have been more homogenous and clustered than in a non-uniform study.

Another study limitation is the lack of lingual diversity (see Table 1). Most participants reported that their first or primary language was English. In addition, the study did not include an item that asked about bilingualism and was thus unable to account for any differences in behavior based on either different primary languages or bilingual participants. Current research has suggested that language may be able to change the way that people behave (Athanasopoulos & Bylund, 2023). Specifically, researchers have suggested that language may be able to change the way that individuals perceive time (Athanasopoulos & Bylund, 2023). However, due to the homogeneity present in the study, no comparisons can be made between different language groups.

Another study limitation is the number of individuals who reported a diagnosed psychological condition (see Table 1). Of the 62 participants in the study, only about a quarter said that they had been formally diagnosed with any mental or psychological disorder. This limitation severely limits the number of inferences and conclusions that can be made regarding the performance of those with such conditions. Furthermore, although several participants scored high on the AQ-10 and autistic behaviors were of interest in the study, no participants reported that they had been officially diagnosed with autism spectrum disorder. This limitation implies that it is unfeasible to perform inter-

individual comparisons between those who scored highly on the AQ-10 and those who reported being diagnosed with autism spectrum disorder.

The education demographics for the study were divergent between those reported by the individuals completing the study and their parents' reported education level (see Table 1). The self-reported education levels of the research participants were necessarily homogenous, which is a direct result of our recruitment procedures. All participants were enrolled in college courses and were compensated for completing the study with course credit. However, the participants' reported parental education levels were more heterogeneous. Because we observed no significant correlations between screen time and behavioral variability, no additional analyses were conducted on potential differences between participants based on their parental education level. However, education may be an important factor in future research.

Future Directions

Several different future directions can be taken in subsequent research. First, additional research should be conducted to know if the behavioral variability scores in the task can generalize toward behavioral variability outside of a controlled environment. Although the task has been used to assess behavioral variability in a controlled setting (Galizio et al., 2020; Ross & Neuringer, 2002), future studies could perform the task and do other follow-up assessments of behavioral variability using different methods. For example, future studies may use the rectangle task and behavioral observations to assess a participant's behavioral variability in a less structured environment. An additional element that may be added to the study is a monetary component. For example, future

research could reward participants with a monetary reward based on the points they earned in the behavioral variability task.

Second, future research should seek to test a larger, more diverse sample. Although the current research largely mirrors the undergraduate student body of MTSU, future research could conduct even more diverse sampling to understand possible racial, ethnic, or cultural influences that may change a person's behavior or screen time usage. Additionally, forthcoming research may be able to use samples from racial, ethnic, and cultural groups that were not heavily represented in the current study (such as Native American or Pacific Islander populations).

Furthermore, future studies can use the methodology in the current study with a more diverse age and education-level sample. The present study utilized nearly exclusively younger and bachelor-level participants. Future studies can build off the present research by stratifying the sample to include several different age groups and those of all different types of education. Due to the simplicity of the methods used in the study, many other individuals can participate in the study.

Conclusion

Our findings continue to validate the utility of the behavioral variability task used in previous studies (Galizio et al., 2020; Ross & Neuringer, 2002). In addition, using objective screen time measures (ScreenTime and Digital Wellbeing® systems) opens the door to additional usage of the measures in understanding screen time usage exclusively, as well as screen time connected to different adaptive or maladaptive behaviors. The correlations found in the study between some of the other screeners may also help inform

clinicians in applied psychological testing environments and initiate a further use of the screeners to identify specific behavioral traits. Although no significant correlation was observed between behavioral variability and screen time, this study adds to the limited research exploring the relationship. Future research should continue to examine whether and how screen time and behavioral variability may be connected.

REFERENCES

Adler, L. A., Faraone, S. V., Sarocco, P., Atkins, N., & Khachatryan, A. (2019). Establishing US norms for the Adult ADHD Self-Report Scale (ASRS-v1.1) and characterising symptom burden among adults with self-reported ADHD. *International Journal of Clinical Practice*, *73*(1), 1-10. https://doi.org/10.1111/ijcp.13260

Adler, L. A., Spencer, T., Faraone, S. V., Kessler, R. C., Howes, M. J., Biederman, J., & Secnik, K. (2006). Validity of pilot Adult ADHD Self-Report Scale (ASRS-V1.1) to rate adult ADHD symptoms. *Annals of Clinical Psychiatry*, *18*(3), 145–148. https://doi.org/10.1080/10401230600801077

American Psychiatric Association. (2022). *Diagnostic and statistical manual of mental disorders* (5th ed., text rev.). https://doi.org/10.1176/appi.books.9780890425787

Allison, C., Auyeung, B., & Baron-Cohen, S. (2012). 'Toward brief 'red flags' for autism screening: The short autism spectrum quotient and the short quantitative checklist for autism in toddlers in 1,000 cases and 3,000 controls': erratum. *Journal of the American Academy of Child & Adolescent Psychiatry*, *51*(3), 338. https://doi.org/10.1016/j.jaac.2012.01.017

Anderson, D. R., Huston, A. C., Schmitt, K. L., Linebarger, D. L., & Wright, J. C. (2001). Early childhood television viewing and adolescent behavior: The recontact study. *Monographs of the Society for Research in Child Development*, *66*(1). http://www.jstor.org/stable/3181552

Antonitis, J. J. (1951). Response variability in the white rat during conditioning, extinction, and reconditioning. *Journal of Experimental Psychology*, *42*, 273-281. https://doi.org/10.1037/h0060407

American Association on Intellectual and Developmental Disabilities. (2022). *Defining criteria for intellectual disability*. https://www.aaidd.org/intellectual-disability/definition

Athanasopoulos, P., & Bylund, E. (2023). Cognitive restructuring: Psychophysical measurement of time perception in bilinguals. *Bilingualism: Language and Cognition*, 1-10. https://doi.org/10.1017/S1366728922000876

Bancroft, S. L., Thompson, R. H., Peters, L. C., Dozier, C. L., & Harper, A. M. (2016). Behavioral variability in the play of children with autism and their typically developing peers. *Behavioral Interventions*, *31*(2), 107-119. https://doi.org/10.1002/bin.1438

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall, Inc.

Baron-Cohen, S., Wheelwright, S., Skinner, R., Martin, J., & Clubley, E. (2001). The autism-spectrum quotient (AQ): Evidence from asperger syndrome/high-functioning autism, males and females, scientists and mathematicians. *Journal of Autism and Developmental Disorders*, *31*(1), 5-17. https://doi.org/10.1023/a:1005653411471

Beck, A. T., Beck, A. T., Ward, C. H., Mendelson, M., Mock, J., & Erbaugh, J. (1961). An Inventory for measuring depression. *Archives of General Psychiatry*, *4*, 561-571. https://doi.org/10.1001/archpsyc.1961.01710120031004

Belkaid, M., Bousseyrol, E., Durand-de Cuttoli, R., Dongelmans, M., Duranté, E. K., Ahmed Yahia, T., Didienne, S., Hanesse, B., Come, M., Mourot, A., Naudé, J., Sigaud, O., & Faure, P. (2020). Mice adaptively generate choice variability in a deterministic task. *Communications Biology*, *3*(1), 1-9. https://doi.org/10.1038/s42003-020-0759-x

Bock, Y., Nikolaidis, R. M., de Jonge, P. J., & Bevis, M. (2000). Instantaneous geodetic positioning at medium distances with the Global Positioning System. *Journal of Geophysical Research*, *105*(B12), 28. https://doi.org/10.1029/2000JB900268

Brodhead, M. T., Higbee, T. S., Gerencser, K. R., & Akers, J. S. (2016). The use of a discrimination-training procedure to teach mand variability to children with autism. *Journal of Applied Behavior Analysis*, *49*(1), 34-48. http://doi.org/10.1002/jaba.280

Brugger, P. (1997). Variables that influence the generation of random sequences: An update. *Perceptual and Motor Skills*, *84*(2), 627-661. https://doi.org/10.2466/pms.1997.84.2.627

Calvert, S. L., & Valkenburg, P. M. (2013). The influence of television, video games, and the internet on children's creativity. In M. Taylor (Ed.), (pp. 438-450). Oxford University Press.

Cavalli, E., Anders, R., Chaussoy, L., Herbillon, V., Franco, P., & Putois, B. (2021). Screen exposure exacerbates ADHD symptoms indirectly through increased sleep disturbance. *Sleep Medicine*, *83*, 241-247. https://doi.org/10.1016/j.sleep.2021.03.010

Chonchaiya, W., Nuntnarumit, P., & Pruksananonda, C. (2011). Comparison of television viewing between children with autism spectrum disorder and controls. *Acta Paediatrica*, *100*(7), 1033-1037. https://doi.org/10.1111/j.1651-2227.2011.02166.x

Collier-Meek, M., Sanetti, L. M. H., & Fallon, L. M. (2017). Incorporating applied behavior analysis to assess and support educators' treatment integrity. *Psychology in the Schools*, *54*(4), 446-460. http://doi.org/10.1002/pits.22001

Cooper, J. O., Heron, T. E., & Howard, W. L. (2019). *Applied behavior analysis* (3rd ed.). Pearson.

Contreras, S., Fernandez, S., Malcarne, V. L., Ingram, R. E., & Vaccarino, V. R. (2004). Reliability and validity of the Beck Depression and Anxiety Inventories in caucasian americans and latinos. *Hispanic Journal of Behavioral Sciences*, *26*(4), 446–462. https://doi.org/10.1177/0739986304269164

Dancey, C. P., & Reidy, J. (2007). *Statistics without maths for psychology*. Pearson education.

Darwin, C. (1859). *On the origin of species by means of natural selection, or the preservation of favoured races in the struggle for life*. Natural History Museum.

Denney, J., & Neuringer, A. (1998). Behavioral variability is controlled by discriminative stimuli. *Animal Learning & Behavior*, *26*(2), 154-162. https://doi.org/10.3758/BF03199208

Doolan, K. E., & Bizo, L. A. (2013). Reinforced behavioral variability in humans. *Psychological Record*, *63*(4), 725-734. https://doi.org/10.11133/j.tpr.2013.63.4.002

Doughty, A. H., Giorno, K. G., & Miller, H. L. (2013). Effects of reinforcer magnitude on reinforced behavioral variability. *Journal of the Experimental Analysis of Behavior*, *100*(3), 355-369. https://doi.org/10.1002/jeab.50

DuPaul, G. J., McGoey, K. E., Eckert, T. L., & VanBrakle, J. (2001). Preschool children with attention-deficit/hyperactivity disorder: Impairments in behavioral, social, and school functioning. *Journal of the American Academy of Child & Adolescent Psychiatry*, *40*(5), 508. https://doi.org/10.1097/00004583-200105000-00009

Ferguson, C. J. (2011). The influence of television and video game use on attention and school problems: A multivariate analysis with other risk factors controlled. *Journal of Psychiatric Research*, *45*(6), 808-813. https://doi.org/10.1016/j.jpsychires.2010.11.010

Forte, C., McDowell, C. P., McDonnacha, C., & Herring, M. P. (2021). Anxiety and depressive symptoms differ between levels of physical activity and screen time among adolescents. *Medicine & Science in Sports & Exercise*, *53*(8), 309. https://doi.org/10.1249/01.mss.0000762736.40087.09

Galizio, A., Friedel, J. E., & Odum, A. L. (2020). An investigation of resurgence of reinforced behavioral variability in humans. *Journal of the Experimental Analysis of Behavior*, *114*(3), 381-393. https://doi.org/10.1002/jeab.637

Galizio, A., & Odum, A. L. (2022). Reinforced behavioral variability in the valproate rat model of autism spectrum disorder. *Journal of the Experimental Analysis of Behavior*, *117*(3), 576-596. https://doi.org/10.1002/jeab.760

Goetz, E. M., & Baer, D. M. (1973). Social control of form diversity and the emergence of new forms in children's blockbuilding. *Journal of Applied Behavior Analysis*, *6*(2), 209-217. https://doi.org/10.1901/jaba.1973.6-209

Grøntved, A., Singhammer, J., Froberg, K., Møller, N. C., Pan, A., Pfeiffer, K. A., & Kristensen, P. L. (2015). A prospective study of screen time in adolescence and depression symptoms in young adulthood. *Preventive Medicine*, *81*, 108-113. https://doi.org/10.1016/j.ypmed.2015.08.009

Hadders-Algra, M. (2010). Variation and variability: Key words in human motor development. *Physical Therapy*, *90*(12), 1823-1837. https://doi.org/10.2522/ptj.20100006

Hansson, J., & Neuringer, A. (2018). Reinforcement of variability facilitates learning in humans. *Journal of the Experimental Analysis of Behavior*, *110*(3), 380-393. https://doi.org/10.1002/jeab.475

Healthy Minds Study. (2020). *The healthy minds study: Fall 2020 Data Report*. https://healthymindsnetwork.org/wp-content/uploads/2021/02/HMS-Fall-2020-National-Data-Report.pdf

Hines, M. (2010). Sex-related variation in human behavior and the brain. Trends in Cognitive Sciences, 14(10), 448–456. https://doi.org/10.1016/j.tics.2010.07.005

Hodes, L. N., & Thomas, K. G. F. (2021). Smartphone screen time: Inaccuracy of self-reports and influence of psychological and contextual factors. *Computers in Human Behavior, 115*. https://doi.org/10.1016/j.chb.2020.106616

Hopkinson, J., & Neuringer, A. (2003). Modifying behavioral variability in moderately depressed students. *Behavior Modification*, *27*(2), 251. https://doi.org/10.1177/0145445503251605

Hunziker, M. H. L., Saldana, L., & Neuringer, A. (1996). Behavioral variability in SHR and WKY rats as a function of rearing environment and reinforcement contingency. *Journal of the Experimental Analysis of Behavior*, *65*(1), 129-144. https://doi.org/10.1901/jeab.1996.65-129

Jari, M., Qorbani, M., Motlagh, M. E., Heshmat, R., Ardalan, G., & Kelishadi, R. (2014). A nationwide survey on the daily screen time of Iranian children and adolescents: The CASPIAN-IV Study. *International Journal of Preventive Medicine*, *5*(2), 224-229.

Jensen, G., & Neuringer, A. (2008). Choice as a function of reinforcer "hold": From probability learning to concurrent reinforcement. *Journal of Experimental Psychology: Animal Behavior Processes*, *34*(4), 437–460. https://doi.org/10.1037/0097-7403.34.4.437

Jones, A., Armstrong, B., Weaver, R. G., Parker, H., von Klinggraeff, L., & Beets, M. W. (2021). Identifying effective intervention strategies to reduce children's screen

time: A systematic review and meta-analysis. *International Journal of Behavioral Nutrition & Physical Activity*, *18*(1), 1-20. https://doi.org/10.1186/s12966-021-01189-6

Keikha, M., Qorbani, M., Tabaee, M. S. K., Djalalinia, S., & Kelishadi, R. (2020). Screen time activities and aggressive behaviors among children and adolescents: A systematic review. *International Journal of Preventive Medicine*, *11*(5), 1-12. https://doi.org/10.4103/ijpvm.IJPVM_71_20

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-V1.1): A short screening scale for use in the general population. *Psychological medicine*, *35*(2), 245–256. https://doi.org/10.1017/s0033291704002892

King James Bible. (2022). King James Bible Online. https://www.kingjamesbibleonline.org/ (Original work published 1769)

Kristensen, P. L., Olesen, L. G., Egebæk, H. K., Pedersen, J., Rasmussen, M. G., & Grøntved, A. (2022). Criterion validity of a research-based application for tracking screen time on android and iOS smartphones and tablets. *Computers in Human Behavior Reports*, *5*. https://doi.org/10.1016/j.chbr.2021.100164

Lalli, J. S., & Others, A. (1994). Using extinction to promote response variability in toy play. *Journal of Applied Behavior Analysis*, *27*(4), 735-736. https://doi.org/10.1901/jaba.1994.27-735

Liu, J., Liu, C. X., Wu, T., Liu, B., Jia, C., & Liu, X. (2019). Prolonged mobile phone use is associated with depressive symptoms in Chinese adolescents. *Journal of Affective Disorders*, *259*, 128-134. https://doi.org/10.1016/j.jad.2019.08.017

Lundin, A., Kosidou, K., & Dalman, C. (2019). Measuring Autism Traits in the Adult General Population with the Brief Autism-Spectrum Quotient, AQ-10: Findings from the Stockholm Public Health Cohort. *Journal of Autism & Developmental Disorders*, *49*(2), 773–780. https://doi.org/10.1007/s10803-018-3749-9

Ma, L., Evans, B., Kleppang, A. L., & Hagquist, C. (2021). The association between screen time and reported depressive symptoms among adolescents in Sweden. *Family Practice*, *38*(6), 773-779. https://doi.org/10.1093/fampra/cmab029

MacDonald, R., Green, G., Mansfield, R., Geckeler, A., Gardenier, N., Anderson, J., Holcomb, W., & Sanchez, J. (2007). Stereotypy in young children with autism and typically developing children. *Research in Developmental Disabilities*, *28*(3), 266-277. https://doi.org/10.1016/j.ridd.2006.01.004

Manabe, K., Staddon, J. E. R., & Cleaveland, J. M. (1997). Control of vocal repertoire by reward in budgerigars (Melopsittacus undulatus). *Journal of Comparative Psychology*, *111*(1), 50–62. https://doi.org/10.1037/0735-7036.111.1.50

Martin, K. B., Bednarz, J. M., & Aromataris, E. C. (2021). Interventions to control children's screen use and their effect on sleep: A systematic review and meta-analysis. *Journal of Sleep Research*, *30*(3), 1-17. https://doi.org/10.1111/jsr.13130

Meline, C. W. (1976). Does the medium matter? print, audiotape, or videotape form. *Journal of Communication*, *26*, 81-89. https://doi.org/10.1111/j.1460-2466.1976.tb01908.x

Miller, N., & Neuringer, A. (2000). Reinforcing variability in adolescents with autism. *Journal of Applied Behavior Analysis*, *33*(2), 151-165. https://doi.org/10.1901/jaba.2000.33-151

Mishra, P., Pandey, C. M., Singh, U., Gupta, A., Sahu, C., & Keshri, A. (2019). Descriptive statistics and normality tests for statistical data. *Annals of cardiac anaesthesia*, *22*(1), 67–72. https://doi.org/10.4103/aca.ACA_157_18

Mottweiler, C. M., & Taylor, M. (2014). Elaborated role play and creativity in preschool age children. *Psychology of Aesthetics, Creativity & the Arts*, *8*(3), 277-286. https://doi.org/10.1037/a0036083

Myerson, J., Robertson, S., & Hale, S. (2007). Aging and intraindividual variability in performance: analyses of response time distributions. *Journal of the experimental analysis of behavior*, *88*(3), 319–337. https://doi.org/10.1901/jeab.2007.88-319

National Center for Education Statistics. (2021). *Middle Tennessee State University*. College Navigator - Middle Tennessee State University. https://nces.ed.gov/collegenavigator/?id=220978#enrolmt

Neuringer, A. (1991). Operant variability and repetition as functions of interresponse time. *Journal of Experimental Psychology: Animal Behavior Processes*, *17*(1), 3-12. https://doi.org/10.1037/0097-7403.17.1.3

Neuringer, A. (2002). Operant variability: evidence, functions, and theory. *Psychonomic Bulletin & Review*, *9*(4), 672-705. https://doi.org/10.3758/bf03196324

Neuringer, A. (2004). Reinforced variability in animals and people: Implications for adaptive action. *American Psychologist*, *59*(9), 891-906. https://doi.org/10.1037/0003-066X.59.9.891

Neuringer, A. (2009). Operant variability and the power of reinforcement. *The Behavior Analyst Today*, *10*(2), 319-343. https://doi.org/10.1037/h0100673

Neuringer, A., & Jensen, G. (2013). Operant variability. In G. J. Madden, W. V. Dube, T. D. Hackenberg, G. P. Hanley, & K. A. Lattal (Eds.), *APA handbook of behavior analysis, Vol. 1. Methods and principles* (pp. 513–546). American Psychological Association. https://doi.org/10.1037/13937-022

Neuringer, A. (2012). Reinforcement and induction of operant variability. *The Behavior Analyst*, *35*(2), 229-235. https://doi.org/10.1007/BF03392281

Neuringer, A. (2014). Operant variability and the evolution of volition. *International Journal of Comparative Psychology*, *27*(2), 62-81. https://doi.org/10.46867/ijcp.2014.27.02.09

Neuringer, A., & Huntley, R. W. (1992). Reinforced variability in rats: Effects of gender, age and contingency. *Physiology & Behavior*, *51*(1), 145-149. https://doi.org/10.1016/0031-9384(92)90216-O

Nigg J. T. (2001). Is ADHD a disinhibitory disorder?. *Psychological bulletin*, *127*(5), 571–598. https://doi.org/10.1037/0033-2909.127.5.571

Ohme, J., Araujo, T., de Vreese, C. H., & Piotrowski, J. T. (2021). Mobile data donations: Assessing self-report accuracy and sample biases with the iOS Screen Time function. *Mobile Media & Communication*, *9*(2), 293-313. https://doi.org/10.1177/2050157920959106

Olson, J. A., Sandra, D. A., Colucci, É S., Al Bikaii, A., Chmoulevitch, D., Nahas, J., Raz, A., & Veissière, S. P. L. (2022). Smartphone addiction is increasing across the world: A meta-analysis of 24 countries. *Computers in Human Behavior*, *129*, N.PAG. https://doi.org/10.1016/j.chb.2021.107138

Orkibi, H. (2021). Creative adaptability: Conceptual framework, measurement, and outcomes in times of crisis. *Frontiers in Psychology*, *11*. https://doi.org/10.3389/fpsyg.2020.588172

Öztuna, D., Atilla Halil Elhan, & Tüccar, E. (2006). Investigation of four different normality tests in terms of type 1 error rate and power under different distributions. *Turkish Journal of Medical Sciences*, *36*(3), 171–176.

Page, S., & Neuringer, A. (1985). Variability is an operant. *Journal of Experimental Psychology. Animal Behavior Processes*, *11*, 429-452. https://doi.org/10.1037/0097-7403.11.3.429

Paulich, K. N., Ross, J. M., Lessem, J. M., & Hewitt, J. K. (2021). Screen time and early adolescent mental health, academic, and social outcomes in 9- and 10- year old children: Utilizing the Adolescent Brain Cognitive Development ℠ (ABCD) study. *PLoS ONE*, *16*(9), 1-23. https://doi.org/10.1371/journal.pone.0256591

Pishkin, V., & Williams, W. V. (1983). Cognitive deficit in schizophrenia: Subvocal mediation, rigidity, and complexity parameters. *Journal of Nervous and Mental Disease*, *171*, 24-29. https://doi.org/10.1097/00005053-198301000-00005

Portugal, A. M., Bedford, R., Cheung, C. H. M., Mason, L., & Smith, T. J. (2021). Longitudinal touchscreen use across early development is associated with faster exogenous and reduced endogenous attention control. *Scientific Reports*, *11*(1), 1-12. https://doi.org/10.1038/s41598-021-81775-7

Pryor, K. W., Haag, R., & O'Reilly, J. (1969). The creative porpoise: Training for novel behavior. *Journal of the Experimental Analysis of Behavior*, *12*(4), 653-661. https://doi.org/10.1901/jeab.1969.12-653

Radley, K. C., Battaglia, A. A., Dadakhodjaeva, K., Ford, W. B., & Robbins, K. (2018). Increasing behavioral variability and social skill accuracy in children with autism spectrum disorder. *Journal of Behavioral Education*, *27*(3), 395-418. https://doi.org/10.1007/s10864-018-9294-y

Richter, P., Werner, J., Heerlein, A., Kraus, A., & Sauer, H. (1998). On the validity of the Beck Depression Inventory. *Psychopathology*, *31*(3), 160–168. https://doi.org/10.1159/000066239

Rodriguez, N. M., & Thompson, R. H. (2015). Behavioral variability and autism spectrum disorder. *Journal of applied behavior analysis*, *48*(1), 167–187. https://doi.org/10.1002/jaba.164

Roelofs, J., van Breukelen, G., de Graaf, L. E., Beck, A. T., Arntz, A., & Huibers, M. J. H. (2013). Norms for the Beck Depression Inventory (BDI-II) in a large Dutch

community sample. *Journal of Psychopathology and Behavioral Assessment*, *35*(1), 93–98. https://doi.org/10.1007/s10862-012-9309-2

Ross, C., & Neuringer, A. (2002). Reinforcement of variations and repetitions along three independent response dimensions. *Behavioural Processes*, *57*(2-3), 199-209. https://doi.org/10.1016/S0376-6357(02)00014-1

Romão, X., Delgado, R., & Costa, A. (2010). An empirical power comparison of univariate goodness-of-fit tests for normality. *Journal of Statistical Computation and Simulation, 80*(5), 545-591. https://doi.org/10.1080/00949650902740824

Rubia, K., Smith, A. B., Brammer, M. J., & Taylor, E. (2007). Temporal lobe dysfunction in medication-naïve boys with attention-deficit/hyperactivity disorder during attention allocation and its relation to response variability. *Biological Psychiatry*, *62*(9), 999-1006. https://doi.org/10.1016/j.biopsych.2007.02.024

Saldana, L., & Neuringer, A. (1998). Is instrumental variability abnormally high in children exhibiting ADHD and aggressive behavior? *Behavioural Brain Research*, *94*(1), 51–59. https://doi.org/10.1016/S0166-4328(97)00169-1

Sampasa-Kanyinga, H., Colman, I., Goldfield, G. S., Janssen, I., Wang, J., Tremblay, M. S., Barnes, J. D., Walsh, J. J., & Chaput, J. (2021). 24-hour movement behaviors and internalizing and externalizing behaviors among youth. *Journal of Adolescent Health*, *68*(5), 969-977. https://doi.org/10.1016/j.jadohealth.2020.09.003

Schultz, P. W., & Searleman, A. (2002). Rigidity of thought and behavior: 100 years of research. *Genetic, Social, and General Psychology Monographs*, *128*(2), 165-207.

Schusterman, R. J., & Reichmuth, C. (2008). Novel sound production through contingency learning in the Pacific walrus (Odobenus rosmarus divergens). *Animal Cognition*, *11*(2), 319–327. https://doi.org/10.1007/s10071-007-0120-5

Shah, P., Boilson, M., Rutherford, M., Prior, S., Johnston, L., Maciver, D., & Forsyth, K. (2022). Neurodevelopmental disorders and neurodiversity: Definition of terms from Scotland's national autism implementation team. *The British Journal of Psychiatry*, *221*(3), 577-579. https://doi.org/10.1192/bjp.2022.43

Shapiro, S. (2015). The Shapiro-Wilk and related test for normality. *Statistics (Ber)*.

Shapiro, S. S., & Wilk, M. B. (1965). An analysis of variance test for normality (complete samples). *Biometrika*, *52*(3/4), 591–611. https://doi.org/10.2307/2333709

Slobodin, O., Heffler, K. F., & Davidovitch, M. (2019). Screen media and autism spectrum disorder: A systematic literature review. *Journal of Developmental and Behavioral Pediatrics*: *JDBP*, *40*(4), 303–311. https://doi.org/10.1097/DBP.0000000000000654

Soares, P. S. M., de Oliveira, P. D., Wehrmeister, F. C., Menezes, A. M. B., & Gonçalves, H. (2021). Screen time and working memory in adolescents: A longitudinal study. *Journal of Psychiatric Research*, *137*, 266-272. https://doi.org/10.1016/j.jpsychires.2021.02.066

Soares, P. S. M., de Oliveira, P. D., Wehrmeister, F. C., Menezes, A. M. B., & Gonçalves, H. (2022). Is screen time throughout adolescence related to ADHD? Findings from 1993 Pelotas (Brazil) birth cohort study. *Journal of Attention Disorders*, *26*(3), 331-339. https://doi.org/10.1177/1087054721997555

Sparrow, S. S., Cicchetti, D. V., & Saulnier C. A. (2016). *Vineland Adaptive Behavior Scales, Third Edition Comprehensive Interview Form Report: Technical manual.* Pearson.

Stahlman, W. D., & Leising, K. J. (2016). Midsession shifts in reward probability and the control of behavioral variability. *Learning & Behavior*, *44*(3), 270-282. https://doi.org/10.3758/s13420-016-0211-8

Stevens, T., & Mulsow, M. (2006). There is no meaningful relationship between television exposure and symptoms of attention-deficit/hyperactivity disorder. *Pediatrics*, *117*(3), 665-672. https://doi.org/10.1542/peds.2005-0863

Stokes, P. D. (1995). Learned variability. *Animal Learning & Behavior*, *23*(2), 164-176. https://doi.org/10.3758/BF03199931

Subica, A. M., Fowler, J. C., Elhai, J. D., Frueh, B. C., Sharp, C., Kelly, E. L., & Allen, J. G. (2014). Factor structure and diagnostic validity of the Beck Depression Inventory-II with adult clinical inpatients: Comparison to a gold-standard diagnostic interview. *Psychological assessment*, *26*(4), 1106–1115. https://doi.org/10.1037/a0036998

Temple, D. H., & Stojanowski, C. M. (2019). Interrogating the alterity of hunter-gatherers in bioarcheological context: Adaptability, transformability, and resilience of hunter-gatherers in the past. In D. H. Temple & C.M. Stojanowski (Eds.), *Hunter-gatherer adaptation and resilience: A bioarcheological perspective* (1st ed., pp. 1-25). Cambridge University Press. https://doi.org/10.1017/9781316941256

Vaidyanathan, S., Manohar, H., Chandrasekaran, V., & Kandasamy, P. (2021). Screen time exposure in preschool children with ADHD: A cross-sectional exploratory study from south India. *Indian Journal of Psychological Medicine*, *43*(2), 125-129. https://doi.org/10.1177/0253717620939782

Wagner, K., & Neuringer, A. (2006). Operant variability when reinforcement is delayed. *Learning & Behavior*, *34*(2), 111-123. https://doi.org/10.3758/BF03193187

Wang, W., Du, X., Guo, Y., Li, W., Zhang, S., Zhang, W., McIntyre, R. S., Tamura, J. K., Guo, L., & Lu, C. (2021). Associations among screen time, sleep duration and depressive symptoms among Chinese adolescents. *Journal of Affective Disorders*, *284*, 69-74. https://doi.org/10.1016/j.jad.2021.01.082

Weiss, A., & Neuringer, A. (2012). Reinforced variability enhances object exploration in shy and bold rats. *Physiology & Behavior*, *107*(3), 451-457. https://doi.org/10.1016/j.physbeh.2012.07.012

Westby, C. (2018). Why children with autism are more at risk for the negative effects of screen time. *Word of Mouth*, *29*(5), 9-13. https://doi.org/10.1177/1048395018772844b

Whisman, M. A., & Richardson, E. D. (2015). Normative data on the Beck Depression Inventory - Second Edition (BDI-II) in college students. *Journal of Clinical Psychology*, *71*(9), 898–907. https://doi.org/10.1002/jclp.22188

Wolfe, K., Slocum, T. A., & Kunnavatana, S. S. (2014). Promoting behavioral variability in individuals with autism spectrum disorders: A literature review. *Focus on*

Autism & Other Developmental Disabilities, *29*(3), 180-190. https://doi.org/10.1177/1088357614525661

Wright, T. F., Eberhard, J. R., Hobson, E. A., Avery, M. L., & Russello, M. A. (2010). Behavioral flexibility and species invasions: The adaptive flexibility hypothesis. *Ethology Ecology & Evolution*, *22*(4), 393-404. https://doi.org/10.1080/03949370.2010.505580

Yu, B., Gu, Y., Bao, X., Meng, G., Wu, H., Zhang, Q., Liu, L., Sun, S., Wang, X., Zhou, M., Jia, Q., Song, K., & Niu, K. (2019). Distinct associations of computer/mobile devices use and TV watching with depressive symptoms in adults: A large population study in China. *Depression and Anxiety*, *36*(9), 879-886. https://doi.org/10.1002/da.22932

Zlotowski, M., & Bakan, P. (1963). Behavioral variability of process and reactive schizophrenics in a binary guessing task. *The Journal of Abnormal and Social Psychology*, *66*(2), 185-187. https://doi.org/10.1037/h0043864

TABLES

Table 1

Sociodemographic Characteristics of Participants

Sociodemographic Characteristics	Full Data		IQR*3 Data	
	n	*%*	*n*	*%*
Total	58		53	
Gender				
Women	35	60%	30	57%
Men	19	33%	18	34%
Nonbinary	2	3%	3	4%
Genderfluid	2	3%	2	6%
Age				
18-24 years old	55	95%	51	96%
25-34 years old	3	5%	2	4%
Ethnicity				
Caucasian or White	30	52%	29	55%
African American	12	21%	11	21%

Asian	5	9%	3	6%
Latino or Hispanic	8	14%	6	11%
Mixed	3	5%	4	8%
Education Level				
High school	43	74%	40	75%
Associate's Degree	1	2%	1	2%
Some Bachelor's	13	22%	12	23%
Master's Degree	1	2%	0	0%
Parental Education				
High School	13	22%	14	26%
Associate's	4	7%	3	6%
Bachelor's	21	36%	17	32%
Master's	11	19%	10	19%
Ed.D., PsyD., Ph.D.	5	8%	5	9%
Some Bachelor's	3	5%	3	6%
Prefer not to say	1	2%	1	2%
Psychological Cond.	15	26%	15	28%

Speech Impediment	1	2%	1	2%
ADHD	5	8%	5	9%
Anxiety	11	19%	10	19%
Depression	10	17%	9	17%
PTSD	4	7%	3	6%
Insomnia	1	2%	1	2%
Avoidant Restrictive Food Intake	1	2%	1	2%
Bulimia	1	2%	1	2%
Sensory Processing Disorder	1	2%	1	2%
Obsessive Compulsive Disorder	1	2%	1	2%
First or Primary Language				
English	55	95%	52	98%
Other	2	4%	0	0%

Prefer Not to Say	1	1%	1	2%

Note. For the psychological conditions in the table, the percentages for all disorders will add up to over 100%, as several disorders were comorbid.

Table 2

Descriptive Statistics for the Screen Time Assessment, Behavioral Variability Task, and Psychopathology Screeners

Behavioral Variability Task	Full Data		IQR*3 Data	
	M	*SD*	*M*	*SD*
Autism Quotient 10 (0-10)	4.02	1.76	4.06	1.78
Beck Depression Inventory (0-63)	15.31	9.33	15.04	8.95
ADHD Self-Report Scale (0-6)	3.36	1.56	3.40	1.55
Rectangle Task (Points Earned)	429.7	68.3	443.1	47.42
U-Value (0-1)	0.89	0.10	0.90	0.09
Obj. Smartphone Screen Time Values (Hours)	6.91	3.38	7.05	3.46
Subj. Total Screen Time Values (Hours)	7.84	3.45	8.12	3.40

FIGURES

Figure 1.
Results for Behavioral Variability Task

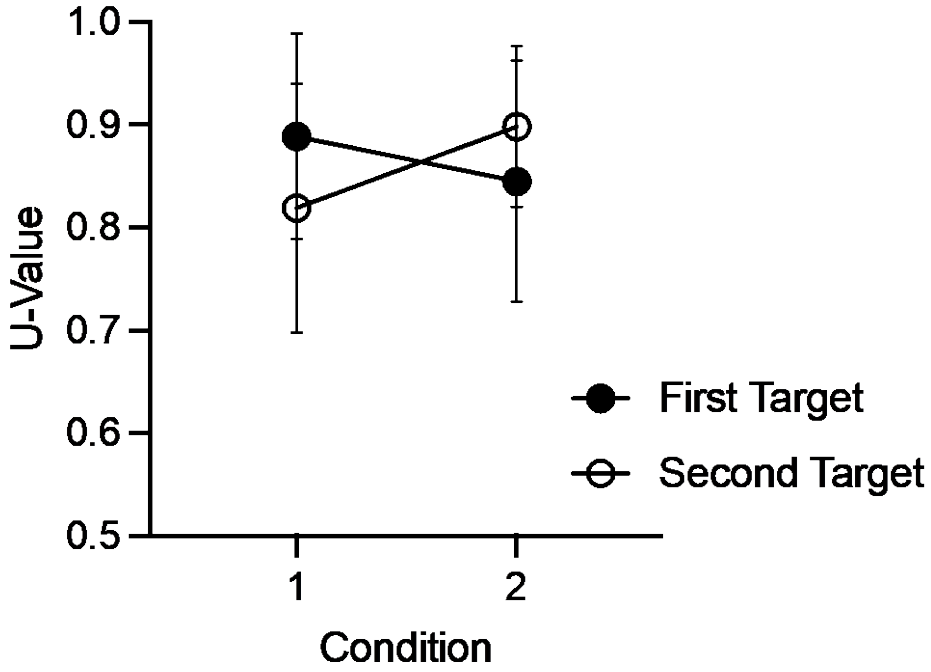
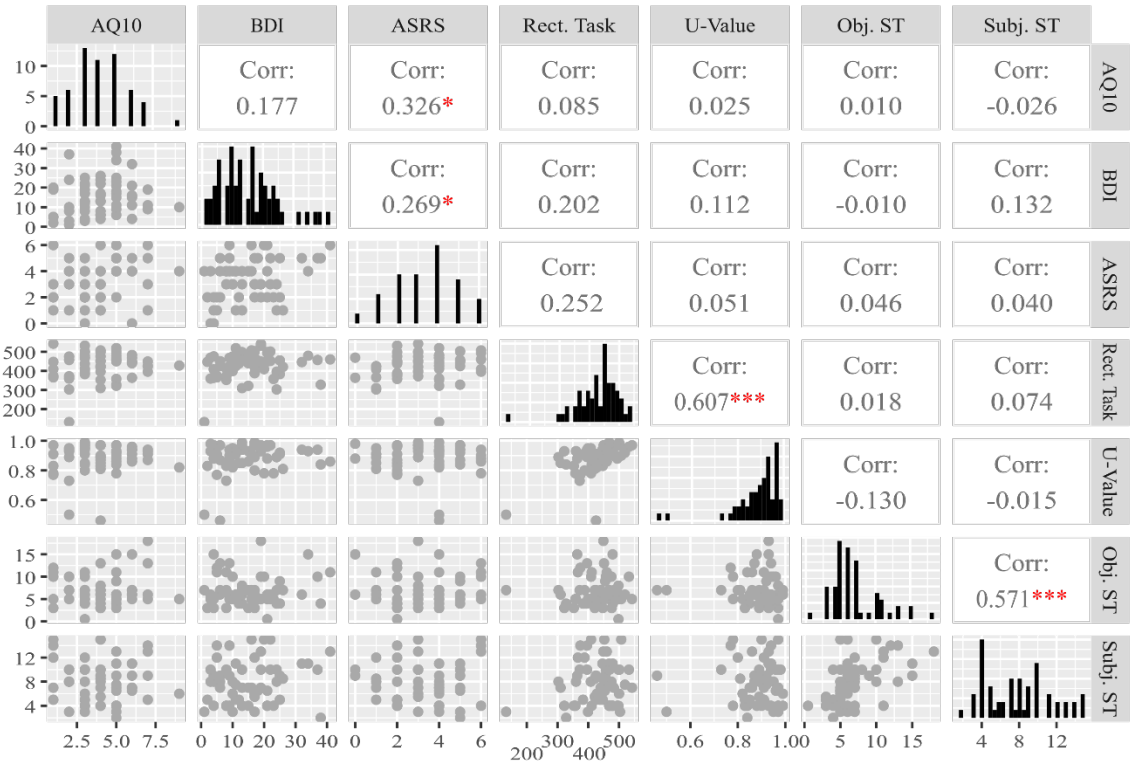


Figure 2

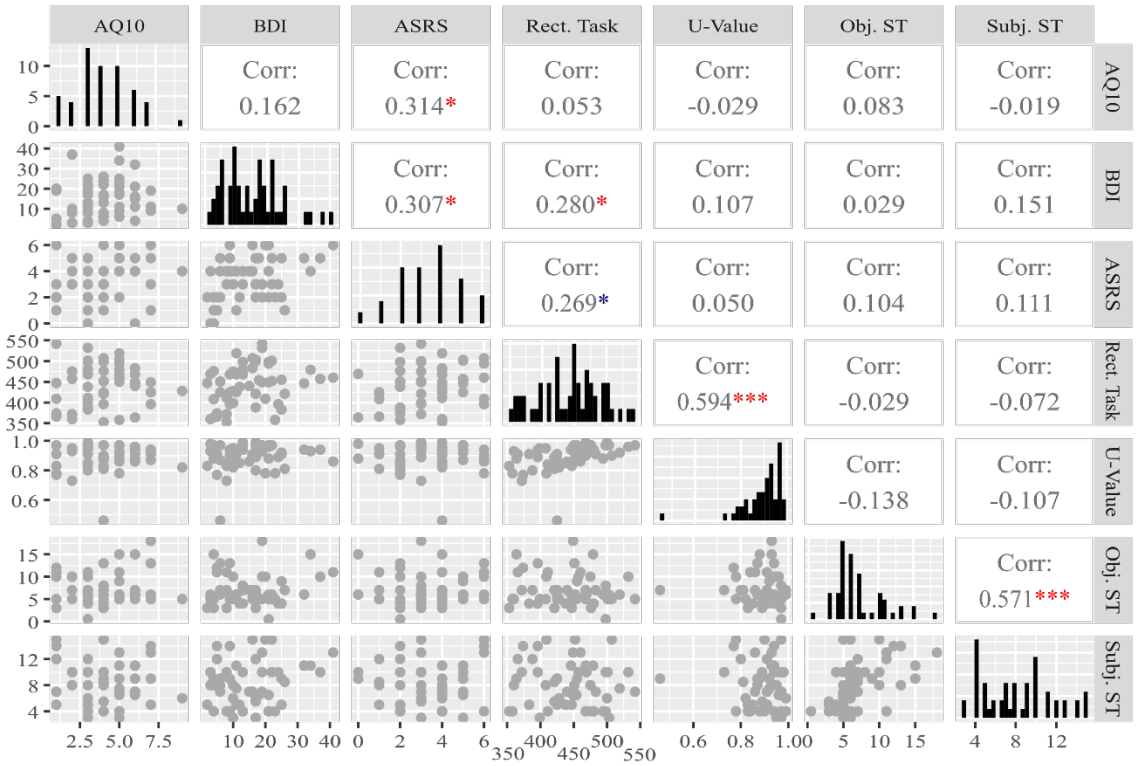
Correlogram for Full-Data Set



* $p < .05$
** $p < .01$
*** $p < .001$

Figure 3.

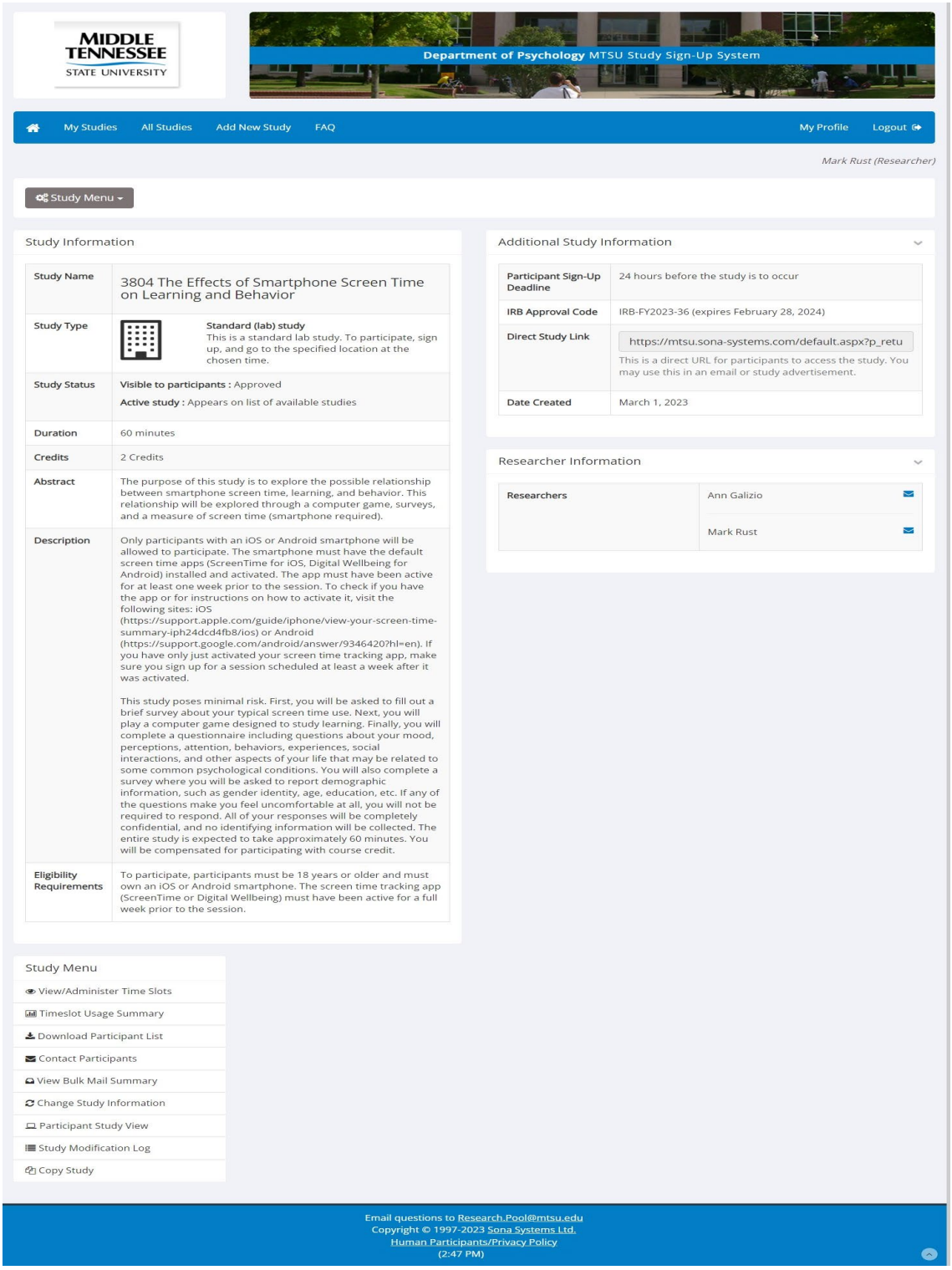
*Correlogram for IQR*3 Data Set*



* $p = .05$
* $p < .05$
** $p < .01$
*** $p < .001$

APPENDICES

APPENDIX A: SONA Study Description



APPENDIX B: Informed Consent

Study Title: *The Effects of Smartphone Screen Time on Learning and Behavior*
Protocol Number: IRB-FY2023-36
Approval Date: 02/28/2023
Principal Investigator: *Mark Rust (faculty advisor: Dr. Annie Galizio)*
Institution: *Middle Tennessee State University*

Name of participant: _____ Age: _____

You are being asked to participate in a research project. The following information is provided to inform you about the research project and your participation in it. Please read this form carefully. You will be given an opportunity to ask questions, and your questions will be answered. Also, you will be given a copy of this consent form.

Your participation in this research study is voluntary. You are free to withdraw from this study at any time with no penalty and no loss of benefits already earned. In the event new information becomes available that may affect the risks or benefits associated with this research study or your willingness to participate in it, you will be notified so that you can make an informed decision about whether or not to continue your participation.

1. Purpose of the study:

The purpose of the present research study is to explore the possible relationship between smartphone screen time, learning, and behavior. This relationship will be explored through a computer-based task, self-report assessments, and a screen time measure.

2. Description of procedures to be followed and approximate duration of the study:

First, you will be asked to fill out a brief survey about your typical screen time use. The researcher will help you access the relevant screen time tracking apps on your smartphone. This survey will take approximately 5 minutes to complete. Next, you will play a computer game designed to study learning. Your task is to use the mouse and click and drag to form rectangles on the screen. Some of these rectangles will produce points, and your goal is to earn as many points as possible. This task will take approximately 20 minutes to complete. Finally, you will complete a questionnaire including questions about your mood, perceptions, attention, behaviors, experiences, social interactions, and other aspects of your life that may be related to some common psychological conditions. You will also complete a survey in which you will be asked to report demographic information, such as gender identity, age, education, etc. If any of these questions make

you feel uncomfortable at all, you will not be required to respond. The surveys will take approximately 30 minutes to complete. The entire study is expected to take approximately 60 minutes. If you need to take a break, please let the researcher know.

The information you provide in this study will be analyzed to help us understand the relationship between screen time, learning, and behavior. After you provide informed consent, you will be assigned a participant number, so the data you provide during the study will never be linked to your name. Any personal identifiers, such as your name, will not be included in the data set. Your signed consent form will be stored securely in the faculty researcher's office for at least three years, after which it will be destroyed. The de-identified data will be posted in an online data repository after all data collection is complete. All of your responses will be kept completely confidential.

3. Expected costs:

None.

4. Description of the discomforts, inconveniences, and/or risks that can be reasonably expected as a result of participation in this study:

This study poses minimal risk. A potential risk arises when you are asked potentially psychologically challenging questions about your own behavior and experiences. Some of these survey questions are about your mood, perceptions, attention, behaviors, experiences, social interactions, and other aspects of your life that may be related to some common psychological conditions. These questions could expose you to challenging topics. In addition, you will be asked about your screen-time habits, which will require you to consider your own screen-time use. All aspects of this study are optional, so if you are uncomfortable proceeding at any point, please let the researcher know. After the study, we will provide resources which you should feel free to utilize if you experience emotional distress or if you have any health concerns as a result of the study.

5. Compensation in case of study-related injury:

N/A

6. Anticipated benefits from this study:

a) The potential benefits to science and humankind that may result from this study include:

The results of this study will contribute to the scientific understanding of learning and behavior, especially as related to screen time, which will benefit society as a whole.

b) The potential benefits to you from this study include:

This study may directly benefit you by asking you to think about your own behavior, which may provide valuable insight.

7. Alternative treatments available:

N/A

8. Compensation for participation:

You will be compensated for your participation through course credit using the SONA system.

9. Circumstances under which the Principal Investigator may withdraw you from study participation:

The study requires a measure of screen time taken from the participant's smartphone. If the screen time app (ScreenTime for iOS or Digital Wellbeing for Android) has not active on your phone for at least one week, the researcher may withdraw you from the study or ask you to reschedule. If, at any point, you request to stop participating, you exhibit health concerns, or show signs of emotional distress, the PI will withdraw you from the study. After your participation, you may request for your data to be withdrawn, and the PI will destroy your data.

10. What happens if you choose to withdraw from study participation:

You may refuse to participate in the study. You will not be required to complete any of the tasks, and you will be allowed to leave. You may also withdraw at any point during the study, and any data you provided will be destroyed. You will not be penalized in any way, and no one will be informed of your choice. However, you will only receive your full course credit for participating if you complete the study.

11. Contact Information: If you should have any questions about this research study or possible injury, please contact:

Principal Investigator: Mark Rust

Contact Information: mdr6t@mtmail.mtsu.edu / (440) 318-4731

Faculty Advisor: Dr. Annie Galizio
Contact Information: ann.galizio@mtsu.edu / (615) 898-2319

For additional information about giving consent or your rights as a participant in this study, please contact the Middle Tennessee State University (MTSU) Office of Compliance at (615) 494-8918 or via email at irb_information@mtsu.edu. (http://www.mtsu.edu/irb)

12. Confidentiality: All efforts, within reason, will be made to keep the personal information in your research record private, but total privacy cannot be promised. Your information may be shared with people at MTSU (such as the MTSU Institutional Review Board) or other agencies (such as the Federal Government Office for Human Research Protection) if you or someone else is in danger or if we are required to do so by law.

13. STATEMENT BY PERSON AGREEING TO PARTICIPATE IN THIS STUDY

I have read this informed consent document, and the material contained in it has been explained to me. I understand each part of the document, my questions have been answered, and I freely and voluntarily choose to participate in this study.

_____ _____

Date Signature of participant

Consent obtained by:

_____ _____

Date Signature

_____

Printed name and title

APPENDIX C: Demographics Survey

1. Please choose your gender from the list below:
   Agender
   Woman
   Man
   Gender Fluid
   Nonbinary
   If none of the above accurately describes your gender, please type it in below:
   Prefer not to say

2. What race/ethnicity do you identify as? (You may select multiple choices)
   Caucasian or White
   African American or Black
   Latino or Hispanic
   Asian or Asian American
   Native American, Indigenous. or First Nation
   Native Hawaiian or Pacific Islander
   Other (Please Specify)
   Prefer not to say

3. What is the highest degree or level of education you have completed?
   High School
   Associate’s Degree
   Some Bachelor's Degree
   Bachelor's Degree
   Master's Degree
   Ed.D., PsyD., Ph.D. or higher
   Trade School
   Prefer not to say

4. What is the highest level of formal education completed by either of your parents?
   High School
   Associate's Degree
   Some Bachelor’s degree
   Bachelor's Degree
   Master's Degree
   Ed.D., PsyD., Ph.D. or higher
   Trade School
   Prefer not to say

5. What is your age?
 18-24 years old
 25-34 years old
 35-44 years old
 45-54 years old
 55-64 years old
 65-74 years old
 75 years or older
 Prefer not to say

6. Have you ever been diagnosed with a mental disorder, psychological condition, or educational disability of any kind? (You may list more than one)
 Yes (Please specify)
 No
 Prefer not to say

7. What is your first or primary language?
 English
 Spanish
 Chinese (Mandarin or Cantonese)
 Arabic
 German
 French
 Prefer not to say
 Other (please specify)

8. How did you earn points in the rectangle game?

9. What do you think the study was about?

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APPENDIX D: Debriefing Materials

Thank you for participating in our study!

The goal of the study was to assess the relationship between screen time use and learning. We are also interested in the potential connection to several common psychological conditions. We are excited to see how our moods, perceptions, attention, behaviors, experiences, social interactions, and other aspects of our lives may be related to screen time use and learning. The surveys you completed were non-diagnostic, and your responses are completely confidential. If you have any concerns about the questions you answered, we recommend that you see a healthcare professional and/or seek counseling using the resources provided below.

If you have any concerns about your health and you want to speak to a healthcare professional at MTSU, please contact:

MTSU Student Health Services
https://www.mtsu.edu/healthservices/
(615) 898-2988
MTSU REC

If you are experiencing distress or discomfort or have concerns about your psychological, emotional, mental, or behavioral health, and you want to speak to a counselor at MTSU, please contact:

MTSU Counseling Services
https://mtsu.edu/counseling/
(615) 898-2670
MTSU KUC 326-S

If you have any concerns about your psychological, emotional, mental, or behavioral health and are looking for an off-campus resource, we recommend:

Volunteer Behavioral Health Center
https://www.vbhcs.org/locations/murfreesboro/
(615) 898-0771
1504 Williams Drive
Murfreesboro, TN 37129

If you have thoughts of suicide or self-harm, or simply need someone to talk to, we urge you to seek help as soon as possible. You can utilize the national Suicide & Crisis Lifeline at 988

(https://988lifeline.org/talk-to-someone-now/). Call or text 988 for free and confidential emotional support 24/7.

If you have questions or concerns about this research study, please contact the researchers or the MTSU Institutional Review Board using the contact information provided on your copy of the informed consent form.

Debriefing Script for Researchers

"Thank you for participating in this study. Before you go, I have some final information to share with you. The goal of our study was to better understand the relationship between screen time use and learning. We are also interested in the potential connection to several common psychological conditions. We are excited to see how our moods, perceptions, attention, behaviors, experiences, social interactions, and other aspects of our lives may be related to screen time use and learning. The surveys you completed were non-diagnostic, and your responses are completely confidential. If you have any concerns about the questions you answered, we recommend that you see your healthcare professional and/or seek counseling. We have provided the contact information for MTSU Health Services, MTSU Counseling Services, and a local community behavioral health center. If you have thoughts of suicide or self-harm, we urge you to seek help as soon as possible and utilize the resources listed here, including the crisis lifeline. Do you have any questions about the study or this information? Remember, you have a copy of the informed consent form you signed before we started. It includes contact information for the researchers and IRB if you have any questions or concerns about the study. Thank you for your participation, and your SONA credits will be added shortly."

APPENDIX E: Screen Time Assessment

1. Please estimate your daily average screen time in hours from the past week (in your estimate, please include all of your screen time devices). _____

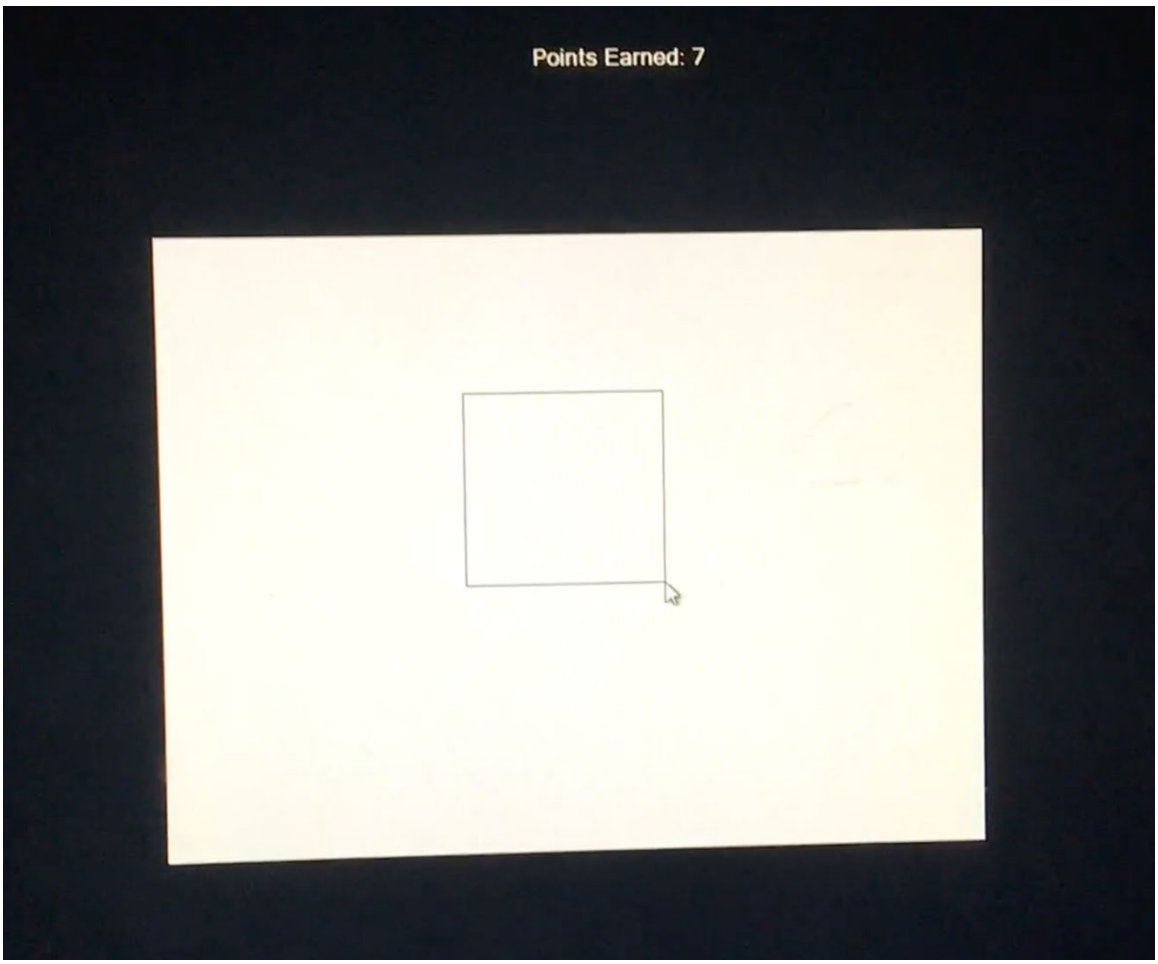
2. What screentime devices do you currently own? (You may select multiple choices)
Personal computer (PC)
Laptop
Tablet (iPad, Kindle, etc.)
Television
Smartphone (iPhone, Google Pixel, Samsung Galaxy, etc.)
Videogame console {Xbox, PlayStation, Nintendo Switch, etc.)
Other (Please Specify)

3. Please look in your phone's screen time tracking app now (Screen Time for iOS, Digital Wellbeing for Android). Enter the number of hours of smartphone screen time recorded for the last week. *[Researcher verified]*

https://mtsu.yul1.qualtrics.com/jfe/preview/previewId/c0124ddc-802d-47b3-a0f7-9b08e9ca975a/SV_b12GXLEP9g5R4YS?Q_CHL=preview&Q_SurveyVersionID=current

APPENDIX F: Behavioral Variability Task

Instructions: To play, simply click the mouse and drag on any diagonal to create a rectangle. Release the mouse button when you are satisfied with your rectangle. The object of this game is to get the most points. You have received points for your actions whenever you hear a tone. There will be two versions of this game. The game will notify you when you are starting a new version. Press “Start” when you are ready to begin.



APPENDIX G: Autism Quotient-10

Note: Due to copyright reasons, only a partial sample of the survey is provided here.

1. I often notice small sounds when others do not

Definitely Agree
Slightly Agree
Slightly Disagree
Definitely Disagree

2. I usually concentrate more on the whole picture, rather than the small details

Definitely Agree
Slightly Agree
Slightly Disagree
Definitely Disagree

3. I find it easy to do more than one thing at once

Definitely Agree
Slightly Agree
Slightly Disagree
Definitely Disagree

4. If there is an interruption, I can switch back to what I was doing very quickly

Definitely Agree
Slightly Agree
Slightly Disagree
Definitely Disagree

5. I find it easy to 'read between the lines' when someone is talking to me

Definitely Agree
Slightly Agree
Slightly Disagree
Definitely Disagree

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APPENDIX H: Beck Depression Inventory-II (BDI-II)

Note: Due to copyright reasons, only a partial sample of the survey is provided here.

1. Please read the group of statements carefully. Then, pick out the one statement in the group that best describes the way you have felt during the past two weeks, including today.

I do not feel sad.
I feel sad much of the time.
I am sad all the time.
I am so sad or unhappy that I can't stand it.

2. Please read the group of statements carefully. Then, pick out the one statement in the group that best describes the way you have felt during the past two weeks, including today.

I am not discouraged about my future.
I feel more discouraged about my future than I used to.
I do not expect things to work out for me.
I feel my future is hopeless and will only get worse.

3. Please read the group of statements carefully. Then, pick out the one statement in the group that best describes the way you have felt during the past two weeks, including today.

I do not feel like a failure.
I have failed more than I should have.
As I look back, I see a lot of failures.
I feel I am a total failure as a person.

4. Please read the group of statements carefully. Then, pick out the one statement in the group that best describes the way you have felt during the past two weeks, including today.

I get as much pleasure as I ever did from the things I enjoy.
I don't enjoy things as much as I used to.
I get very little pleasure from the things I used to enjoy.
I can't get any pleasure from the things I used to enjoy.

5. Please read the group of statements carefully. Then, pick out the one statement in the group that best describes the way you have felt during the past two weeks, including today.

I don't feel particularly guilty.
I feel guilty over many things I have done or should have done.
I feel quite guilty most of the time.
I feel guilty all of the time.

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APPENDIX I: Adult ADHD Self-Report Scale (ASRS-v1.1)

Note: Due to copyright reasons, only a partial sample of the survey is provided here.

1. How often do you have trouble wrapping up the final details of a project, once the challenging parts have been done?

Never
Rarely
Sometimes
Often
Very Often

2. How often do you have difficulty getting things in order when you have to do a task that requires organization?

Never
Rarely
Sometimes
Often
Very Often

3. How often do you have problems remembering appointments or obligations?

Never
Rarely
Sometimes
Often
Very Often

https://mtsu.yul1.qualtrics.com/jfe/preview/previewId/379b4db7-99fd-431b-b432-bf391e16e338/SV_d1pu0Nt4ToCINnw?Q_CHL=preview&Q_SurveyVersionID=current

APPENDIX J: R Code

```
Thesis_Data <- DESCRIPTIVE_STATS_FINAL_Clean_1[,c(1,2,3,4,5,6)]

head(Thesis_Data, 6)

library("Hmisc")

Results <- rcorr(as.matrix(Thesis_Data))

library("tidyverse")

library("dplyr")

Results$P

flattenCorrMatrix <- function(cormat, pmat) {
  ut <- upper.tri(cormat)
  data.frame(
    row = rownames(cormat)[row(cormat)[ut]],
    column = rownames(cormat)[col(cormat)[ut]],
    cor  =(cormat)[ut],
    p = pmat[ut]  )}
Results<- rcorr(as.matrix(Thesis_Data[,1:6]),type=c("pearson","spearman"))
flattenCorrMatrix(Results$r, Results$P)

View(Results)

library("corrplot")

corrplot(Results, type = "upper", order = "hclust",
         tl.col = "black", tl.srt = 45)
?rcorr

library("ggcorrplot")

header <- names(Thesis_Data)
mat <- Thesis_Data
mat <- as.matrix(Thesis_Data)
str(mat)

library(corrplot)
corrplot(cor(mat, method = "spearman"),
```

```
        method = "circle",
        order = "hclust",
        diag = FALSE)

library("PerformanceAnalytics")

cor(Thesis_Data, method = "spearman")

Cor = round(cor(Thesis_Data,method = "spearman"),2)
write.csv(Cor, file = "C:\\Users\\markr\\OneDrive\\Documents\\Thesis\\Data
Analysis\\correlation_coeffs.csv", quote = F, row.names = F)

library("GGally")

col.labels <- c("AQ10", "BDI", "ASRS", "Rect. Task", "Obj. ST", "Subj. ST")
ax.labels <- c("AQ10", "BDI", "ASRS", "RT", "OST", "SST")

library("dplyr")

Thesis_Data %>%
  ggpairs(upper = list(continuous = wrap("cor",method= "spearman")),
        columnLabels = col.labels,
        axisLabels = ax.labels)
## Changing to histogram
Thesis_Data %>%
  ggpairs(upper = list(continuous = wrap("cor",method= "spearman")),
        diag = list(continuous = wrap("barDiag", fill = "black")),
        columnLabels = col.labels,
        axisLabels = ax.labels)
## Changing to histogram & removing the r values
Thesis_Data %>%
  ggpairs(upper = list(continuous = "blank"),
        diag = list(continuous = wrap("barDiag", fill = "black")),
        lower = list(continuous = wrap("points", color = "darkgray")),
        columnLabels = col.labels,
        axisLabels = ax.labels)
## Changing to histogram & removing the p values
Thesis_Data %>%
  ggpairs(upper = list(continuous = wrap("cor",method= "spearman", stars = F)),
        diag = list(continuous = wrap("barDiag", fill = "black")),
        lower = list(continuous = wrap("points", color = "darkgray")),
        columnLabels = col.labels,
        axisLabels = ax.labels)
```

```
## First correlogram
# correlogram <- ggpairs(Thesis_Data, columnLabels = col.labels, axisLabels =
ax.labels)
# correlogram

## Save this to a TIFF
# tiff(file = "Thesis.tiff", width = 7.5, height = 5, units = "in", res = 800)
# correlogram
# dev.off()

## Shapiro-wilk test with QQplots
shapiro.test(Thesis_Data$AQ10_SCORES)
qqnorm(Thesis_Data$AQ10_SCORES)
qqline(Thesis_Data$AQ10_SCORES, col = "blue")

shapiro.test(Thesis_Data$RECTANGLE_TASK)
qqnorm(Thesis_Data$RECTANGLE_TASK)
qqline(Thesis_Data$RECTANGLE_TASK, col = "blue")
hist(Thesis_Data$RECTANGLE_TASK)

shapiro.test(log(Thesis_Data$RECTANGLE_TASK))
hist(log(Thesis_Data$RECTANGLE_TASK))
shapiro.test(sqrt(Thesis_Data$RECTANGLE_TASK))
hist(sqrt(Thesis_Data$RECTANGLE_TASK))


## Build a full model to test the regression residuals for normality
data.reg <- Thesis_Data[, -6]
mod.full <- lm(RECTANGLE_TASK ~ ., data = data.reg)
shapiro.test(resid(mod.full))
qqnorm(resid(mod.full))
qqline(resid(mod.full), col = "blue")

plot(mod.full)

mod.full <- lm(sqrt(RECTANGLE_TASK) ~ ., data = data.reg)
shapiro.test(resid(mod.full))
qqnorm(resid(mod.full))
qqline(resid(mod.full), col = "blue")

# Generalized Linear model
# Poisson
library("lme4")
```

```
full.mod.pois <- glm(RECTANGLE_TASK ~ ., data = data.reg, family = "poisson")
summary(full.mod.pois)
full.mod.quasipois <- glm(RECTANGLE_TASK ~ ., data = data.reg, family =
"quasipoisson")
summary(full.mod.quasipois)

#1 do a Poisson
#2 Check for overdispersion
#3 SAS checks for it for you
#4 Think about another aspect of the metric (use negative binomial?)

?ggpairs

library("dplyr")

##Thesis Data with U VAlue#

Thesis_Data2 <- DESCRIPTIVE_STATS_FINAL_Clean_2_U_value[,c(1,2,3,8,4,5,6)]

header <- names(Thesis_Data2)
mat <- Thesis_Data2
mat <- as.matrix(Thesis_Data2)
str(mat)

corrplot(cor(mat, method = "spearman"),
        method = "circle",
        order = "hclust",
        diag = FALSE)

col.labels <- c("AQ10", "BDI", "ASRS","Rect. Task", "U-Value", "Obj. ST", "Subj. ST")

#ax.labels <- c("AQ10", "BDI", "ASRS","RT", "UV", "OST", "SST")

Thesis_Data2 %>%
  ggpairs(upper = list(continuous = wrap("cor",method= "spearman")),
          columnLabels = col.labels)
#Just using the IQR

IQR(Thesis_Data2$RECTANGLE_TASK)

quantile(Thesis_Data2$RECTANGLE_TASK, probs = c(0.25,0.75))
Thesis_Data3 <- Thesis_Data2 %>% filter(RECTANGLE_TASK >= 396.0 &
RECTANGLE_TASK <= 473.5)
```

```
Thesis_Data3 %>%
  ggpairs(upper = list(continuous = wrap("cor",method= "spearman")),
          diag = list(continuous = wrap("barDiag", fill = "black")),
          lower = list(continuous = wrap("points", color = "darkgray")),
          columnLabels = col.labels,
          axisLabels = ax.labels)

Thesis_Data2 %>% filter(RECTANGLE_TASK < 396.0 | RECTANGLE_TASK > 473.5)

#Tukey method 1.5xIQR

#make sure to report median as well w/in data analysis in thesis

IQR(Thesis_Data2$RECTANGLE_TASK)*1.5

#quantile(Thesis_Data2$RECTANGLE_TASK, probs = c(0.25,0.75))*1.5

median(Thesis_Data2$RECTANGLE_TASK)-
(IQR(Thesis_Data2$RECTANGLE_TASK)*1.5)/2

median(Thesis_Data2$RECTANGLE_TASK)+(IQR(Thesis_Data2$RECTANGLE_TAS
K)*1.5)/2

Thesis_Data4 <- Thesis_Data2 %>% filter(RECTANGLE_TASK >= 388.375 &
RECTANGLE_TASK <= 504.625)

Thesis_Data4 %>%
  ggpairs(upper = list(continuous = wrap("cor",method= "spearman")),
          diag = list(continuous = wrap("barDiag", fill = "black")),
          lower = list(continuous = wrap("points", color = "darkgray")),
          columnLabels = col.labels,
          axisLabels = ax.labels)

Thesis_Data2 %>% filter(RECTANGLE_TASK < 388.375 | RECTANGLE_TASK >
504.625)


##Doing IQR 3x##

IQR(Thesis_Data2$RECTANGLE_TASK)*3.0
```

```
median(Thesis_Data2$RECTANGLE_TASK)-
(IQR(Thesis_Data2$RECTANGLE_TASK)*3.0)/2

median(Thesis_Data2$RECTANGLE_TASK)+(IQR(Thesis_Data2$RECTANGLE_TAS
K)*3.0)/2

Thesis_Data5 <- Thesis_Data2 %>% filter(RECTANGLE_TASK >= 330.25 &
RECTANGLE_TASK <= 562.75)

Thesis_Data5 %>%
  ggpairs(upper = list(continuous = wrap("cor",method= "spearman")),
          diag = list(continuous = wrap("barDiag", fill = "black")),
          lower = list(continuous = wrap("points", color = "darkgray")),
          columnLabels = col.labels,
          axisLabels = ax.labels)

Results2 <- rcorr(as.matrix(Thesis_Data2))

Results2$P

Thesis_Data5 %>%
  ggpairs(upper = list(continuous = wrap("cor",method= "spearman")),
          diag = list(continuous = wrap("barDiag", fill = "black")),
          lower = list(continuous = wrap("points", color = "darkgray")),
          columnLabels = col.labels,
          axisLabels = ax.labels)

correlogram2 <- ggpairs(Thesis_Data5, columnLabels = col.labels, axisLabels =
ax.labels)
correlogram2

tiff(file = "Thesis.tiff", width = 7.5, height = 5, units = "in", res = 800)
correlogram2

##Correlogram Full Data Set##

Thesis_Data2 %>%
  ggpairs(upper = list(continuous = wrap("cor",method= "spearman")),
          diag = list(continuous = wrap("barDiag", fill = "black")),
          lower = list(continuous = wrap("points", color = "darkgray")),
          columnLabels = col.labels,
          axisLabels = ax.labels)
```

```
Results3 <- rcorr(as.matrix(Thesis_Data2))

Results3$P

correlogram3 <- ggpairs(Thesis_Data2, columnLabels = col.labels, axisLabels =
ax.labels)
correlogram3
```

APPENDIX K: Probability (*P*) Values for Full and IQR*3 Data Sets

P Values for Full Data Set

	AQ10	BDI	ASRS	Rect. Task	U-Value	Obj. ST	Subj. ST
AQ10	NA	0.184	**0.0124***	0.526	0.855	0.940	0.848
BDI		NA	**0.041***	0.129	0.403	0.941	0.321
ASRS			NA	0.056	0.703	0.729	0.768
Rect. Task				NA	**< 0.0001*****	0.896	0.579
U-Value					NA	0.331	0.913
Obj. ST						NA	**< 0.0001*****
Subj. ST							NA

* $p < .05$
** $p < .01$
*** $p < .001$

*P Values for IQR*3 Data Set*

	AQ10	BDI	ASRS	Rect. Task	U-Value	Obj. ST	Subj. ST
AQ10	NA	0.246	**0.022***	0.705	0.834	0.557	0.891
BDI		NA	**0.025***	**0.042***	0.447	0.836	0.281
ASRS			NA	0.051	0.722	0.459	0.429
Rect. Task				NA	**< 0.0001*****	0.837	0.609
U-Value					NA	0.324	0.446
Obj. ST						NA	**< 0.0001*****
Subj. ST							NA

* $p < .05$
** $p < .01$
*** $p < .001$