The Effects of Smartphone Screen Time on Behavioral Variability

Mark Rust

ABSTRACT

Individuals diagnosed with conditions such as attention-deficit/hyperactivity disorder (ADHD), autism spectrum disorder (ASD), and depressive disorders tend to display variable behavior, disparate from their peers. Studies have shown that variable behavior can be either enhanced or reduced through reinforcement. However, these factors are poorly understood. Screen time has been hypothesized as a factor that may influence behavioral variability. The following study explores the possible relationship between smartphone screen time, behavioral variability, and self-reported ADHD, ASD, and depressive symptoms, using a threefold methodology: first, participants reported their screen time use through a smartphone application. Next, participants completed a computer-based task assessing behavioral variability, during which they drew rectangles on a screen. Points were awarded for rectangles that differed from those previously made. 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 the ASRS-v1.1, as well as between the ASRS-v1.1 and the BDI-II. At the same time, there were moderate correlations between different measures of behavioral variability, and a correlation between objective and subjective screen time scores, revealing consistency in these assessments. Results nevertheless indicated no systematic relation between screen time and behavioral variability.

Variability in behavior is adaptive for numerous reasons. Reaction to unique and differing situations adaptively can facilitate both survival and learning. The degree to which an organism exhibits variability has significant implications for its physical and psychological well-being. Numerous factors contribute to enhanced or reduced behavioral variability in humans. Social, cultural, biological, and psychological factors all contribute to shaping behavioral variability. While many factors may play a vital role, research on what can affect behavioral variability remains ongoing. Of recent concern has been the psychological and behavioral influence of screen-based technologies. Since introducing these technologies, researchers have sought to understand the potential consequences of their use. This study investigates the possible relationship between screen time and behavioral variability.

Behavioral Variability

Adapting and changing in response to specific external influences is evolutionarily beneficial, as it 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 serve as a protective factor in overcoming crises and fostering resilience (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., disrobing when it is not appropriate), 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).

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 behavior fall outside the bounds of typical societal norms) may 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 enable practitioners to gain a deeper understanding 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). This behavioral inflexibility can lead 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). 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; Hunziker et al., 1996; Mook et al., 1993). 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). 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. Another psychological disorder related to low behavioral variability is major depressive disorder. Although the literature regarding behavioral variability and depressive disorders is not extensive, preliminary research suggests that depressed individuals show lower levels of behavioral variability than their neurotypical peers (Hopkinson & Neuringer, 2003).

Screen Time

The duration of time spent staring at electronic screens, or screen time, has been a concern among parents and educators since the pre-internet television era. The type of technology used in the study of screen use varies depending on the year, but it may 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 is 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.

Autism spectrum disorder (ASD), which is characterized by restricted interests and deficits in social skills, has frequently been associated with increased screen time (American Psychiatric Association, 2022; Slobodin et al., 2019). A number of studies have suggested that higher use of screen time may lead to an increased risk of social anxiety, which has significant implications for those with ASD (Westby, 2018). Although hypotheses on these findings draw different conclusions, inferences remain inconclusive, and causality between the different factors has not been definitively determined. Additionally, although the literature on the effects of screen time on individuals with ADHD is limited, some preliminary studies have investigated this relationship (Cavalli et al., 2021; Soares et al., 2022; Vaidyanathan et al., 2021). Still, a relationship between screen time and ADHD has not been conclusive. Further, little literature addresses the potential effects of screen time on depression. Some evidence points to the idea that youth exposed to more screen time get less sleep, resulting in a higher risk of developing depressive symptoms than their peers (Liu et al., 2019; Wang et al., 2021).

It has been proposed that screen time may be a factor influencing behavioral variability, or vice versa. Two seminal hypotheses exist to explain the potential relationship between screen time and behavioral variability. The stimulation hypothesis suggests that behavioral variability can be stimulated by viewing certain behaviors on electronic devices. The reduction hypothesis posits that screen time disrupts thought processes and can ultimately lead to a decrease in creativity (Calvert & Valkenburg, 2013). Both hypotheses can point to research that may substantiate the claims, yet 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 from college students to 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; if participants with more screen time use behaved less variably, the results would show a negative correlation. Either result could provide evidence supporting or refuting the hypothesis that screen time displaces creative, or variable, behavior, or vice versa. If no systematic relationship between behavioral variability and screen time was observed, we would gain more insight, yet further research would be required to draw this conclusion definitively.

Past studies on screen time have primarily relied on self-reports instead of objective measures to track the screen time of their participants. Continual technological advances have led to the development of more impartial methods. We monitored participants utilizing the default screen time tracking feature included with iOS and Android smartphones. However, we also asked participants to self-report estimates of their total screen time on other devices.

Various methods have been employed to assess behavioral variability and creativity, including play activities such as coloring (Bancroft et al., 2016) and block building (Goetz & Baer, 1973). The current experiment used an established computer-based rectangle game to measure participant variability (Galizio et al., 2020; Ross & Neuringer, 2002). In this task, participants created rectangles of varying sizes and locations. We assessed variability as it occurred under different schedules of reinforcement (i.e., points), to consider also the possibly relationship between screen time and reinforcement.

As both behavioral variability and screen time have been linked with specific psychopathologies, a secondary purpose of the study was to investigate individual differences in

behavioral variability and screen time, especially related to symptoms of certain psychopathologies, including ASD, ADHD, and depression. To do so, we administered health screeners to detect ASD, ADHD, and depressive symptoms. Any of these relationships would contribute to the current literature on screen time and behavioral variability.

Method

Participants and Setting

Participants in the study were college students enrolled in introductory psychology courses and recruited through the psychology department's research pool via Sona Systems®. All students were at least 18 years old. Only students with a smartphone that had the default screen time tracking application were eligible to participate. Participants gave informed consent before completing any surveys or tasks. After completing the tasks, participants completed a demographics survey through Qualtrics® to assess participant characteristics. To minimize possible emotional or psychological distress, participants were debriefed immediately following their session. Experimental procedures were conducted in line with the guidelines provided by the American Psychological Association and approved by the Institutional Review Board (IRB) of (blinded) (Protocol Number: FY2023-36). Each participant was assigned a participant identification number to maintain confidentiality.

A total of 63 participants began the study. One participant did not complete the experiment because their screen time tracking app was not activated before the study began. Additionally, four participants experienced technical difficulties during the behavioral variability task, which resulted in their data not being saved correctly; these participants were also excluded from the data analysis. Following these exceptions, a total of 58 participants completed the entire study with usable data. After five outliers without usable data were identified and excluded, 53 participants remained.

Participants completed the study in a small on-campus computer lab with minimal distractions. Each participant used one computers in the room; when multiple participants were tested in the same room, the start time was staggered. Each individual was seated at least two seats away from other participants. After arrival, participants were instructed to complete several computer-based tasks: (1) a survey in which they reported their screen time, (2) a behavioral variability task, and (3) several different psychopathology screeners. After completing all of the tasks, participants responded to a demographics survey (see Table 1) and were then debriefed by the researcher. After completing the study, participants received course credit and were reminded to contact the researchers if they had questions or concerns.

Table 1

Demographics

Sociodemographic Characteristics	*n*	%
Total	53	
Women	30	57%
Men	18	34%
Nonbinary	3	4%
Genderfluid	2	6%
Age		
18-24 years old	51	96%
25-34 years old	2	4%
Ethnicity		
Caucasian or White	29	55%
African American	11	21%
Asian	3	6%
Latino or Hispanic	6	11%
Mixed	4	8%
Education Level		
High school	40	75%
Associate's Degree	1	2%
Some Bachelor's	12	23%
Master's Degree	0	0%
Parental Education		
High School	14	26%
Associate's	3	6%
Bachelor's	17	32%
Master's	10	19%
Ed.D., PsyD., Ph.D.	5	9%
Some Bachelor's	3	6%
Prefer not to say	1	2%
Psychological Condition	15	28%
English	52	98%
Other	0	0%
Prefer Not to Say	1	2%

Materials and Design

Screen Time Assessment

In the first task, participants completed a Qualtrics® survey in which they reported their screen time use. The survey began with questions related to general screen time use. Participants were first 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 devices they owned that had screen time capabilities.

On the next page, participants were asked to find their researcher for assistance. The researcher described the ScreenTime programs used to track their smartphone use and provided a general description of the program for either Android® users or iPhone® (iOS) users. The programs were the ScreenTime system for iOS users and the Digital Wellbeing® system for AndroidOS users. These applications are included in the default operating systems of the iPhone and Android phones and track the time a person spends on their phone. Both systems operate by measuring the time an individual interacts with their device after it is opened. The researcher instructed each participant to locate records of their screen time use on their phone. If needed, the researcher assisted the participant in locating 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 total amount of screen time used, not the particular applications and websites visited by the individuals.

Behavioral Variability Task

Next, participants were given a computer-based task assessing behavioral variability. This task required participants to use the mouse to click and drag on the screen to form rectangles. The participant was seated in front of a computer as the researcher loaded the program displaying the instructions. The researcher then read the instructions aloud to the participant and asked whether the participant had any questions. Instructions informed participants that they were about to play a game that involved creating rectangles. They were then 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 game's purpose was to earn as many points as possible. The participant was then given a pair of headphones to listen to the tones and instructed 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. The white space did not include grid lines or any other spatial parameters to guide participants in the areas in which they draw rectangles. Participants used the lab computer's mouse to create the rectangles by pressing the mouse's left button and drawing 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, while some rectangles had no programmed consequence. Between each trial of the task, there was a 1-s interval in which the computer screen turned 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 several 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 awarded for some rectangles based on a relative frequency threshold contingency, which requires behavioral variability. The relative frequency of each dimension 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 (either size or location) in which 20% or less of the rectangles had already occurred. This value was selected because it is relatively lenient, allowing for the observation of more significant 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 on 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) 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 .89 for adolescents) 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 is assessed using a four-point Likert scale, progressing from "Definitely Agree" to "Definitely Disagree," with "Slightly Agree" and "Slightly Disagree" used to indicate 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) 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 determinant 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) is a screening tool developed to help determine if a person exhibits symptoms consistent with the 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 consists of six brief statements that require the individual to indicate their level of agreement on a five-point Likert scale, ranging from "Never" to "Very Often" (Kessler et al., 2005). These statements self-report in a range from 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 indicate whether an individual exhibits symptoms consistent with a diagnosis of ADHD and is not intended for use 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. 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, which should objectively represent the participant's smartphone use. The subjective measure was the participant's self-reported estimate of their daily screen time, 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:

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

In this equation, Rf_i refers to the relative frequency at which a response is emitted, and n is the number of response categories (in 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 Šídák's multiple comparison tests 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 enable a participant to be quickly screened for certain behavioral traits common among 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). Next, 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, it is considered mild; from 20 to 28, it is regarded as moderate; and from 29 to 63, it is deemed severe self-reported depression (Beck et al., 1961). 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 the 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).

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 chosen due to its stature as 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). Additionally, the Shapiro-Wilk test is employed in studies with relatively small 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,

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

In this equation, d_i^2 is the difference between the two ranks. Additionally, *n* represents the number of observations in 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).

Upon analyzing the results, it became apparent that some data points may have been outliers. We also had four participants who had technical difficulties in the behavioral variability task. We removed five participants who were outliers. Thus, nine in total were removed. 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, essentially a measure of statistical dispersion (Bock et al., 2000; Mishra et al., 2019). Each quartile represents one-fourth of the data, and the interquartile range signifies the difference between the 25th and 75th percentiles. 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 from five participants were identified as probable outliers on at least one dependent variable; therefore, these participants were excluded from the second analysis. This reduced the data set to n = 53 participants.

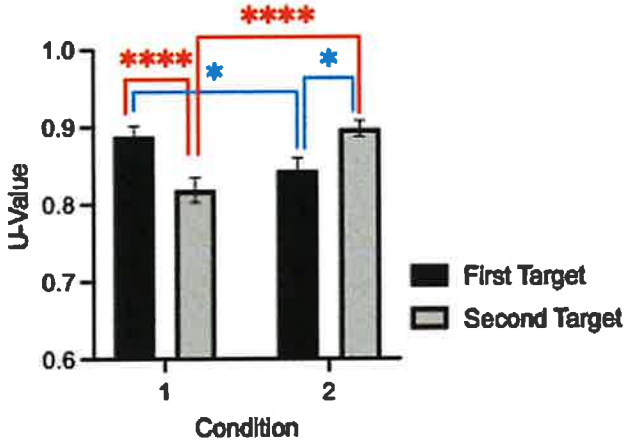
An a *priori* power analysis was conducted using G*Power to estimate the necessary sample size required to ensure sufficient power to detect a significant correlation. To detect a significant correlation with a moderate effect size (ρ = 0.4), assuming a two-tailed test, an alpha level of 0.05, and high 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.

Results

Participants performed highly variably on the rectangle task, as evidenced by high U-values and points earned for most rectangles created. Although participants' performance was

highly variable in both conditions across both dimensions, size and location, they did show a differential responding according to the contingencies in place. 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 and an accurate assessment of behavioral variability.

Figure 1.
Levels of Behavioral Variability in the Rectangle Task

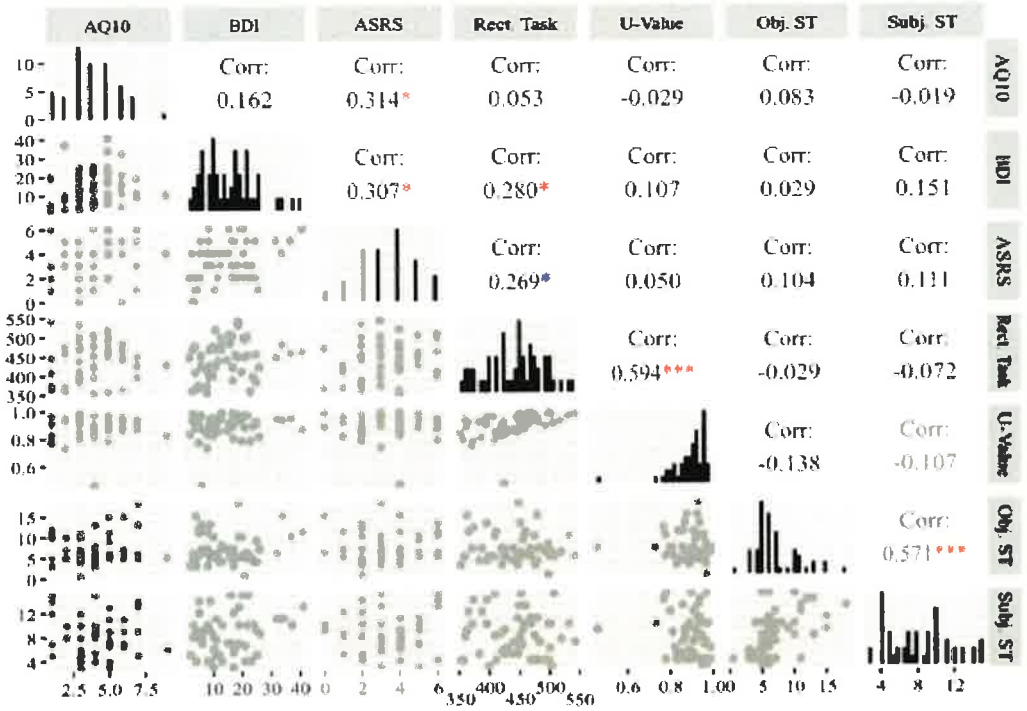


Note: Bars represent mean U-values (error bars represent SEM) for all participants (n = 58). Significant within-subjects comparisons are identified.

* $p < .05$
**** $p < .0001$

Figure 2 displays a correlogram for the 'IQR*3 Data' set (n = 53). In this figure, the right-most panels show the ρ correlation for each comparison, the left-most panels show scatter plots for each comparison, and the center diagonal panels show frequency histograms for each variable.

Figure 2.
*Correlogram for IQR*3 Data Set*



Note: The right-most panels show the ρ correlation for each comparison, the left-most panels show scatter plots for each comparison, and the center diagonal panels show frequency histograms for each variable. The variables being compared were defined as follows. AQ-10 = scores on the AQ-10 assessment of ASD symptoms; BDI = scores on the BDI-II assessment of depression symptoms; ASRS = scores on the ASRS v.1.1 assessment of ADHD symptoms; Rect. Task = number of points earned on the rectangle task assessing behavioral variability; U-Value = level of behavioral variability observed for the target dimension during the first condition; Obj. ST = objective measure of screen time, taken from the participant's smartphone. Subj. ST = subjective measure of screen time, estimated by the participant prior to verification on the smartphone.

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

As shown in Figure 2, several positive associations were seen between the different psychopathology screeners, the behavioral variability task, and the screen time measures. The strongest correlation was observed between U-values and the number of points received in the rectangle task (ρ = 0.594). 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. The next strongest positive correlation (ρ = 0.571) was found between objective and subjective screen time use. This association may suggest that participants can provide a relatively accurate estimate of their screen time use.

Several small-to-moderate positive associations were also observed in the psychopathology measures. Scores on the ASRS and AQ-10 were positively correlated (ρ = 0.314), indicating that participants who tended to score highly on the ADHD screener also tended to score

highly on the ASD screener (Dancey & Reidy, 2007). There was also a small positive association between BDI-II scores and ASRS scores ($\rho = 0.307$), indicating a possible relationship between symptoms of depression and ADHD. These detections are consistent with previous findings that suggest that individuals often receive comorbid diagnoses of ASD and ADHD, as well as depression and ADHD (American Psychiatric Association, 2022). Weak positive correlations were observed between BDI-II scores and the points earned on the rectangle task ($\rho = 0.280$) and between ASRS scores and points earned on the rectangle task ($\rho = 0.269$). These results suggest that individuals with more symptoms of depression or more symptoms of ADHD behaved more variably.

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 participants earned points for creating rectangles in a variable manner, and similarly high levels of variability were observed.

Contrary to our hypothesis, levels of variability were not systematically correlated with screen time. However, other meaningful relationships were uncovered. The study found a moderate positive correlational relationship between U-values in the rectangle task and the points earned in the rectangle task. This correlation indicates 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), which, consistent with previous literature, may confirm the task as an accurate assessment of behavioral variability (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 noted is a moderate positive correlation between the subjective and objective screen time scores. This correlation suggests that participants could predict their screen time usage relatively accurately. This finding differs from previous research, which suggests that participants were unable to accurately report their screen time use (Hodes & Thomas, 2021; Ohme et al., 2021). However, it is worth noting that the description of the experiment in the present study may have influenced 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 participants had to have the screen time tracking app activated on their smartphone for at least a week prior to 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, which is 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.

Weak-to-moderate positive correlations were also observed between scores on the psychological assessments. Our results showed a positive association between ASD and ADHD symptoms, which is consistent with reports that these two conditions are often diagnosed comorbidly (American Psychiatric Association, 2022). However, it is also possible that participants' scores were similar across assessments due to the content similarity within items on the AQ-10 and ASRS-v1.1. More in-depth diagnostic tools would likely represent symptoms better than the 10-item and 6-item self-report assessments. A similar association was observed between ADHD and depressive symptoms. Again, the ASRS-v1.1 and the BDI-II share resemblances in the

specific items within the screeners, which could explain this correlation. It is also possible that the scores on these two assessments were correlated due to the population used in 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.

Two additional correlations are particularly noteworthy. Although these correlations were weak and only revealed after excluding probable outliers from analysis, they raise questions about interpreting the existing literature and therefore warrant further exploration. First, performance on the rectangle variability task was positively associated with scores on the ADHD screener. The existing literature on the relationship between ADHD symptoms and levels of behavioral variability is mixed. Some previous research suggests that people with symptoms consistent with an ADHD diagnosis often display more variable behavior than their neurotypical peers (American Psychiatric Association, 2022; DuPaul et al., 2001; Neuringer, 2009). Similar findings have been demonstrated in rodent models of ADHD (Hunziker et al., 1996; Mook et al., 1993). However, other research has failed to demonstrate this relationship; Saldana and Neuringer (1998) compared behavioral variability in a computer game across children with and without an ADHD diagnosis. Although the individuals with ADHD engaged in more off-task responses, their behavior in the task was not significantly more variable than controls. The mixed nature of this research indicates a need for more systematic study of the potential relationship between ADHD and behavioral variability.

The second noteworthy correlation not entirely consistent with previous research was between behavioral variability and depression. Very little research has examined the relationship between variability and depression. Hopkinson and Neuringer (2003) found that more depressed individuals behaved less variably than controls. According to the diagnostic criteria, symptoms of depression include loss of interest or pleasure in activities, psychomotor retardation, low energy levels, and difficulty making decisions (American Psychiatric Association, 2022), all of which would likely lead to more repetitive, less variable behavior. In the present study we observed the opposite relation—a weak positive association between performance on the rectangle variability task and scores on the BDI-II assessment of depressive symptoms. Given these inconsistencies, future research will be needed to establish the directionality and strength of the relationship between variability and depression.

Limitations and Future Directions

Several limitations exist for this study. One is the measure of screen time used. Although the ScreenTime and Digital Wellbeing® applications possibly reduce the subjectivity of utilizing self-report measures that have been used in other studies (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. Another limitation is that a few survey participants reported being 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, yet they may have been confused about if their estimate should have been their total weekly usage or average daily usage. Clearer wording in future research would address this potential concern. Another limitation of the study regarding the screen time assessments is the one-week activation period required for the screen time applications used in the study. This requirement necessarily limits the number of participants that could be included in the study. Additionally, simply owning a smartphone limits the type of individuals who can be involved in the study. Individuals with a smartphone may have different screen time habits and usage than those without a smartphone.

The psychopathology screeners we 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 Asperger's (Allison et al., 2012). This diagnosis is now outdated

with the Diagnostic Statistical Manual, 5th Ed. update (American Psychiatric Association, 2022). In addition, the specific nature of the behaviors exhibited by the adults, from which the screener was created, may limit its generalizability to other, different presentations of adult autism.

The Beck Depression Index (BDI-II) has several crucial limitations. First, the BDI-II only measures an individual's feelings over 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 symptoms, may be unrealized if a person were to take the BDI-II and not feel depressed or distraught for the past two weeks. Further, the discriminant validity of the BDI-II. Although Beck et al. (1961) can demonstrate the discriminant validity between depressives and nondepressives, it is less effective at discriminating between other disorders or symptoms such as anxiety (Richter et al., 1998). This limits the ability of the BDI-II to accurately assess if a person has depression. Finally, researchers have noted 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, which focuses on short-term, current issues.

The Adult ADHD Self-Report Scale (ASRS-v1.1) utilized in our study to measure ADHD symptoms 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 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.

The behavioral variability task demonstrates several limitations. One limitation 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), or outside of a lab setting. Some parts of the task may have led to boredom or decreased motivation due to its stagnant nature and arbitrary point values. Also, the compensation for participating in the study was course credit, but performance on the task had no impact on receiving it. Another potential factor was the lenient variability requirements; this study utilized a threshold value of 0.20. This value means that for a point to be delivered, the rectangle had to be in a category of the target dimension (time or location) where 20% or fewer of the rectangles occurred. The data may have differed if more stringent or lenient requirements had been used. Another limitation of the task is the use of U-values to measure variability (Galizio et al., 2020). U-values cannot explain a participant's specific response patterns, instead measuring variability on a general, global level.

Several different future directions can be taken in subsequent research. Additional research should be conducted to determine 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 replicate the task and conduct additional 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 effective 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. Additionally, the study could be larger, and involve a more diverse sample. The demographics of the study align with those of (blinded) (National Center for Education Statistics, 2021). Most of the students were younger, aged 18 to 24 years old. There was a difference between the participants' and their parents' education levels. Future research could conduct even more diverse sampling to understand influences that may change a person's behavior or screen time usage. Due to the simplicity of the methods used in the study, many other individuals would be eligible to participate.

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 (such as ScreenTime and Digital Wellbeing systems) opens the door to additional insights into total screen time usage, as well as screen time associated with 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 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 will surely lead to greater understanding of how screen time and behavioral variability may be connected.

References

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

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

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. 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

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

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.

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

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

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

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

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.

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

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

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

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

Mook, D. M., Jeffrey, J., & Neuringer, A. (1993). Spontaneously hypertensive rats (SHR) readily learn to vary but not repeat instrumental responses. *Behavioral and Neural Biology*, 59(2), 126–135. https://doi.org/10.1016/0163-1047(93)90847-B

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

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

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

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

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

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. (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

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

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

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