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Impact of digital screen media activity on functional brain organization in late childhood: Evidence from the ABCD study

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ABSTRACT

The idea that the increased ubiquity of digital devices negatively impacts neurodevelopment is as compelling as it is disturbing. This study investigated this concern by systematically evaluating how different profiles of screen-based engagement related to functional brain organization in late childhood. We studied participants from a large and representative sample of young people participating in the first two years of the ABCD study (ages 9–12 years) to investigate the relations between self-reported use of various digital screen media activity (SMA) and functional brain organization. A series of generalized additive mixed models evaluated how these relationships related to functional outcomes associated with health and cognition. Of principal interest were two hypotheses: First, that functional brain organization (assessed through resting state functional connectivity MRI; rs-fcMRI) is related to digital screen engagement; and second, that children with higher rates of engagement will have functional brain organization profiles related to maladaptive functioning. Results did not support either of these predictions for SMA. Further, exploratory analyses predicting how screen media activity impacted neural trajectories showed no significant impact of SMA on neural maturation over a two-year period.

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1. Introduction

Digital screens are now a staple of childhood and adolescence (Common Sense Media, 2017; Ofcom, 2017). Driven by concerns voiced about the potential impact of screens on young people, a growing literature of screen media impact studies have failed to reach a consensus surrounding the links between digital technology use and adolescent well-being and development (Beyens, Valkenburg, & Piotrowski, 2018; LeBourgeois et al., 2017; Orben & Przybylski, 2019; Paulus et al., 2019; Robinson et al., 2017). Given the lack of conclusive evidence, pediatricians, policymakers, and other interested parties have resorted to backing the precautionary principle, that is, "when human activities may lead to morally unacceptable harm that is scientifically plausible but uncertain, actions shall be taken to avoid or diminish that harm" (UNESCO COMEST, 2005). The specific advice given to parents has varied over time: early advice included the 2x2 rule, that children under two years of age should not be exposed to digital screen media and those over two should only use 2 h of digital screen media a day (AAP, 2010), which was unworkable on practical grounds (Houghton et al., 2015). Later guidance insisted on parents tracking and improving the quality of screen media their children engage with (AAP, 2016). Based on only the contentious, lacking, or inconclusive evidence available, many policies have gotten well ahead of the available scientific consensus. Responsible professional organizations now highlight this scientific uncertainty present in the literature, and resort to recommending that rules and limits should be set on a child-by-child basis (RCPCH, 2019).

This uncertainty is keenly felt in the area of developmental cognitive neuroscience as the central topic of study, the ways by which the minds of young people pass safely from childhood to adulthood is something parents and policymakers want to protect at all costs. The changing nature of the brain during the first two decades of life suggests that environmental inputs could impact brain development (Blakemore & Mills, 2014). Despite the lack of research investigating how digital screen engagement is related to measures of brain development during childhood and adolescence (Mills, 2014), there are, nevertheless, concerns that digital screens might harm the developing brain. The most recent concerns involving digital screen technologies revolve around internet use and online behaviors, although only a few studies have measured the relationship between digital screen technologies and brain functionality in representative samples of the developing population.

The majority of scientific work that has related brain measures to internet use has focused on unrepresentative samples of the developing population—namely, individuals who have been identified as dysregulated internet users (Park, Han, & Roh, 2016). A widely held misconception is that the results gathered from these studies are applicable to most children or adolescents, which likely stems from a misconception that most children or adolescents are excessive internet users. However, the majority of children and adolescents are not excessive users of the internet (Blinka et al., 2015), and do not experience the problems associated with dysregulated internet use (Durkee et al., 2012; Strittmatter et al., 2015). The results of studies on children and adolescents with dysregulated internet use, as well as the corresponding warnings and media headlines, should therefore not be generalized to the majority of the population.

Another common concern is that digital screens "rewire" the developing brain. However, no studies to date can tell us if, or how, screen engagement is altering brain connections. Probable causes of this concern are misunderstandings regarding brain plasticity and sensitive periods of brain development. While the brain is plastic throughout life—meaning it can change in response to experience—it is even more amenable to change during the period when brain connections are being pruned away to adult levels. The timing of this period of heightened sensitivity differs across the brain, with some regions possessing relatively short windows of sensitivity (e.g. visual processing areas) and some regions experiencing longer windows of sensitivity (e.g. the prefrontal cortex) (Huttenlocher & Dabholkar, 1997; Petanjek et al., 2011). Few studies have demonstrated definitive evidence of cellular changes in the developing human brain in response to environmental influences, and these are often limited to perceptual circuits like those implicated in vision (Huttenlocher, de Courten, Garey, & Van der Loos, 1982). Most studies investigating how environmental influences impact the developing human brain have inferred cellular changes from macroscopic changes observed through MRI. These studies investigated the effect of environmental influences such as socioeconomic status (Hackman & Farah, 2009), chronic stress (Lupien, McEwen, Gunnar, & Heim, 2009), and early life deprivation (Fox, Levitt, & Nelson III, 2010)—factors that already possess strong empirical support for affecting cognitive development and well-being. Unlike these severe environmental influences, there is still little evidence that screens impact cognitive development (Mills, 2016) or mental well-being (Przybylski & Weinstein, 2017) in childhood and adolescence.

If we want to know how digital screen engagement systematically impacts the developing mind, we need to relate relevant brain measures to behavior, cognition, and well-being. Studies that include measures of how screen engagement relates to brain measures as well as functional outcomes should be given greater consideration than studies that just correlate levels of screen use with a given brain measure alone. This is because there is substantial individual variability in brain structure and function, as well as in how an individual's brain structure and function relates to that individual's cognition, behavior, and well-being (Anandakumar et al., 2018; Mills et al., 2012; Mills & Tamnes, 2014). While it is one thing to know whether a certain brain measure correlates with screen use, it is another to know if that means the brain region is impaired or functioning at a suboptimal level.

1.1. *Policy and evidence*

With many policy and industry initiatives currently being implemented to negate the potential negative effect of digital screen engagement on our youngest generations, transparent scientific investigation becomes paramount. The wide variety of campaigns to improve adolescent outcomes are all united by their lack of underlying evidence (e.g. Scroll Free

September, https://www.waituntil8th.org, https://www.papayaparents.com/the-problem/). The American Academy of Pediatrics recommends limiting daily screen media usage to 1 h of high-quality engagement for preschool children between ages 2–5 years (AAP, 2011). Technological interventions like those from Apple (e.g., "iOS 12 introduces new features to reduce interruptions and manage Screen Time," 2018), Google (e.g., https://wellbeing.google), and Facebook (https://www.facebook.com/safety/wellbeing) have been introduced without evidence that these tools which limit screen media use, provide feedback on use, or batch notifications have any substantial positive health effects. In the United Kingdom, a Ministry of Health initiative is trying to specify new screen engagement guidelines (Kidron & Rudkin, 2017); this is proving a difficult task because the existing literature does not provide the actionable evidence necessary to support evidence-based policy.

There is a current lack of evidence because no study has fully examined how screen engagement impacts brain development using longitudinal sampling, which is necessary to accurately characterize brain development (Mills & Tamnes, 2014). To date, studies have only employed cross-sectional (one measure per participant) sampling methods. This kind of evidence provides information about how differences between young people might be explained by different patterns of digital screen engagement but does not help us understand how within-person variation in cognitive development might be explained by how young people use technology. Further, as stated above, most studies that have examined pediatric populations, focusing on differences between individuals with and without some form of dysregulated internet use. For example, studies have compared the brains of individuals who have been categorized as showing dysregulated internet use with those individuals whose use does not meet the criteria for dysregulated internet use (Park et al., 2016). By design, these comparison studies are only able to describe group-average differences, and thus absorb any heterogeneity across individuals within a group.

One review found that areas of the brain involved in reward processing, cognitive control, and memory appear to show differences between groups of individuals with dysregulated internet use and groups who use the internet at typical levels (Park et al., 2016). For example, one study found decreased baseline functional brain connectivity between brain regions involved in reward processing in individuals with dysregulated internet gaming behavior compared to healthy controls (Zhang et al., 2015). However, these observed brain differences do not necessarily reflect dysfunction or abnormalities, they could be: 1) a compensatory mechanism in the dysregulated group, 2) an impairment in brain functioning, or 3) a process related to an unmeasured variable. In the above study, for example, one way to understand the functional meaning of the observed differences in brain connectivity in the dysregulated group would be to correlate how brain connectivity relates to cognitive functioning or well-being. If such an analysis finds the same direction of effect, that would give further clarity that the actual difference in brain connectivity between groups was a sign of dysfunction.

Studies that relate digital screen engagement with both brain measures and assessments of daily functioning bring us one step closer to understanding how screen use affects the brain. One recent example of this kind of study focused on the relation between self-reported daily gaming behavior to cognitive abilities and brain function in adolescents and young adults aged 13–24 years (Moisala et al., 2017). Unlike previous studies of individuals with dysregulated gaming, the participants in this study were representative of the population in terms of how much gaming they engaged in, ranging from very little to moderate amounts. Behaviorally, the participants who reported more daily gaming were better at keeping track of many items in their mind, and were faster at switching their attention, than participants who reported less daily gaming. While participants who reported higher levels of daily gaming displayed less activity in a network of brain regions involved in cognitive control when trying to keep track of just a few items, these participants also showed much more activity in the same areas of the brain when they had to keep track of many items. The authors suggest that this pattern of brain activity could reflect an alternative cognitive strategy for participants who are more frequent gamers than individuals who game less (Moisala et al., 2017). However, given that this study is cross-sectional, it cannot tell us if daily gaming causes the differences in brain measures and functionality.

1.2. *Using the ABCD dataset to examine digital screen engagement and brain development*

The Adolescent Brain Cognitive Development (ABCD) study presents an unprecedented opportunity for developmental scientists to investigate how changes in the brain across the second decade of life relate to the emergence of mental health disorders in adolescence. Several aspects of the ABCD study distinguish it from previous investigations of brain development, including its large, nationally representative sample (~11,500 children), longitudinal single cohort design, and data collection spanning measures from biological assessments to culture and environment.

While making data accessible presents a major step forward, it also opens up the possibility for counterproductive data mining and broad dissemination of false positive results. On a large dataset, traditional statistical approaches emphasizing null-hypothesis testing may yield findings that are statistically significant but lack practical significance (Orben & Przybylski, 2019). Questionable research practices, such as conducting many tests but only reporting the ones that reach a predefined level of statistical significance (i.e. selective reporting) and hypothesizing after the results are known, exacerbate these problems (Munafò et al., 2017), blocking progress toward obtaining meaningful insights into mental health. Functional MRI research has proven susceptible to non-replicable findings due to analytic and statistical errors (Bennett, Wolford, & Miller, 2009; Vul, Harris, Winkielman, & Pashler, 2009), but also because the analysis of fMRI includes several points of flexibility, which could elevate the number of false positives reported in the literature (Carp, 2012). These issues can be addressed by emphasizing transparency and reproducibility, including preregistration or registered reports of analyses conducted on pre-existing datasets, developing and sharing reproducible code, and using holdout samples to validate model generalizability. The piecemeal release on the

ABCD dataset provides a unique opportunity for researchers to engage in such important robust practices.

1.3. Registered study

While digital screens are regularly used by children of all ages, it is unclear how engaging with digital screens is related to neurodevelopment. The goal of the present study was to investigate how different profiles of digital screen engagement relate to functional brain organization in late childhood. We tested if functional brain organization is related to digital screen engagement and whether children with higher levels of screen engagement have functional brain organization profiles related to maladaptive functioning. In addition, we explored first steps in modelling causal effects over time. We discuss how the results of this investigation can inform ongoing scientific, policy, and public discussions concerning digital screens and children's brain development. Conducting this study as a registered report (https://osf.io/z4eyv) with shared analytic code applied to an openly accessible dataset further increases the replicability and reproducibility of this work.

1.4. Deviations from stage I

In the accepted Stage I Registered Report, we stated that we planned to use ABCD data release 1.1 and the subsequent baseline data. We planned an approach of relating digital screen engagement with brain network correlations and subsequently using these profiles to predict maladaptive functioning. These two steps were meant to be conducted on the first split of the first wave of data (Release 1.1); then, we had planned to replicate our models with the second split data (Release 2.0).

We followed the original analysis plan, but made use of the full data available to use at the time of analysis with one exception. Rather than running our models on the first half of the baseline sample and testing whether the models replicate on the second half of the baseline sample, we ran our models on the full first wave (baseline), and attempted to replicate on the full release of the second wave (two year follow-up). Separately, we also made use of the longitudinal aspect of the new release and we report new exploratory analyses which examine trends over time. This arm of the study uses graph theory to assess the impact of screen time on the network structure of functional brain organization over time. The analysis section and the analysis code present the full details of our approach.

2. Materials and method

We report how we determined our sample size, all data exclusions, all inclusion/exclusion criteria, whether inclusion/exclusion criteria were established prior to data analysis, all manipulations, and all measures in the study. The data under analysis for this study were drawn from the ABCD Study Data Release 4.0. The recruitment strategy for the ABCD study has been designed so that demographic characteristics of the sample is representative of the broader United States population of 9-11 year old children (Garavan et al., 2018). The ABCD Study Data Release 4.0 includes baseline data from 11,878 research participants, including minimally processed brain image volumes and tabulated structural MRI, diffusion MRI, resting-state fMRI and task fMRI results, as well as all non-imaging assessment data from the genetics, physical and mental health, neurocognition, substance use, biospecimens and culture and environment domains.

Data were collected across 21 sites in the United States, and the image acquisition protocols as well as the preprocessing are detailed extensively in Casey et al., 2018; Hagler et al., 2018. Imaging parameters were made as similar as possible across scanner manufacturers, outlined in: https://abcdstudy.org/images/Protocol_Imaging_Sequences.pdf. Participants completed a 2-h scanning session that included two structural (anatomical) MRI scans, one diffusion MRI scan, four resting state fMRI scans, and three sets of two task-fMRI scans. Relevant to the present analysis are the structural MRI and the resting state fMRI scans. The T1-weighted structural MRI scan was a 1 mm isotropic 3D T1w inversion prepared RF-spoiled gradient echo scan, and the resting state fMRI scan was a 2.4 mm isotropic, TR = 800 ms, multiband EPI with slice acceleration factor 6 (Hagler et al., 2018). All fMRI images were corrected for head motion using AFNI's 3dvolreg (Cox, 1996), corrected for distortions due to gradient nonlinearities, and remain in "native-space" with 2.4 mm isotropic resolution (Hagler et al., 2018). Resting state fMRI data then underwent additional processing steps including the removal of initial volumes, normalization, regression, temporal filtering, and calculation of ROI-average time courses (Hagler et al., 2018).

In accordance with our preregistration, to be included in the confirmatory, model-building part of this research, participants had to have at least 10 min of high quality resting-state functional connectivity data, which are necessary to obtain a stable measure of functional brain connectivity (Birn et al., 2013; Laumann et al., 2015). Specifically, participants had to have more than 10 min of data with a framewise displacement (FD) below 0.2 mm using the filtering technique employed by ABCD's Data Analysis and Informatics Center (DAIC), and without y-displacement (Fair et al., 2018), for all scans deemed as "OK" by the DAIC. Framewise displacement is calculated by summing the absolute values of the derivatives of translational and rotational motion estimates at each timepoint in the 4D functional image (Power, Barnes, Snyder, Schlaggar, & Petersen, 2012). Further, participants also had to have an anatomical brain scan that passed the DAIC quality control inspection (Hagler et al., 2018). We applied these data inclusion criteria to ensure that only high quality data are analyzed, and to minimize the possible impact of participant motion on our measures of interest (Power et al., 2012). Of the 11,878 participants, 86 did not have MRI scans, and 3,983 failed at least one benchmark, leaving a total of 7,809 participants for our confirmatory analyses.

The exploratory longitudinal network analysis required two separate timepoints of structural and functional MRI scans. 7,375 children had two scans of MRI data and were included. The inclusion criteria for longitudinal analyses were the same as the above, but participants had to pass the inclusion criteria at both timepoints. This left 4,042 participants

eligible for longitudinal network analysis. A full description of the inclusion pipeline is detailed in Fig. 1.

2.1. Explanatory variables

2.1.1. Digital Screen Engagement

Self-report estimates provided by participants were our predictor variables. Participants used a 7-point scale to estimate the amount of time they spent on each of a series of six digital activities on both "typical" weekday and weekend days; this ranged from "*None*" coded 0, "*< 30 min*" coded .25, "*30 min*" coded .5, "*1 h*" coded 1, "*2 h*" coded 2, "*3 h*" coded 3, and "*4+ hours*" coded 4. While this recoding introduces additional error, it was necessary to allow the question to be used as a continuous measure in the analyses. These six activities included 'traditional' screen pursuits such as watching "*TV shows or movies*" and using digital platforms to "*Watch videos (such as YouTube)?*", as well as interactive pursuits like whether the adolescents "*Play video games on a computer, console, phone or other device (Xbox, Play Station, iPad)?*". In addition to these activities, participants were asked about their use of specific technologies: how much they "*Text on a cell phone, tablet, or computer (GChat, Whatsapp, etc.)?*" and how much they connect with others using apps such as "*Video chat (Skype, Facetime, etc.)?*" and social media platforms ("*Visit social networking sites like Facebook, Twitter, Instagram, etc.?*").

2.1.2. Average functional brain connectivity between and within networks

Brain network connectivity constituted data for our analytical pathway examining which functional brain organization profiles were related to digital screen engagement, to ultimately examine whether these profiles were maladaptive. Brain network connectivity was therefore not the outcome of the study, but part of a predictive measure of maladaptive functioning.

The curated data release of the ABCD data provided the average correlation within and between regions of distinct functional brain networks as defined by the Gordon parcellation (Gordon et al., 2016). This parcellation divides the brain into functionally homogenous regions, with each region assigned to a distinct functional brain network (Fig. 2). As detailed by the ABCD DAIC in Hagler et al., 2018, the average correlation within a functional brain network is calculated as the average of the Fisher-transformed correlations for each unique, pairwise combination of regions belonging to a given network, and the average correlation between networks is calculated by averaging the correlations for each unique, pairwise combination of regions in the two networks of interest.

Across development, regions within the same functional network become more strongly connected, whereas regions between functional brain networks become less strongly connected—a process known as modular segregation (Bassett, Xia, & Satterthwaite, 2018). Measures of connectivity between functional brain networks can inform us about human cognition, development, as well as psychopathology. For example, decreased segregation between the default mode network and the fronto-parietal and salience networks is related to the presence of psychopathology in youth (Xia et al., 2018). Increased connectivity between valuation and cognitive control networks is related to temporal discounting preference in the transition to adolescence (Anandakumar et al., 2018). In the current study we specifically examined the average connectivity within and between the cingulo-opercular, default mode, dorsal attention, fronto-parietal, salience, ventral attention, auditory, visual, cingulo-parietal,

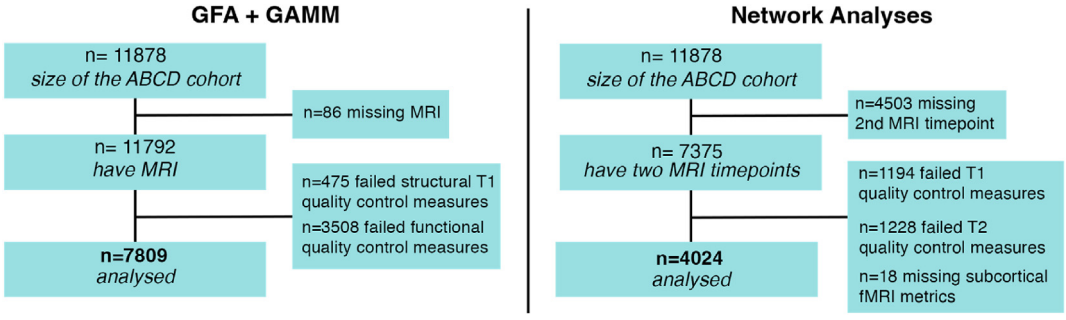

Fig. 1 – Schematic illustrating the reasons for exclusion for GFA + GAMM and network analyses. GFA: Group Factor Analysis; GAMM: Generalized Additive Mixture Model.

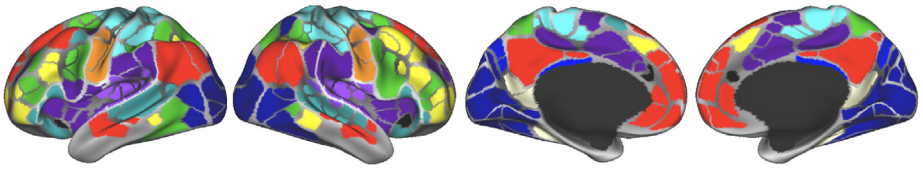

Fig. 2 – Distinct segments of the cortex as defined in the Gordon parcellation. Colors represent functional network communities e.g., Visual (dark blue), Dorsal somatomotor (light blue), Ventral somatomotor (orange), Auditory (light purple), Default (red), Fronto-parietal (yellow), Dorsal attention (green), Cingulo-opercular (purple), Ventral attention (teal), and Salience (black). Figure from Gordon et al., 2016.

retrosplenial temporal, sensorimotor hand, and sensorimotor mouth networks as they relate to digital screen engagement. Profiles of the relationships between these networks and digital screen engagement were examined through Group Factor Analysis, as detailed below. The outcomes of this analysis were then related to adaptive/maladaptive functioning in a later processing step. We included the sensorimotor mouth network in the present analysis as a control network, and we did not expect the within network correlation nor any of the between network correlations with the sensorimotor mouth network to relate to digital screen engagement.

2.2. Criterion variables

2.2.1. Mental health

Caregivers of ABCD participants complete the Child Behavior Checklist (CBCL) to assess child mental health (Achenbach, 2009). We examined the CBCL t-scores of externalizing, and internalizing syndromes scales. The internalizing scale of the CBCL includes the anxious/depressed, withdrawn-depressed, and somatic complaints syndrome subscales, and the externalizing scale includes the rule-breaking and aggressive behavior syndrome subscales.

2.2.2. Cognition

The ABCD study includes measures of several cognitive processes, including episodic memory, executive function, attention, working memory, processing speed, language abilities and fluid reasoning (Luciana et al., 2018). We assessed the relationship between digital screen engagement, rs-fcMRI network correlations, and eight distinct cognitive processes assessed through tests administered to participants (detailed in Table 1).

2.3. Control variables

Research examining how children and adolescents use digital devices indicates a number of background factors shape how they approach a wide range of screen-based technologies (Parkes, Sweeting, Wight, & Henderson, 2013). Measuring variabilities in these constructs is key to disentangling their influence on key developmental and psychological outcomes as well as identifying the unique effects we might ascribe to technology engagement proper. Therefore, when modeling the relationships between digital screen engagement – rs-fcMRI network correlation factors and functional outcomes, the following will be included as predictors in the first step of our regression models (detailed in the analytic plan below): sex assigned at birth, ethnicity, age of child and caregiver education. Caregiver education allows us to control for characteristics that have previously been found to influence child outcomes (Desai, Chase-Lansdale, & Michael, 1989).

2.4. Consideration of outcome neutral conditions

We expected the self-reported weekday and weekend screen time activities to be intercorrelated. In other words, we expected that: a) screen time measures in general will positively correlate with one another and b) that the items related to social communication (texting, video chat, and social network site usage) will show strong correlations among themselves compared to items related to passive viewing (watching television or movies and watching online videos). In turn we expected the items related to passive viewing to be strongly correlated among themselves as well. Effect sizes were the primary measure of interest in the current study. Although fMRI analysis techniques can inflate effect sizes, especially in small samples (Geuter, Qi, Welsh, Wager, & Lindquist, 2018, p. 295048; Vul et al., 2009), the ABCD dataset is large enough to minimize this inflation and detect brain-wide associations (Marek et al., 2022). However, there is a lack of literature detailing a minimum effect size of interest when relating functional brain network connectivity to screen engagement. Consequently, correlations less than .20 were operationalized as background noise (vs. signal) (Ferguson, 2009). This means that digital screen engagement associations that explain less than 4 % (i.e. $r^2 < .04$) of functional brain network connectivity were judged as being too modest in practical terms to be worthy of extended scientific discussion. By anchoring our smallest effect size to screen engagement effects in self-report literature (which are in the realm of $r = .20$), our hypothesis tests allowed us to examine whether the effect we observed on brain-related outcomes was larger or smaller than self-report outcomes. 95 % confidence intervals that are inferior to this standard were identified as a null result that disconfirmed the hypothesis, whereas 95 % confidence intervals that are superior to this standard would demonstrate strong support for the hypothesis and any 95 % confidence intervals overlapping with this standard would demonstrate weak support for the hypothesis.

2.5. Analytic approach

Our primary analytic approach for our confirmatory analyses was split into two parts: 1) relating digital screen engagement

Table 1 – Selected outcomes from the neurocognitive battery. All tests are part of the NIH Toolbox.

Test name	Underlying construct
Dimensional Change Card Sort Test (Ages 8–11 v2.0)	Executive Functioning (Zelazo, 2006)
Flanker Test (Ages 8–11 v2.0)	Inhibitory Control and Selective Attention (Zelazo et al., 2014)
Picture Sequence Memory Test (Age 8+, Form A, v2.0)	Episodic Memory (Dikmen et al., 2014)
Pattern Comparison (Age 7+, v2.0)	Processing Speed (Carlozzi et al., 2015)
List Sort Test (Age 7+, v2.0)	Working Memory (Tulsky et al., 2014)
Oral Reading Recognition Test (Age 3+ v2.0)	Reading Decoding (Gershon et al., 2014)
Picture Vocabulary Test (Age 3+, v2.0)	Vocabulary Comprehension (Gershon et al., 2014)
WISC-V Matrix Reasoning Total Scaled Score	Fluid Intelligence (Sudarshan et al., 2016)

with brain network correlations and 2) relating these profiles with maladaptive functioning. A third, exploratory step examined the impact of screen engagement on changes in the network structure of the brain over time. For the first step, we applied a group factor analysis (GFA) with self-report digital screen engagement and resting-state brain network correlations (within and between prespecified networks). Group factor analysis provides linear factors that describe relationships between groups of related variables that differs from a traditional factor analysis by prioritizing between-group factors (Klami, Virtanen, Leppäaho, & Kaski, 2015). This approach was employed by the first study published using the ABCD dataset to examine brain measures and digital screen engagement (Paulus et al., 2019). Applying this approach to the current study increased interpretability of the findings and allowed for comparisons across brain measures. Paulus et al., examined how *brain structure* (e.g. cortical thickness, surface area, and sulcal depth) related to digital screen engagement using GFA, whereas the current study investigated how *functional brain connectivity* related to digital screen engagement. While structural brain measures showed overall low correlations with digital screen engagement, GFA revealed factors with loadings that included both structural brain measures and digital screen engagement (Paulus et al., 2019). To keep consistent with the threshold applied in Paulus et al., 2019, only GFA factors that accounted for >1 % of the variance across screen time and rs-fcMRI network correlations groups were used in the second step, namely analyses examining the relationship between factors and functional outcomes.

In this second step of our analytic approach, these factors were then modeled as predictors of functional outcomes using Generalized Additive Mixture Modeling (GAMM). We first examined a null model that included relevant covariates (sex assigned at birth, ethnicity, caregiver education, and age of the child) as fixed effects with data acquisition site and family used as random effects. We then compared these null models to models including digital screen engagement − rs-fcMRI network correlation factors. Parameters were estimated using Maximum Likelihood Estimation. The best fitting model was determined by Akaike Information Criterion (AIC) and likelihood ratio (LR) statistics using the heuristic of parsimony. That is, the model with the lowest AIC value that was significantly different ($p < .05$), as determined from LR tests, from less complex models was chosen. These parameters of interest from these models were then interpreted.

As outlined above, here we deviated from the original phase 1 analysis plan to make the most of the available data. Originally, we planned to run these models for participants within the first release of data (ABCD Release 1.1), and tested again on the participants in the second release of data (ABCD Release 2.0). Any effects that did not replicate in the second release would be interpreted as false positives obtained from the first release. The current study still followed this plan but expanded its scope by running the models on the full baseline dataset, and then testing the models again on the two-year follow-up dataset. In essence, the current study made use of an extra wave of data to conduct more powerful hypothesis tests using more data to inform our findings. Furthermore, our original analysis was planned for cross-sectional observational data; therefore, we did not interpret any brain pattern as reflecting "harm," as it is not possible to infer the direction of the effects observed here, just relationships. We only interpreted certain brain patterns as problematic if they were related to lower levels of mental health or cognitive abilities. To augment this approach, we added an exploratory analysis section making use of the longitudinal nature of the new data release.

Our first set of exploratory analyses employed graph theory analysis to assess whether changes in the network structure of brain connections over a two year period were impacted by screen time. To conduct a longitudinal analysis, network graphs were constructed in accordance with Tillem, Conley, and Baskin-Sommers (2021). Each of the 13 cortical networks included in the ABCD dataset was coded as a single node and the correlations between networks were operationalized as edges. rsfMRI correlations to all the subcortical regions were averaged, creating a single node of subcortical structures. This resulted in 14 nodes in a fully connected graph.

Graphs were assessed with clustering (a measure of global separability of communities in the network), max degree (denoting the node with the highest number of connections to other nodes, acting as an integrator for the network), efficiency (assessing signaling between nodes that minimizes the number of edges), and max betweenness centrality (the node with the most centralized location, delineating a hub of the network). Operationalizing the functional connectome as a network offers a number of analysis opportunities that can be used to longitudinally model change. To assess clustering, max degree, efficiency, and betweenness centrality for each participant, graphs of differing densities were constructed, simulating differing assumptions of sparsity in the brain network. Each participant began with a minimum spanning, fully connected graph created using Kruskal's algorithm (Kruskal, 1956). There were 196 (14x14) possible edges connecting these nodes, so to simulate differing levels of sparsity, edges were added sequentially in order of their strength (Fisher's r-to-z score). The top 1 % of nodes were added, then each network characteristic was calculated before adding another 1 % of nodes and repeating the analyses. This process repeated until the top 40 % of nodes were represented in the network. Fig. 3 outlines this process with an example and shows how features of the network like a two-module community of networks can evolve over this process.

This process extracted 40 values of clustering, max degree, efficiency, and betweenness centrality for each participant. These were plotted, and the area under the curve (AUC) for each metric was calculated, producing a single value per metric, per participant.

Tillem and colleagues examined the effects of conduct disorder symptomology on functional network characteristics in a single timepoint. This study expands upon their analysis by creating functional connectome network simulations at two timepoints. Thus, the difference between each metric at timepoint 1 and 2 was regressed in a generalized linear mixed model against total averaged screen time alongside standardized covariates for age, sex, race, parental marriage, parental income, parental educational history, site ID, and twin status like the GAMMs. Because the distribution of screen time within the population was positively skewed, the data were square root transformed prior to analysis (see OSM-3).

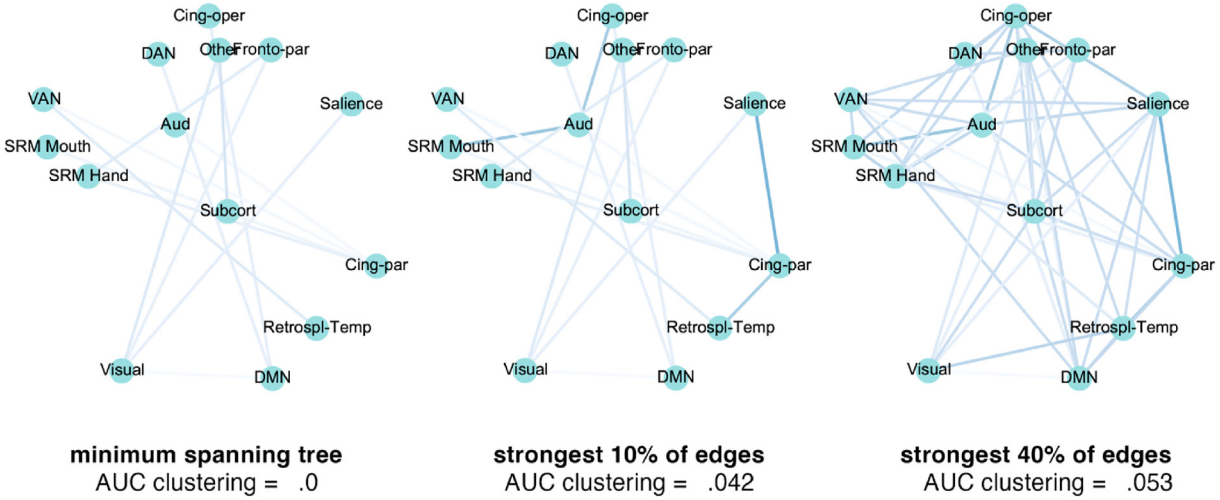

Fig. 3 – Sparsity constraints in the network modeling.

Network measures were natural log transformed prior to regressions in line with the past literature predicting these metrics (Tillem et al., 2021; Gonzalez et al., 2016). Only participants with two processed MRI scans were included ($n = 4024$). Subtracting connectivity network metrics from the first timepoint from metrics of the second timepoint provided a within-subjects difference score for each metric, which were regressed against ST.

Our second exploratory analysis was conducted in response to a reviewer at the second stage of the registered report review. The reviewer noted that academic and popular debates concerning the associations between digital technology use and youth outcomes have changed since the time since the stage one review was conducted. In particular, interest in associations between digital screens generally and youth outcomes has shifted to a focus on time spent on social media. In line with this recommendation and our own reading of the literature, we added additional analyses examining the associations between time spent on social media and all study outcomes to our study. These analyses extended the same GAMMs and covariate measures from the first part of the study, predicting cognitive and wellbeing outcomes at the 2-year follow-up from average weekly social media usage at baseline. Inclusion criteria were the same as the original, preregistered analysis.

3. Results

In the following, we present our results in five steps. First, we present the results of the screen time usage of children in the study and characterize the correlation between digital screen engagement variables. Second, we present the relations between digital screen engagement and brain network correlations (through GFA). Third, we assessed the relationship between brain network profiles and maladaptive functioning by using GFA scores to predict cognitive and wellbeing outcomes. Next, we used the recently released second timepoint (two-year follow-up; Release 4.0) to explore how screen time might impact the development of a functional connectome. Finally, we use the second timepoint again to measure the impact of social media in isolation from other screen time and brain network variables.

3.1. *Screen time behavior*

The 11,309 participants with valid screen time data reported a weekly mean screen time of 26.50 h (SD = 21.52). As expected, all individual screen activities were positively correlated with each other. For descriptive results on participant demographics, their screen time, and functional connectivity, see the online supplementary materials (OSM-1).

3.2. *Relationship between digital screen engagement variables and brain network correlations*

To extract profiles of screen media activity and functional connectivity, we ran a group factor analysis (GFA). The GFA identified 67 latent variables explaining the variance of screen engagement and neural measures. Three of the latent variables explained more than 4 % of the variance and thus were included in the rest of the analyses in accordance with the preregistered analysis plan (https://osf.io/z4eyv). Collectively, these three components explained 22.7 % of the total variance between the groups and were highly orthogonal. Fig. 4 shows that one of the GFA groupings (factor 3) explained variance exclusively using resting state network data. Thus, in accordance with the registered plan, this factor was excluded from analysis, leaving a total of two GFA groupings of screen time and functional network variables.

To aid in the interpretability of these groupings, we discuss general trends in factor loadings of the remaining two GFAs. Because each GFA grouping represents an entire network connectome, factors with high magnitude as well as general network-level trends are discussed. Figs. 5 and 6 depict the full sets of factor loadings in each grouping. While reporting, "significant" factor loadings are ones in which the 95 % confidence interval for the loading lies outside the mean of the metric, although this is done without correction for multiple comparisons and thus should be treated with caution.

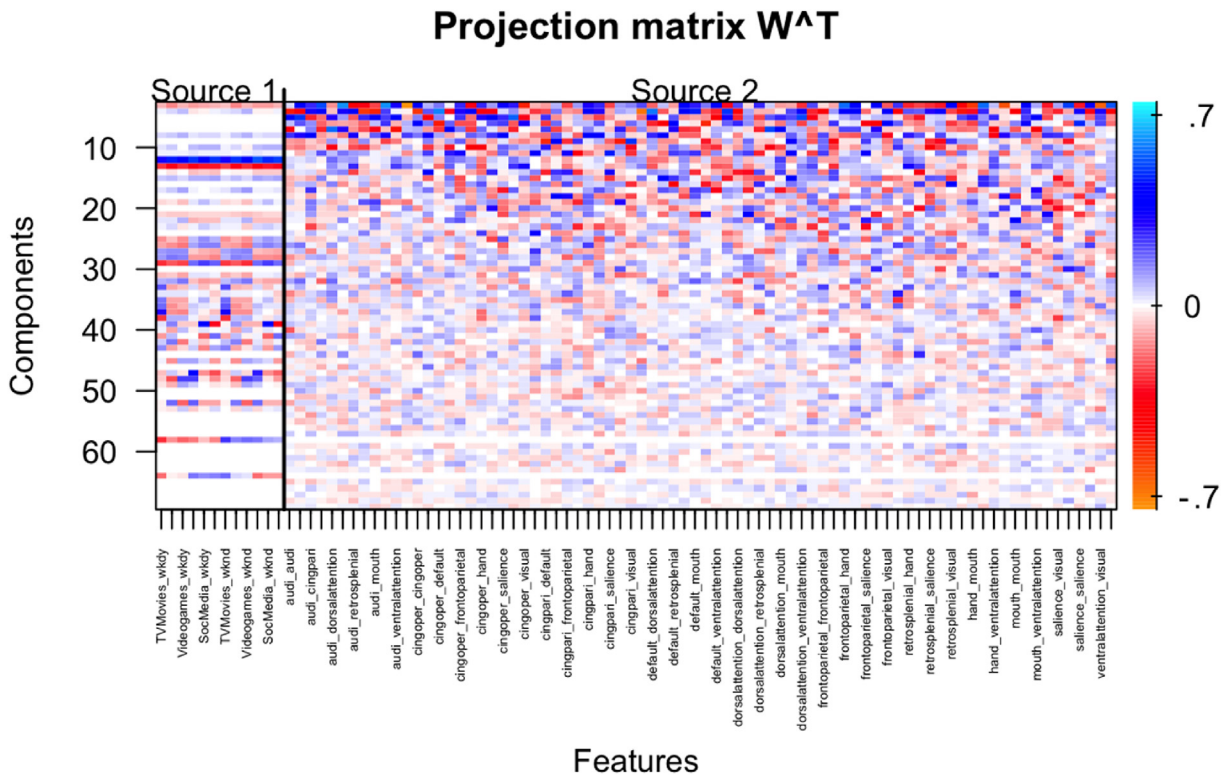

Fig. 4 – GFA matrix showing factor loadings of each GFA grouping. Each rectangle represents a screen time or functional connectivity metric, with blue rectangles denoting positive correlations and red networks denoting anticorrelations.

GFA grouping 1 (Fig. 5) explained 9.34 % of the variance in the GFA variables. The factor loaded negatively onto all screen media activity variables. Within the functional connectivity metrics, there was high connectivity to and within the ventral attention network. In general, the default mode network had high connectivity with other networks, and the visual cortex had several very low connectivity metrics with other networks, most chiefly with the auditory network.

GFA grouping 2 (Fig. 6) explained 8.56 % of the total variance and loaded positively onto videogame play during the weekdays and weekends. The factor showed a clear pattern of differential within-network connectivity. Every network except for the salience network had lower-than-average within-network connectivity, indicative of slightly less modular structure of separable networks. This structure is further exemplified with large positive factor loadings between functionally separable networks like between the dorsal and ventral attentional networks and between the DMN and the DAN.

Crucially, the second timepoint of full data enabled us to test the robustness of these groupings. GFAs create profiles connecting screen media habits to neurological profiles. If these factors were representative of a brain-behavior neurodevelopmental trajectory, we would expect them to replicate across neurodevelopment. However, a separate GFA conducted on the same participants in the two-year follow-up data showed that these profiles of screen media activity and functional connectivity were not stable across a two-year period. Though parts of the structure of GFA 1 were replicated at the second timepoint, functional connectivity loadings varied, and GFA 2 did not persist to the second timepoint (see OSM-2) For a fully detailed comparison).

3.3. *Relations between brain network profiles and maladaptive functioning*

To assess whether the GFA factors predicted wellbeing or cognitive outcomes, we estimated a series of generalized additive mixed models (GAMMs). Despite being short-lived as a potential organizing factor, the wellbeing and cognitive predictiveness of these factor groupings were assessed with a GAMM and tested against a "null" GAMM that included only covariates featured in both models: sex, ethnicity/race, parental education (as a continuous variable representing number of years), parental age, parental marriage status, age, and annual family income (in four strata). Only cases with complete data for every covariate and outcome variables were included in the GAMMs. Missing data was mainly a result of missing cognitive test result data. Before each model, the sample size of included participants with full data is reported. Because 12 separate sets of GAMMs were compared against null models, model and coefficient significance was set at (.05/12 = .004).

3.4. *Mental health outcomes*

In line with our analysis plan, we analyzed the Child Behavior Checklist divided into internalizing (anxious/

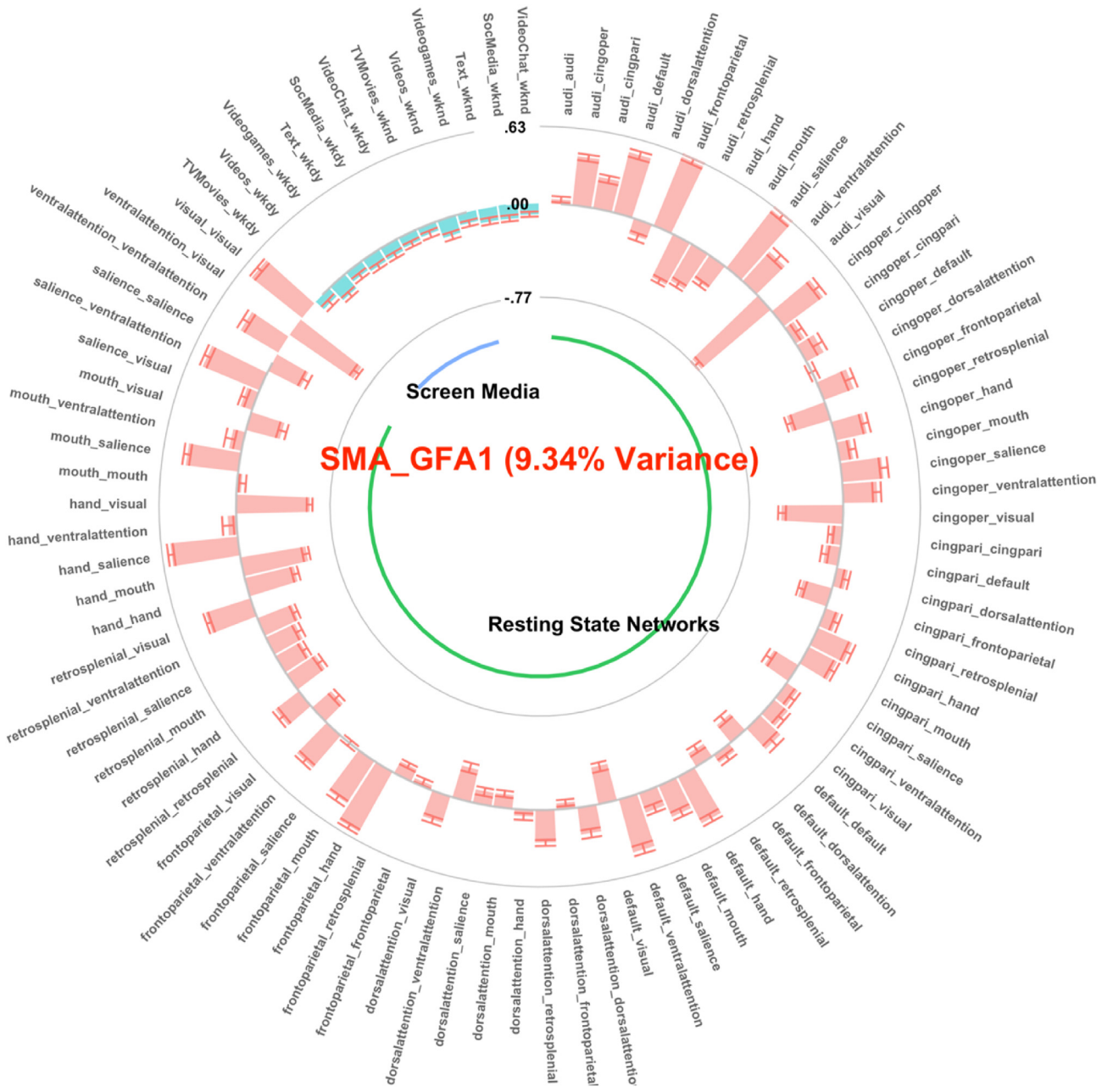

Fig. 5 – Factor loading with 95 % confidence interval for GFA grouping 1. Screen media variables are shown in blue, while functional network metrics are shown in red. The central circle represents the normalized mean of each construct, and error bars represent 95 % confidence intervals.

depressed, withdrawn/depressed, and somatic complaints scores) and externalizing (rule-breaking and aggressive behavior) symptomatology to further examine whether including screen media engagement in our models had predictive power.

Including GFAs in the model did not improve predictive performance of the GAMM for either mental health metric. Summary statistics for each model are reported in Table 2, and a visual representation of the standardized effect of each GFA on each wellbeing metric is shown in Fig. 7.

3.5. *Cognitive outcomes*

Of the eight cognitive outcome metrics, GFAs only improved prediction on one of the models: picture vocabulary. Including GFAs in the picture vocabulary model improved predictiveness from 18.4 % to 18.7 %. Though the first GFA factor was a significant predictor in the model ($\beta = .052$, $p < .001$), the second GFA factor was not ($\beta = .02$, $p = .057$).

All of the remaining seven models of outcome variables (episodic and working memory, reading, inhibitory control and selective attention, processing speed, executive functioning,

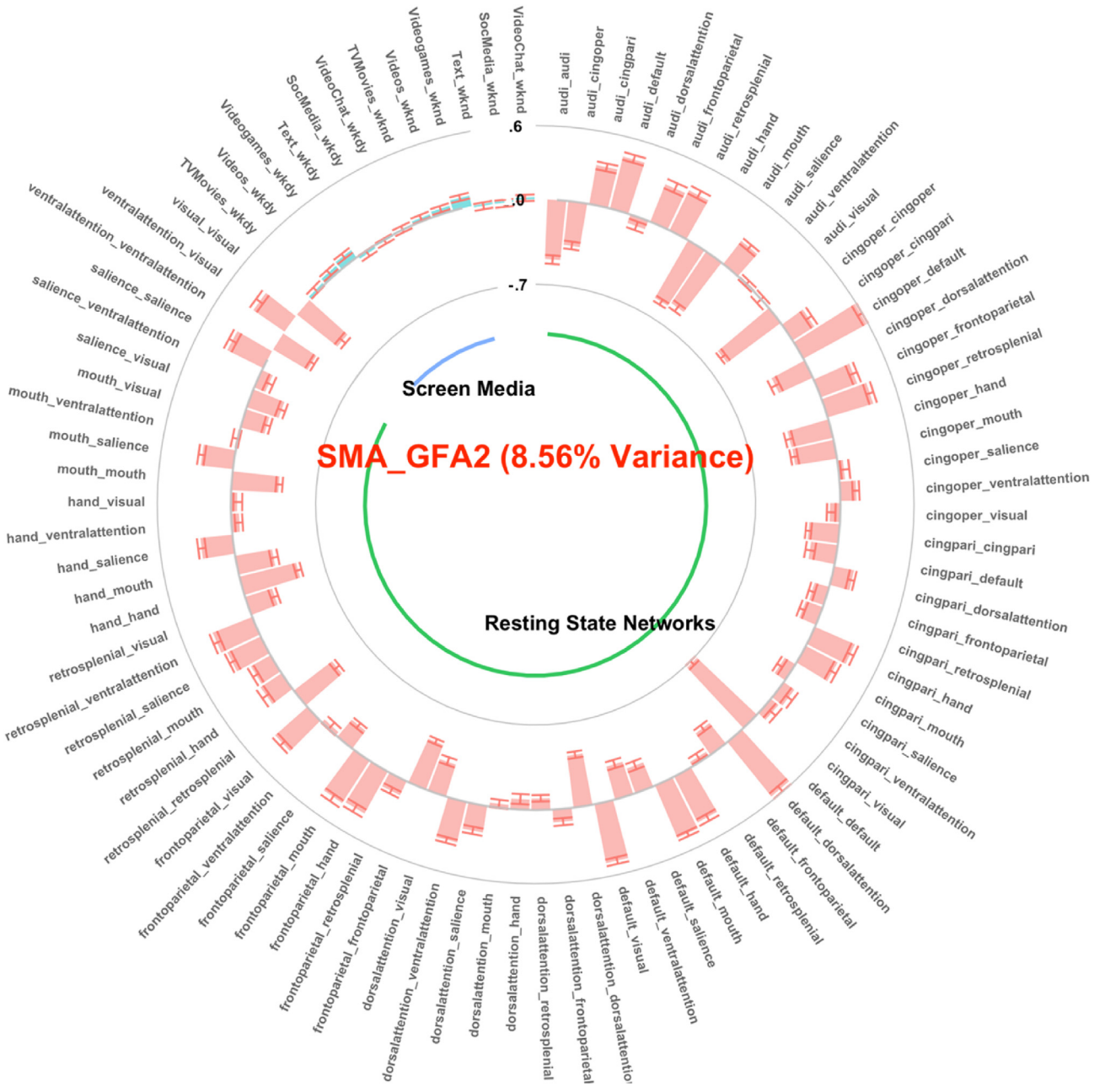

Fig. 6 – Factor loading with 95 % confidence interval for GFA grouping 2. Design of the plot is analogous to Fig. 5.

Table 2 – Predictive Power of GFAs in Mental Health Outcomes. AC = accounted covariance.

	n	AC_{NULL}	AC_{GFA}	*p*
Internalizing	7714	.0265	.0273	.08
Externalizing	7714	.0367	.0365	.94

and intelligence) were not improved by adding the GFAs. The models are summarized in Table 3 and presented visually in Fig. 8.

3.6. *Exploratory analyses of changes in network over time*

To assess longitudinal change, we calculated a series of metrics to characterize functional neurodevelopment. First, we examined whether these metrics changed over a two-year period, essentially to measure the substantial neurodevelopment that had occurred over this time. We then tested whether screen media activity had a significant predictive power accounting for variation in these neurodevelopment markers.

3.6.1. *Changes in networks between timepoints*

Collectively, the network measures suggest segregation (clustering) and integration (max degree, efficiency, and betweenness centrality) of the different brain networks, with higher values on each denoting a more mature functional architecture. Each of the network statistics positively correlated between timepoints, showing that, on average, by these metrics, children's functional connectomes developed in the two years following their baseline functional MRI scans.

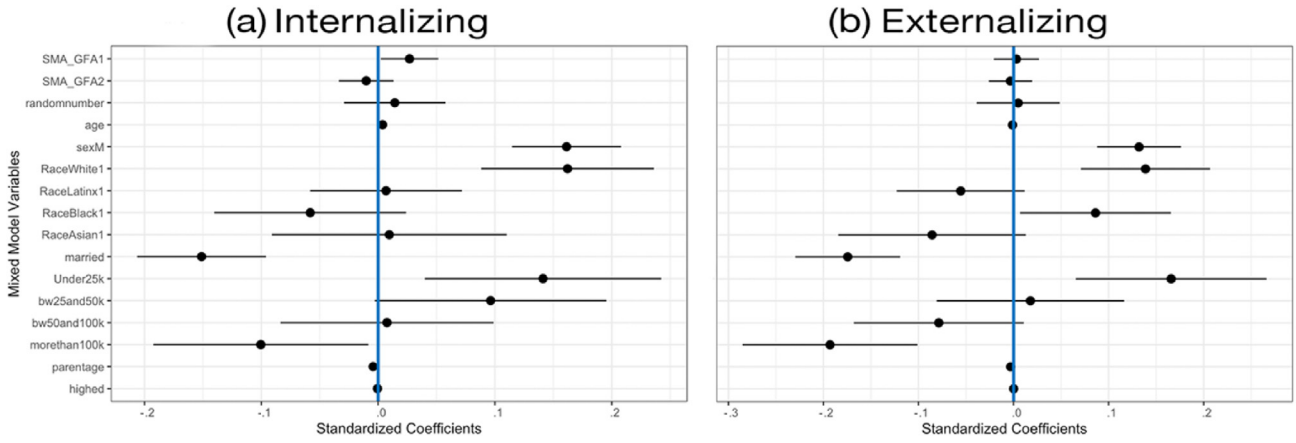

Fig. 7 – Standardized coefficients of the GAMMs predicting mental health outcomes for internalizing (a) and externalizing (b) behaviors. Lines represent 95 % confidence intervals. Coefficients (from top to bottom) are: the two GFA factors, a random number variable intended to contextualize the effect size, age, sex, race, parental marriage status, family income, parental age, and parental education achievement.

Table 3 – Predictive Power of GFAs in Cognitive Outcomes. AC = accounted covariance.

		n	AC_{NULL}	AC_{GFA}	*p*
Memory	Picture Sequence	7629	.0547	.0546	.68
	List Sort	7605	.0826	.0824	.60
Reading	Oral Reading Recognition	7630	.0888	.0883	.49
	Picture Vocabulary	7635	.184	.187	<.001*
Executive Functioning	Flanker Task	7632	.0291	.0295	.06
	Pattern Comparison	7616	.0347	.0344	.04
	Card Sort Task	7631	.0419	.0421	.08
Fluid Intelligence	Matrix Reasoning Task	7559	.0909	.0911	.15

Importantly, there was considerable variation within the networks, and no regression explained more than 5.2 % of the total variation in network scores at the second timepoint. Full statistics of the between-timepoint regressions are shown in Table 4, and Fig. 9 depicts the associations visually.

3.6.2. *Predictiveness of screen time*

Fig. 10 shows kernel density estimation (kde) plots that visualize the association between changes in the network statistics over time with total weekly screen time. In general, across network metrics, there were not very strong associations between the shape of the networks over time and screen media use. A series of generalized linear mixed models using the same covariates as the GAMMs tested the predictiveness of ST on these associations statistically. In the models predicting all four network metrics, screen time was not a significant predictor and showed an extremely modest effect size (β between .0067 and .025). Full details of each model can be found in the Online Supplement.

3.7. *Exploratory analyses of social media on study outcomes*

Although results from the full GAMMs with all six engagement measures did not provide a strong basis for believing any single screen-based activities had differential associations with youth outcomes, we conducted a parallel series of analyses using only time spent using social media platforms as a predictor at the request of a reviewer. These analyses provided β's ranging from .013 to .026, detailed fully in the S.O.M. (OSM-4), and indicated that estimated time spent engaged with social media had no statistically significant associations above the smallest effect size of interest threshold with cognitive or wellbeing outcomes. Although it is a tentative result derived from testing an exploratory question motivated by a request from a reviewer, it nonetheless provides an interesting datapoint for those debating the putative harmful effects of social media on young people.

4. Discussion

Adolescence is a period of rapid cognitive change accompanied by systematic changes in the structural (Mills et al., 2016) and functional (Luna, 2017, pp. 29–35) composition of the brain. As children grow, they develop an emerging connectome of functional brain networks that underpin the development of higher order cognitive constructs like cognitive control (Marek, Hwang, Foran, Hallquist, & Luna, 2015), executive functioning (Baum et al., 2017), and sustained attention (Rosenberg, 2016). As the prevalence of digital devices among children has increased (Ofcom, 2015, 2019), the ways in which screen time could alter these neurodevelopmental trajectories has received considerable

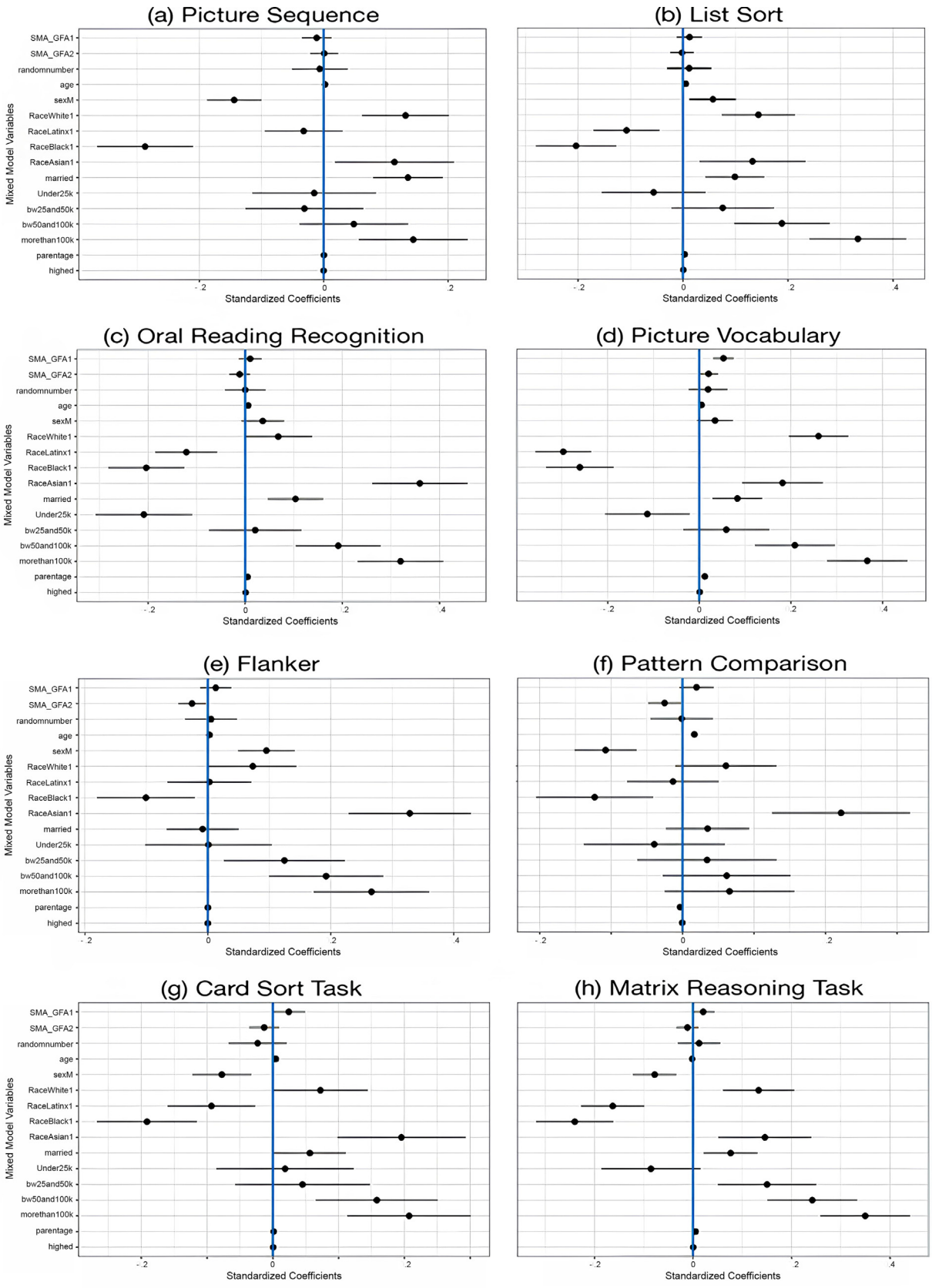

Fig. 8 – Standardized coefficients of the GAMMs predicting cognitive outcomes. Lines represent 95 % confidence intervals. Coefficients (from top to bottom) are: the two GFA factors, a random number variable intended to contextualize the effect size, age, sex, race, parental marriage status, family income, parental age, and parental education achievement.

Table 4 – Results of linear regression between timepoints of network statistics.

Network metric	*β for timepoint 1*	*p*	R^2 for regression
Clustering	.0855	<.001	.007
Max Degree	.3007	<.001	.090
Efficiency	.2280	<.001	.052
Betweenness Centrality	.0861	<.001	.007

academic inquiry. Due to studies with small sample sizes, unidimensional screen time variables, and a lack of adequate covariate considerations, there is no clear consensus on the impact of screen media activity on development.

Using the ABCD dataset of over 10,000 children across the US, we set out to rigorously test the extent to which functional brain organization is related to screen activities and determine if these associations might be practically meaningful. Our analysis of the data indicated that concerns about a general effect across young people are not supported. We identified two groupings with different patterns of screen media activity and functional connectivity.

Though one group had higher screen time, these patterns of screen-based media use did not improve our predictions of key outcomes in our preregistered or exploratory analyses. The first factor grouping was associated with low screen engagement on all ten metrics, and a highly connected ventral attention network. The second factor loaded positively onto videogame play during weekends and weekdays and was associated with slightly less functional separation of brain networks. Though prior work using GFA on neurostructural metrics (Paulus et al., 2019) showed relatively consistent factor loadings within each GFA profile, this study revealed that factor loadings in the functional domain are much more varied.

These factors improve upon past research in this area by encompassing 10 modalities of screen usage while also using a large sample of children with a normal range of screen usage. However, the two extracted profiles only explained 17.9 % of variability of screen time and functional connectivity and failed to replicate in the same sample two years later, demonstrating the instability of the brain behavioral profiles created in the GFA process. There are two possible explanations for the failure to replicate across a two-year time period: (1) the profile of screen media activity is not a meaningful

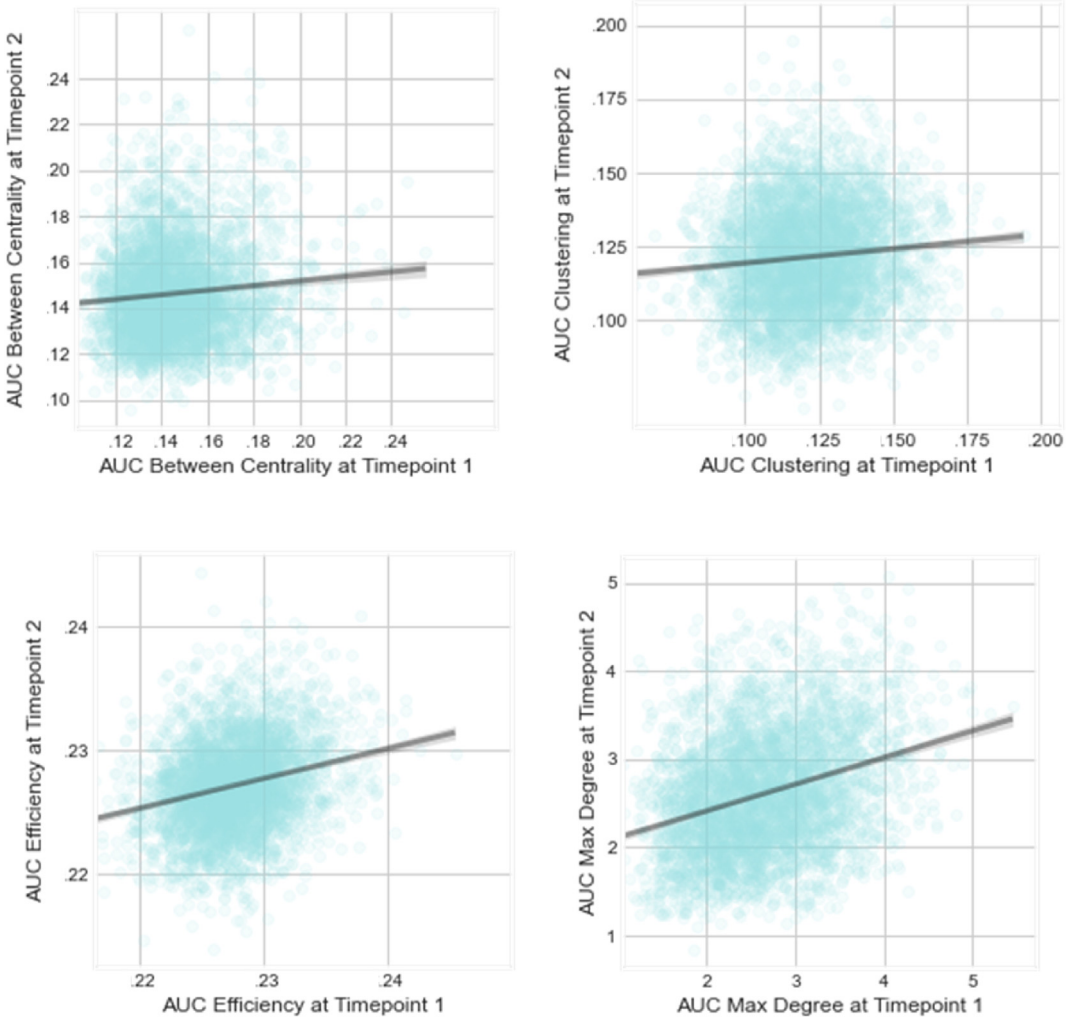

Fig. 9 – Scatterplots between timepoints for the different network statistics.

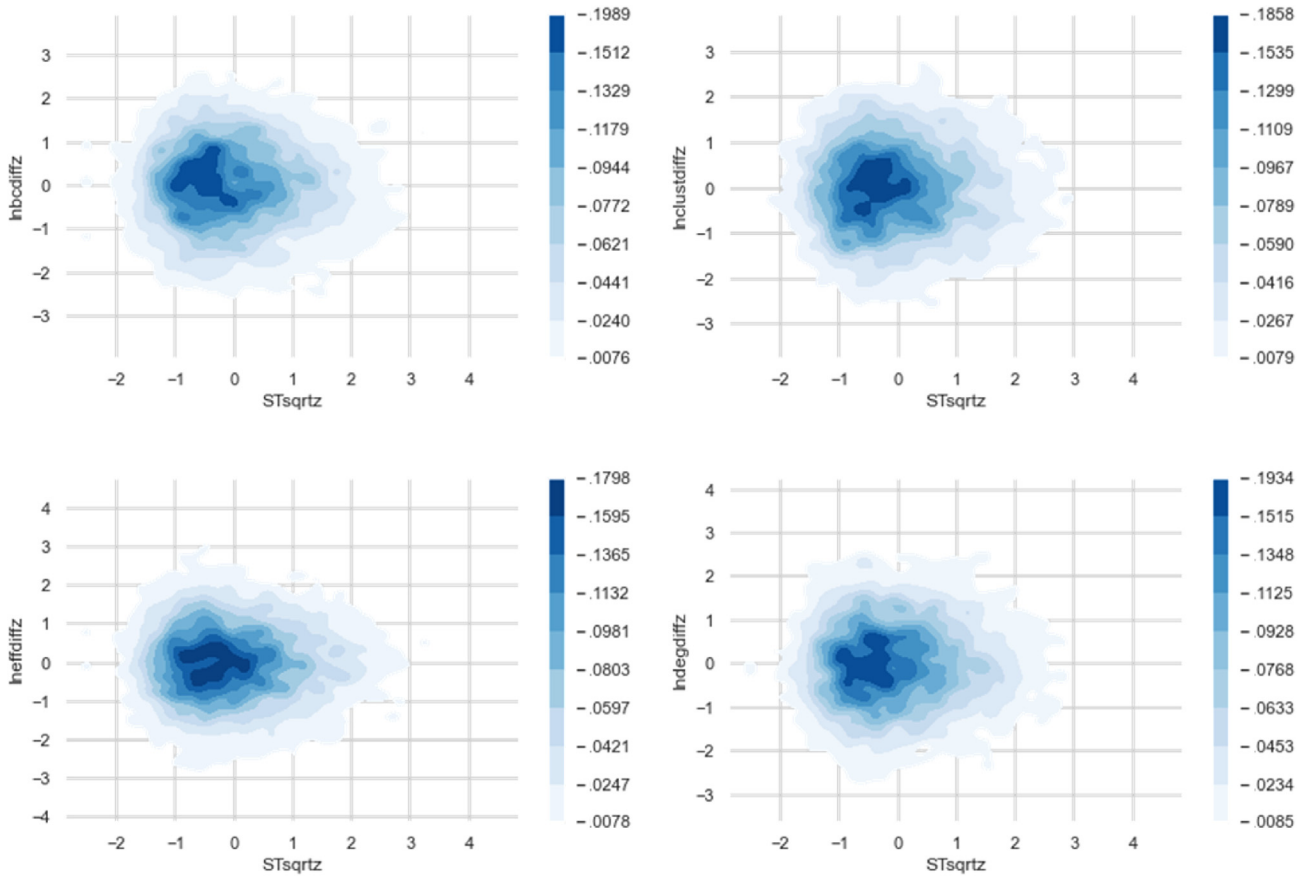

Fig. 10 – Kernel density plots showing the distribution of data for between-timepoint network statistics (natural log transformed) and total weekly screen time (square root transformed). Darker blue areas contain more data.

organizer of functional connectome or (2) there are non-linearities in the relationship between screen media and neurodevelopment that cannot be captured in two timepoints. Together, these results provide a clear pattern of results that do not support the idea of "screens changing brains" in young people in a consistent or enduring way as many have proposed.

If screen time impacted the cognition of children, we expected these GFA profiles to predict observed variability across a variety of cognitive and wellbeing outcomes. A series of generalized additive mixed models showed that GFA groupings only improved prediction on one of the ten outcome variables. Thus, even if there were profiles of screen engagement and neurodevelopment, these were not meaningfully related to most cognitive and mental wellbeing outcomes. A study of this size is powered to detect even very small associations, so the fact that the groupings were not significantly predictive in 9 of 10 models is interesting in its own right. The only significant association, GFA grouping 1 on picture vocabulary scores, had a standardized effect size (β) of .052, which did not exceed the smallest effect size of interest we set for testing our confirmatory hypotheses. Even when including covariates like socioeconomic status and race, GAMMs were able to explain only between 2.73 % (internalizing) and 18.7 % (picture vocabulary) of total variance in the outcomes. These effects are particularly small in context; a parallel study delineating patterns of functional connectivity to psychopathology shared between 46 % and 50 % of observed variability (Xia et al., 2018). Contextualizing the effect sizes of the GFA groupings with the covariates demonstrates how small these effects are, although we are cautious to commit Table 2 Fallacy and directly compare the impacts (Westreich and Greenland, 2013). These underscore the need for researchers investigating the potential pathways linking technology to neurodevelopmental outcomes to carefully consider and formalize how they envision covariates figure into the causal models they test (Magnusson, Johansson, & Przybylski, 2023). That understood, these results show that after considering a couple of demographic factors like socioeconomic status, gender, and race, screen time and functional connectivity are not substantively associated with several important cognitive and behavioral outcomes.

To further assess potential directional effects, we conducted an exploratory analysis examining whether screen time could account for variance in changes in the network dynamics of the brain over a two-year period. Adapting the analysis structure from Tillem, Conley, and Baskin-Summers (2021), we derived networks from the functional connectivity statistics. From these networks, we estimated the neural development of participants, summarized with four metrics encompassing the segregation and integration of their brain networks. Though each of the four metrics changed over a

two-year period, neural development was not associated with screen engagement. Because this is a non-experimental investigation, we cannot directly test causality, but the absence of any correlation is a clear indicator that a causal relationship between screen engagement and functional brain organization over a two-year period is unlikely in this sample.

Taken together, the two analyses conducted in this study do not point towards a practically significant relationship linking screen media engagement and maladaptive neurodevelopment cross-sectionally or over time. This even appeared to be the case where we specifically investigated the associations between social media use and outcomes at the request of a reviewer who expressed interest in us testing this specific hypothesis. Thus, our findings do not support broad-stroke policies centered on the notion that limiting screen time in general, or social media specifically, could plausibly protect neurocognitive development for young people similar to those participating in the ABCD (i.e.with similar backgrounds: in the United States, in early adolescence from 2016 to 2020). This pattern of findings lends further support to the idea that negative effects of screen engagement may only arise by way of more complex developmental pathways of risk and resilience (Orben, Przybylski, Blakemore, & Kievit, 2022). Uncovering these dynamics will require a sustained investment in research infrastructure to determine how young people are doing with digital technology and internet platforms (Johannes, Masur, Vuorre, & Przybylski, 2021; Przybylski et al., 2021). Moving from questions concerning how much to those about how, why, and what young people use technology for. This was not and could not have been examined in the present study.

Furthermore, although the ABCD is a uniquely rich and detailed dataset and our analysis is exhaustive our efforts in this study might not be sufficient to address the totality of the question of how these ten kinds of screen based engagement relate to neurodevelopment in late childhood. It is indeed possible that observable changes might only be significant across shorter or much longer time scales. Because there is a lack of adequately powered studies of functional connectivity, this examined whole-brain changes to explore many possible patterns of risk, which might obfuscate smaller, individual network-based effects. Future studies should use explicit causal modeling to examine specific network-based developmental effects. Additionally, we relied on self-report data, which can sometimes misrepresent actual usage (Burnell, George, Kurup, Underwood, & Ackerman, 2021; Hodes & Thomas, 2021), particularly among children (Koojmans, Langdon, and Moonen, 2022). Future study could enrich data sources like ABCD with digital trace data that more accurately reflects the ways that young people are interacting with screen-based media.

5. Closing

The impact of screen engagement on neurodevelopment in children and adolescents has been a topic of much inquiry. We examined how screen engagement relates to functional brain connectivity in a large sample of U.S. children between ages 9–12 years. While patterns of functional brain connectivity were related to pattern of screen engagement, we found no meaningful associations between overall profiles and measures of cognitive and mental wellbeing, even if we set the evidential threshold very low. Overall, this study does not support policies centered around limiting screen time to protect neurocognitive development.

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Data accessibility

The full and complete data is available directly from the Adolescent Brain Cognitive Development (ABCD) Study (https://abcdstudy.org), held in the NIMH Data Archive (NDA). The data analysis code detailing the analysis procedure for the current study is available here: https://github.com/Miller-Jack/cortex-rsfmri.

CRediT statement

Jack Miller: Conceptualization, Methodology, Software, Formal analysis, Writing - Original Draft, Writing - Review & Editing, Visualization. **Kathryn L Mills**: Conceptualization, Methodology, Writing - Original Draft, Writing - Review & Editing. **Matti Vuorre**: Methodology, Writing - Review & Editing. **Amy Orben**: Conceptualization, Methodology, Writing - Original Draft, Writing - Review & Editing. **Andrew K Przybylski**: Conceptualization, Methodology, Writing - Original Draft, Writing - Review & Editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

AKP's research is currently supported by the Huo Family Foundation and the Economic and Social Research Council (ESRC; ES/S00324X/1) and was recently supported by the ESRC (ES/T008709/1). In the preceding five years AKP has also worked on research grants provided the John Fell Fund, The Diana Award and the children's charity Barnardo's. These research grants were paid to the AKP's employer, the Oxford Internet Institute. During this period, AKP has also engaged unpaid consultations with several organisations including UNICEF, the Organization for Economic Co-operation and Development, Meta Inc., UKIE, UK Research and Innovation, The UK's DCMS, The Office of the UK's Chief Medical Officer, the Office of the US Surgeon General, The UK's Academy of Medical Sciences, and the UK Parliament. There were no

products or benefits resulting from these consultations. MV's research is currently supported by the Economic and Social Research Council (ESRC; ES/W012626/1) and the John Fell Fund, and was recently supported by the Huo Family Foundation (awarded to AKP). AKP is currently serving as a paid scientific advisor to the Sync Digital Wellbeing Program. The authors declare they have no further competing interests.

Open Practices

The study in this article earned Preregistered badge for transparent practices. The preregistered study are available at: https://osf.io/z4eyv

Acknowledgments

Data used in the preparation of this article were obtained from the Adolescent Brain Cognitive Development (ABCD) Study (https://abcdstudy.org), held in the NIMH Data Archive (NDA). This is a multisite, longitudinal study designed to recruit more than 10,000 children age 9–10 and follow them over 10 years into early adulthood. The ABCD Study is supported by the National Institutes of Health and additional federal partners under award numbers U01DA041022, U01DA041028, U01DA041048, U01DA041089, U01DA041106, U01DA041117, U01DA041120, U01DA041134, U01DA041148, U01DA041156, U01DA041174, U24DA041123, and U24DA041147. A full list of supporters is available at https://abcdstudy.org/nih-collaborators. A listing of participating sites and a complete listing of the study investigators can be found at https://abcdstudy.org/principal-investigators.html. ABCD consortium investigators designed and implemented the study and/or provided data but did not necessarily participate in analysis or writing of this report. This manuscript reflects the views of the authors and may not reflect the opinions or views of the NIH or ABCD consortium investigators. The ABCD data repository grows and changes over time. The ABCD data used in this report came from https://dx.doi.org/10.15154/1523041 and the DOI for this study is https://dx.doi.org/10.15154/1503519. DOIs can be found at https://doi.org/10.15154/1460410.

Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cortex.2023.09.009.

REFERENCES

AAP. (2010). Media education. *Pediatrics, 126*(5), 1012–1017. https://doi.org/10.1542/peds.2010-1636

AAP. (2011). Media use by children younger than 2 years. *Pediatrics, 128*(5), 1040–1045. https://doi.org/10.1542/peds.2011-1753

AAP. (2016). Media and young minds. *Pediatrics, 138*(5), Article e20162591. https://doi.org/10.1542/peds.2016-2591

Anandakumar, J., Mills, K. L., Earl, E. A., Irwin, L., Miranda-Dominguez, O., Demeter, D. V., et al. (2018). Individual differences in functional brain connectivity predict temporal discounting preference in the transition to adolescence. *Developmental Cognitive Neuroscience, 34*, 101–113. https://doi.org/10.1016/j.dcn.2018.07.003

Bassett, D. S., Xia, C. H., & Satterthwaite, T. D. (2018). Understanding the emergence of neuropsychiatric disorders with network neuroscience. *Biological Psychiatry. Cognitive Neuroscience and Neuroimaging*. https://doi.org/10.1016/j.bpsc.2018.03.015

Baum, G. L., Ciric, R., Roalf, D. R., Betzel, R. F., Moore, T. M., Shinohara, R. T., et al. (2017). Modular segregation of structural brain networks supports the development of executive function in youth. *Current Biology, 27*(11), 1561–1572.e8. https://doi.org/10.1016/j.cub.2017.04.051

Bennett, C. M., Wolford, G. L., & Miller, M. B. (2009). The principled control of false positives in neuroimaging. *Social Cognitive and Affective Neuroscience, 4*(4), 417–422. https://doi.org/10.1093/scan/nsp053

Beyens, I., Valkenburg, P. M., & Piotrowski, J. T. (2018). Screen media use and ADHD-related behaviors: Four decades of research. *Proceedings of the National Academy of Sciences of the United States of America, 115*(40), 9875–9881. https://doi.org/10.1073/pnas.1611611114

Birn, R. M., Molloy, E. K., Patriat, R., Parker, T., Meier, T. B., Kirk, G. R., et al. (2013). The effect of scan length on the reliability of resting-state fMRI connectivity estimates. *Neuroimage, 83*, 550–558. https://doi.org/10.1016/j.neuroimage.2013.05.099

Blakemore, S. J., & Mills, K. L. (2014). Is adolescence a sensitive period for sociocultural processing? *Annual review of psychology, 65*, 187–207.

Blinka, L., Škařupová, K., Ševčíková, A., Wölfling, K., Müller, K. W., & Dreier, M. (2015). Excessive internet use in European adolescents: What determines differences in severity? *International Journal of Public Health, 60*(2), 249–256. https://doi.org/10.1007/s00038-014-0635-x

Burnell, K., George, M. J., Kurup, A. R., Underwood, M. K., & Ackerman, R. A. (2021). Associations between self-reports and device-reports of social networking site use: An application of the truth and bias model. *Communication methods and measures, 15*(2), 156–163.

Carp, J. (2012). On the plurality of (methodological) worlds: Estimating the analytic flexibility of FMRI experiments. *The Florida Nurse, 6*, 149. https://doi.org/10.3389/fnins.2012.00149

Casey, B. J., Cannonier, T., Conley, M. I., Cohen, A. O., Barch, D. M., Heitzeg, M. M., et al. (2018). The adolescent brain cognitive development (ABCD) study: Imaging acquisition across 21 sites. *Developmental Cognitive Neuroscience, 32*, 43–54. https://doi.org/10.1016/j.dcn.2018.03.001

Common Sense Media. (2017). The common Sense census: Media use by kids age zero to eight. https://www.commonsensemedia.org/research/the-common-sense-census-media-use-by-kids-age-zero-to-eight-2017.

Cox, R. W. (1996). AFNI: Software for analysis and visualization of functional magnetic resonance neuroimages. *Computers and Biomedical Research, an International Journal, 29*(3), 162–173.

Desai, S., Chase-Lansdale, P. L., & Michael, R. T. (1989). Mother or market? Effects of maternal employment on the intellectual ability of 4-year-old children. *Demography, 26*(4), 545–561.

Durkee, T., Kaess, M., Carli, V., Parzer, P., Wasserman, C., Floderus, B., et al. (2012). Prevalence of pathological internet use among adolescents in europe: Demographic and social factors. *Addiction, 107*(12), 2210–2222. https://doi.org/10.1111/j.1360-0443.2012.03946.x

Fair, D. A., Miranda-Dominguez, O., Snyder, A. Z., Perrone, A. A., Earl, E. A., Van, A. N., et al. (2018). Correction of respiratory artifacts in MRI head motion estimates. *BioRxiv*, 337360. https://doi.org/10.1101/337360

Ferguson, C. J. (2009). An effect size primer: A guide for clinicians and researchers. *Professional Psychology: Research and Practice, 40*(5), 532–538. https://doi.org/10.1037/a0015808

Fox, S. E., Levitt, P., & Nelson, C. A., III (2010). How the timing and quality of early experiences influence the development of brain architecture. *Child Development, 81*(1), 28–40. https://doi.org/10.1111/j.1467-8624.2009.01380.x

Garavan, H., Bartsch, H., Conway, K., Decastro, A., Goldstein, R. Z., Heeringa, S., et al. (2018). Recruiting the ABCD sample: Design considerations and procedures. *Developmental Cognitive Neuroscience, 32*, 16–22. https://doi.org/10.1016/j.dcn.2018.04.004

Geuter, S., Qi, G., Welsh, R. C., Wager, T. D., & Lindquist, M. A. (2018). *Effect size and power in fMRI group analysis*. Biorxiv.

Gordon, E. M., Laumann, T. O., Adeyemo, B., Huckins, J. F., Kelley, W. M., & Petersen, S. E. (2016). Generation and evaluation of a cortical area parcellation from resting-state correlations. *Cerebral Cortex (New York, N.Y.: 1991), 26*(1), 288–303. https://doi.org/10.1093/cercor/bhu239

Hackman, D. A., & Farah, M. J. (2009). Socioeconomic status and the developing brain. *Trends in Cognitive Sciences, 13*(2), 65–73. https://doi.org/10.1016/j.tics.2008.11.003

Hagler, D. J., Hatton, S. N., Makowski, C., Cornejo, M. D., Fair, D. A., Dick, A. S., et al. (2018). Image processing and analysis methods for the adolescent brain cognitive development study. *BioRxiv*, 457739. https://doi.org/10.1101/457739

Hodes, L. N., & Thomas, K. G. (2021). Smartphone screen time: Inaccuracy of self-reports and influence of psychological and contextual factors. *Computers in Human Behavior, 115*, 106616.

Houghton, S., Hunter, S. C., Rosenberg, M., Wood, L., Zadow, C., Martin, K., et al. (2015). Virtually impossible: Limiting Australian children and adolescents daily screen based media use. *BMC Public Health, 15*(1), 5. https://doi.org/10.1186/1471-2458-15-5

Huttenlocher, P. R., & Dabholkar, A. S. (1997). Regional differences in synaptogenesis in human cerebral cortex. *The Journal of Comparative Neurology, 387*(2), 167–178.

Huttenlocher, P. R., de Courten, C., Garey, L. J., & Van der Loos, H. (1982). Synaptogenesis in human visual cortex — evidence for synapse elimination during normal development. *Neuroscience Letters, 33*(3), 247–252. https://doi.org/10.1016/0304-3940(82)90379-2

Johannes, N., Masur, P. K., Vuorre, M., & Przybylski, A. K. (2021, October 13). How should we investigate variation in the relation between social media and well-being?. https://doi.org/10.31234/osf.io/xahbg.

Klami, A., Virtanen, S., Leppäaho, E., & Kaski, S. (2015). Group factor analysis. *IEEE Transactions on Neural Networks and Learning Systems, 26*(9), 2136–2147. https://doi.org/10.1109/TNNLS.2014.2376974

Kooijmans, R., Langdon, P. E., & Moonen, X. (2022). Assisting children and youth with completing self-report instruments introduces bias: A mixed-method study that includes children and young people's views. *Methods in Psychology, 7*, 100102.

Laumann, T. O., Gordon, E. M., Adeyemo, B., Snyder, A. Z., Joo, S. J., Chen, M.-Y., et al. (2015). Functional system and areal organization of a highly sampled individual human brain. *Neuron, 87*(3), 657–670. https://doi.org/10.1016/j.neuron.2015.06.037

LeBourgeois, M. K., Hale, L., Chang, A.-M., Akacem, L. D., Montgomery-Downs, H. E., & Buxton, O. M. (2017). Digital media and sleep in childhood and adolescence. *Pediatrics, 140*(Supplement 2), S92–S96. https://doi.org/10.1542/peds.2016-1758J

Luciana, M., Bjork, J. M., Nagel, B. J., Barch, D. M., Gonzalez, R., Nixon, S. J., et al. (2018). Adolescent neurocognitive development and impacts of substance use: Overview of the adolescent brain cognitive development (ABCD) baseline neurocognition battery. *Developmental Cognitive Neuroscience, 32*, 67–79. https://doi.org/10.1016/j.dcn.2018.02.006

Luna, B. (2017). *Neuroimaging and the adolescent brain: a period of plasticity for vulnerabilities and opportunities. UNICEF: The adolescent brain*. A second window of opportunity.

Lupien, S. J., McEwen, B. S., Gunnar, M. R., & Heim, C. (2009). Effects of stress throughout the lifespan on the brain, behaviour and cognition. *Nature Reviews Neuroscience, 10*(6), 434–445. https://doi.org/10.1038/nrn2639

Magnusson, K., Johansson, F., & Przybylski, A. K. (2023, May 28). Harmful compared to what? The problem of gaming and ill-defined causal effects. https://doi.org/10.31234/osf.io/qruhx.

Marek, S., Hwang, K., Foran, W., Hallquist, M. N., & Luna, B. (2015). The contribution of network organization and integration to the development of cognitive control. *PLoS biology, 13*(12), Article e1002328.

Marek, S., Tervo-Clemmens, B., Calabro, F. J., Montez, D. F., Kay, B. P., Hatoum, A. S., … Dosenbach, N. U. (2022). Reproducible brain-wide association studies require thousands of individuals. *Nature, 603*(7902), 654–660.

Mills, K. L. (2014). Effects of internet use on the adolescent brain: Despite popular claims, experimental evidence remains scarce. *Trends in Cognitive Sciences, 18*(8), 385–387. https://doi.org/10.1016/j.tics.2014.04.011

Mills, K. L. (2016). Possible effects of internet use on cognitive development in adolescence. *Media and Communication, 4*(3), 4–12. https://doi.org/10.17645/mac.v4i3.516

Mills, K. L., Bathula, D., Dias, T. G. C., Iyer, S. P., Fenesy, M. C., Musser, E. D., et al. (2012). Altered cortico-striatal-thalamic connectivity in relation to spatial working memory capacity in children with ADHD. *Frontiers in Psychiatry/Frontiers Research Foundation, 3*, 2. https://doi.org/10.3389/fpsyt.2012.00002

Mills, K. L., & Tamnes, C. K. (2014). Methods and considerations for longitudinal structural brain imaging analysis across development. *Developmental Cognitive Neuroscience, 9*, 172–190. https://doi.org/10.1016/j.dcn.2014.04.004

Moisala, M., Salmela, V., Hietajärvi, L., Carlson, S., Vuontela, V., Lonka, K., et al. (2017). Gaming is related to enhanced working memory performance and task-related cortical activity. *Brain Research, 1655*, 204–215. https://doi.org/10.1016/j.brainres.2016.10.027

Munafò, M. R., Nosek, B. A., Bishop, D. V. M., Button, K. S., Chambers, C. D., Percie du Sert, N., et al. (2017). A manifesto for reproducible science. *Nature Human Behaviour, 1*(1), 21. https://doi.org/10.1038/s41562-016-0021

Ofcom. (2015). *Children and parents: Media use and attitudes report 2015*.

Ofcom. (2017). Internet use and attitudes - 2017 metrics bulletin. https://www.ofcom.org.uk/__data/assets/pdf_file/0018/105507/internet-use-attitudes-bulletin-2017.pdf.

Ofcom. (2019). Children and parents: Media use and attitudes report 2018. https://www.ofcom.org.uk/__data/assets/pdf_file/0024/134907/Children-and-Parents-Media-Use-and-Attitudes-2018.pdf.

Orben, A., & Przybylski, A. K. (2019). The association between adolescent well-being and digital technology use. *Nature Human Behaviour, 1*. https://doi.org/10.1038/s41562-018-0506-1

Parkes, A., Sweeting, H., Wight, D., & Henderson, M. (2013). Do television and electronic games predict children's psychosocial adjustment? Longitudinal research using the UK millennium cohort study. *Archives of Disease in Childhood,*

98(5), 341–348. https://doi.org/10.1136/archdischild-2011-301508

Orben, A., Przybylski, A. K., Blakemore, S. J., & Kievit, R. A. (2022). Windows of developmental sensitivity to social media. *Nature Communications, 13*, 1649. https://doi.org/10.1038/s41467-022-29296-3

Park, B., Han, D. H., & Roh, S. (2016). Neurobiological findings related to Internet use disorders. *Psychiatry and Clinical Neurosciences*. https://doi.org/10.1111/pcn.12422

Paulus, M. P., Squeglia, L. M., Bagot, K., Jacobus, J., Kuplicki, R., Breslin, F. J., et al. (2019). Screen media activity and brain structure in youth: Evidence for diverse structural correlation networks from the ABCD study. *Neuroimage, 185*, 140–153. https://doi.org/10.1016/j.neuroimage.2018.10.040

Petanjek, Z., Judaš, M., Šimic, G., Rasin, M. R., Uylings, H. B. M., Rakic, P., et al. (2011). Extraordinary neoteny of synaptic spines in the human prefrontal cortex. *Proceedings of the National Academy of Sciences of the United States of America, 108*(32), 13281–13286. https://doi.org/10.1073/pnas.1105108108

Power, J. D., Barnes, K. A., Snyder, A. Z., Schlaggar, B. L., & Petersen, S. E. (2012). Spurious but systematic correlations in functional connectivity MRI networks arise from subject motion. *Neuroimage, 59*(3), 2142–2154. https://doi.org/10.1016/j.neuroimage.2011.10.018

Przybylski, A. K., Johannes, A., Vuorre, M., Dodel, M., Gottlieb, C., Kaye, L. K., et al. (2021). *An open letter to mr. Mark Zuckerberg: A global call to act now on child and adolescent mental health science*. Oxford Internet Institute. https://www.oii.ox.ac.uk/an-open-letter-to-mark-zuckerberg/#overview.

Przybylski, A. K., & Weinstein, N. (2017). A large-scale test of the goldilocks hypothesis: Quantifying the relations between digital-screen use and the mental well-being of adolescents. *Psychological Science*. https://doi.org/10.1177/0956797616678438, 0956797616678438.

RCPCH. (2019). The health impacts of screen time - a guide for clinicians and parents. https://www.rcpch.ac.uk/resources/health-impacts-screen-time-guide-clinicians-parents.

Robinson, T. N., Banda, J. A., Hale, L., Lu, A. S., Fleming-Milici, F., Calvert, S. L., et al. (2017). Screen media exposure and obesity in children and adolescents. *Pediatrics, 140*(Supplement 2), S97–S101. https://doi.org/10.1542/peds.2016-1758K

Rosenberg, M. D., Finn, E. S., Scheinost, D., Papademetris, X., Shen, X., Constable, R. T., et al. (2016). A neuromarker of sustained attention from whole-brain functional connectivity. *Nature neuroscience, 19*(1), 165–171.

Strittmatter, E., Parzer, P., Brunner, R., Fischer, G., Durkee, T., Carli, V., et al. (2015). A 2-year longitudinal study of prospective predictors of pathological Internet use in adolescents. *European Child & Adolescent Psychiatry*, 1–10. https://doi.org/10.1007/s00787-015-0779-0

UNESCO COMEST. (2005). *The precautionary principle*.

Vul, E., Harris, C., Winkielman, P., & Pashler, H. (2009). Puzzlingly high correlations in fMRI studies of emotion, personality, and social cognition. *Perspectives on Psychological Science, 4*(3), 274–290. https://doi.org/10.1111/j.1745-6924.2009.01125.x

Westreich D. , Greenland, S., The Table 2 Fallacy: Presenting and Interpreting Confounder and Modifier Coefficients, American Journal of Epidemiology, Volume 177, Issue 4, https://doi.org/10.1093/aje/kws412.

Xia, C. H., Ma, Z., Ciric, R., Gu, S., Betzel, R. F., Kaczkurkin, A. N., et al. (2018). Linked dimensions of psychopathology and connectivity in functional brain networks. *Nature Communications, 9*(1), 3003. https://doi.org/10.1038/s41467-018-05317-y

Zhang, J.-T., Ma, S.-S., Yip, S. W., Wang, L.-J., Chen, C., Yan, C.-G., et al. (2015). Decreased functional connectivity between ventral tegmental area and nucleus accumbens in internet gaming disorder: Evidence from resting state functional magnetic resonance imaging. *Behavioral and Brain Functions: BBF, 11*(1), 37. https://doi.org/10.1186/s12993-015-0082-8iOS 12 introduces new features to reduce interruptions and manage Screen Time. (n.d.). Retrieved January 14, 2019, from https://www.apple.com/uk/newsroom/2018/06/ios-12-introduces-new-features-to-reduce-interruptions-and-manage-screen-time/