

Screen Time and Adolescent Brain Development: A Multi-Modal Neuroimaging Study

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Abstract. Adolescents are increasingly engaged with digital media, raising concerns about the potential effects of excessive screen time on the development of neural circuits during critical stages of brain maturation. This study aims to address the lack of large-scale, multimodal research in early adolescence by examining the relationships between screen time, psychiatric symptoms, impulsivity, and brain structure in a well-powered, age-homogeneous group of 9- to 10-year-olds from the Adolescent Brain Cognitive Development (ABCD) study. A total of 11,880 participants underwent high-resolution T1-weighted MRI, from which measures of cortical thickness, surface area, volume, and sulcal depth were extracted across 68 brain regions. Screen use was assessed using standardized questionnaires on weekday and weekend usage, along with parent reports. Linear mixed-effects models, adjusting for demographic and biological covariates (age, sex, race, parental education, BMI, intracranial volume, and site), revealed significant positive associations between increased screen time and externalizing symptoms (e.g., aggression, attention problems), with weaker but reliable associations with internalizing symptoms (e.g., depression). Behavioral analyses indicated that more screen exposure was linked to higher impulsivity and reward sensitivity, particularly traits such as urgency and impaired self-regulation. Neuroimaging results identified structural changes in areas related to visual processing, emotional regulation, and memory—such as the fusiform and lingual gyri, parahippocampal cortex, insula, and orbitofrontal cortex—marked by reduced cortical thickness and surface area. These changes may reflect experience-dependent plasticity in response to repeated digital stimulation, potentially intensifying reward-driven behaviors while impairing self-control mechanisms. Overall, these findings highlight the neurodevelopmental sensitivity of early adolescence to environmental factors like media exposure, emphasize the need for evidence-based screen-use guidelines, and suggest potential targets for brain-informed interventions aimed at reducing psychopathology risk and fostering healthy cognitive-emotional development. As a practical extension, a prototype application was developed to demonstrate how brain-based insights could be translated into strategies for healthier smartphone use.

Keywords: screen time, cortical thickness, psychiatric symptoms, impulsivity, neurodevelopment

1. Introduction

Over the past decade, portable digital devices have become nearly ubiquitous in adolescents' lives. By 2023, 95 % of U.S. 9- to 12-year-olds owned or had daily access to a smartphone, and their average recreational screen time surpassed five hours per day—even before accounting for homework [1].

Social media platforms, short-form videos, and online gaming have become central spaces for peer interactions, identity development, and recreation. While these technologies offer significant opportunities for learning and social connection, they also raise pressing public health concerns regarding their impact on the developing brain. The cerebral cortex undergoes significant structural changes during adolescence, especially in the second decade of life, when gray matter decreases and white matter increases. These structural modifications are shaped by both genetic and environmental influences. Changes in brain structure are part of coordinated alterations affecting cortical thickness. Research has shown that excessive screen time can result in thinning of the cortex, reduced brain volume, and more intricate modifications in sulcal depth patterns [2]. Importantly, rapid cortical pruning during early adolescence is regarded as one of the fundamental neurodevelopmental processes in this stage [3]. Additionally, cognitive impairments emerging during adolescence are strongly linked to the onset of various psychopathologies, making this period a critical window for mental health disorders [4]. Thus, it is essential to examine both the positive and negative effects of screen time on adolescents, particularly in relation to sleep quality, academic achievement, mental health, and social relationships [5].

Previous research has primarily examined the relationship between screen time and adolescent brain development from the perspectives of functional neuroimaging, genetics, neuropsychology, and behavioral science [6]. For instance, both task-based and resting-state neuroimaging techniques have indicated that frequent and extended screen media use is linked to decreased efficiency in adolescent cognitive control systems, including regions within the default mode and central executive networks. Moreover, online activities have been found to exert a strong rewarding effect on the brain, with repeated exposure reinforcing the tendency to seek immediate gratification [7]. Some studies have also connected screen time with both internalizing and externalizing issues in adolescents, showing that screen use is positively associated with anxiety, depression, attention problems, and academic performance. Conversely, other research has highlighted the positive aspects of screen use, such as its correlation with better quality peer relationships [8].

Current research has predominantly focused on preschool-aged children or adults, leaving a gap in understanding how screen time affects adolescent brain development. Existing studies are often limited by small sample sizes and broad age ranges, which diminish the generalizability of their results. Additionally, many studies rely on single-modality methods, such as analyzing cortical surface area, cortical thickness, or volume, which limits the integration of multimodal data. As a result, there is a need for more detailed and comprehensive measurements in this area. To address these gaps, my study utilizes multiple data modalities and integrates information to enhance the scientific validity and generalizability of the findings. Despite growing public concern, three critical knowledge gaps persist. First, much of the research targets either preschoolers or adults, neglecting early adolescence—the developmental period when neural circuits responsible for emotion regulation and psychiatric vulnerability undergo rapid reorganization [9,10]. Second, many studies use small or heterogeneous samples, reducing statistical power and limiting the ability to generalize findings [11,12]. Third, most studies use single-modality approaches, making it challenging to capture the complex, multimodal nature of adolescent brain development [13]. This study aims to fill these gaps in three key ways. (1) By utilizing the nationally representative ABCD cohort, we

focus on a large, age-homogeneous sample of 9- to 10-year-olds to examine the relationship between daily screen time and psychiatric symptoms, impulsivity, self-regulation, and cortical morphology (thickness and surface area) across 68 regions. (2) We integrate high-resolution structural MRI with extensive behavioral assessments and rigorously control for demographic and biological covariates to identify pathways through which excessive screen exposure may impact reward sensitivity, inhibitory control, and neurodevelopment. (3) Our multimodal, multilevel modeling framework offers a nuanced, data-driven foundation for translating basic science into actionable guidance. This research is driven by a critical real-world issue raised by adolescents: as recreational screen time among peers increases, clinicians and educators are seeing a rise in problematic screen use and digital-media addictions. Identifying the specific cortical regions most vulnerable to overexposure is essential—not only to understand the neurobiology of early vulnerability but also to inform future brain-targeted interventions aimed at preventing or alleviating screen-related addictive behaviors.

2. Methods

2.1. Research subjects

This study focuses on early adolescence by analyzing data from the Adolescent Brain Cognitive Development (ABCD) study, a large-scale, multi-site, longitudinal project. The ABCD consortium includes 21 research sites across the United States and recruited 11,880 children aged 9-10 years. The dataset provides extensive measures of brain structure, behavior, and neuropsychological factors, offering a comprehensive and authoritative resource for investigating adolescent development.

2.2. Neuroimaging data

Participants underwent high-resolution T1-weighted structural MRI scanning (1 mm isotropic voxels) on a 3T magnetic resonance imaging scanner (Siemens Prisma, General Electric MR 750, Philips). The structural MRI data were processed using FreeSurfer 5.3.0, following the standardized processing pipeline [14]. To ensure the accuracy of the study and minimize errors, participants who did not pass the visual inspection of T1 images or the FreeSurfer quality control were excluded in advance. The current study used processed data on cortical thickness, surface area, cortical volume, and sulcal depth. Based on the Desikan-Killiany Atlas [15], the analysis was conducted across 34 cortical regions in each hemisphere, totaling 68 regions of interest (ROIs), and examined from four modalities.

2.3. Imaging data process

Cortical structural MRI data were preprocessed with a standard surface-based pipeline (FreeSurfer v6/7). T1-weighted ($\pm$ T2) scans were converted from DICOM to NIfTI, de-faced, and organized in BIDS; raw images underwent visual quality control for motion and artefacts, and severely degraded scans were excluded. Intensity non-uniformity was corrected using N4, and global intensity was normalized; skull stripping was performed to obtain a brain mask, followed by coarse affine alignment to Talairach/MNI space. Tissue segmentation classified voxels into white matter, gray matter, and CSF with automated subcortical labeling; cortical surfaces were reconstructed by generating white and pial meshes with topology correction and surface smoothing. Each hemisphere was spherically registered to a common template (fsaverage) to establish vertexwise correspondence, and cortical parcellations were applied (e.g., Desikan–Killiany or Destrieux).

Vertexwise metrics were then derived—cortical thickness as the minimum distance between white and pial surfaces, surface area from triangle-mesh elements, and cortical volume as the volume between surfaces; data were smoothed for group analyses (CT 10–15 mm FWHM; SA/CV 15–20 mm), resampled to the template mesh, aggregated to ROI level, and exported with intracranial volume estimates for statistical modeling. All reconstructions underwent final quality control to verify white/pial placement and parcellation accuracy (Figure 1).

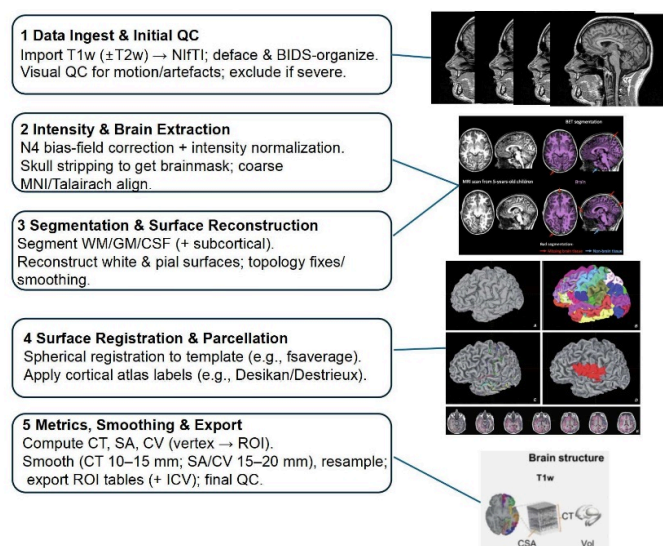


Figure 1. Imaging data process

2.4. Child Behavior Checklist (CBCL)

Emotional and behavioral problems were assessed using the Child Behavior Checklist (CBCL), a standardized parent-report questionnaire appropriate for children aged 9–10 years. The CBCL provides eight syndrome scales (Anxious/Depressed, Withdrawn/Depressed, Somatic Complaints, Social Problems, Thought Problems, Attention Problems, Rule-Breaking Behavior, and Aggressive Behavior), along with three summary scores (Internalizing Problems, Externalizing Problems, and Total Problems). It also includes six DSM-oriented scales (Depressive Problems, Anxiety Problems, Somatic Problems, Attention Deficit/Hyperactivity Problems, Oppositional Defiant Problems, and Conduct Problems), as well as three 2007 scales (Sluggish Cognitive Tempo, Obsessive-Compulsive Problems, and Stress Problems). These scales offer a thorough evaluation of emotional and behavioral concerns within the target age group.

2.5. Screen time usage scale

Screen time was measured using the Screen Time Questionnaire (STQ), a standardized tool that gathers self-reported data on digital media usage. The STQ consists of 14 items, separated into weekday and weekend usage to assess typical screen exposure. Participants indicated the types of media used and the amount of time spent on each, with response options ranging from 0 hours (0) to 4+ hours (4). Screen time was categorized into six media types, excluding schoolwork: television shows and movies, videos, video games, texting, social media, and video calls. The total screen time for a given weekday or weekend was calculated by summing the values across all six media types. Participants also reported how often they played adult-rated video games or watched R-rated movies

(0 = never, 3 = always). Parent or guardian reports offered additional information, including the total screen time (in hours and minutes) for each weekday and weekend. For this analysis, all screen time data were converted and recorded in hours.

2.6. Statistical analysis methods

Linear mixed-effects models (LMMs) were used to evaluate the relationships between screen time (both type and duration) and brain structural measures across four imaging modalities, implemented through the R lme4 package [16]. In these models, screen time measures were treated as dependent variables, while brain structure metrics were the independent variables. Random effects accounted for family structure within research sites, and fixed-effect covariates included factors such as age, sex, race (White, Black, Hispanic, Asian, Other/Multiracial), parental marital status, pubertal stage, parental education, BMI, and total intracranial volume. The general form of the LMM is outlined in Equation (1):

$$Y=X\beta+Z\Gamma+\epsilon \quad (1)$$

2.7. Demographic data

The existing data were processed to ensure the completion of the statistical organization across all data types. For the age variable, both the mean and standard deviation were computed to summarize the distribution. Regarding biological sex, the counts and proportions of participants for each sex were determined to understand the gender distribution. For ethnicity, specific ethnicity codes were assigned, along with corresponding labels, and then grouped counts and proportions were calculated accordingly. Distribution tables were also created for research site locations, parental marital status, and the highest level of education attained by parents. This thorough analysis offers a detailed overview of the key demographic characteristics of the study sample, which is crucial for controlling covariates in the subsequent neuroimaging analyses.

2.8. Connectivity matrix

In examining the relationships between brain structure and behavior, extensive neuroimaging statistical analyses were performed using structural brain data. Once the merged dataset, referred to as the consolidated merged_table, was prepared, a set of homogeneous neuroimaging metrics across 68 cortical regions was selected as independent variables. These included measures such as regional cortical thickness and surface area, which were derived from the Desikan–Killiany atlas. These neuroanatomical features were then systematically evaluated in relation to individual clinical phenotypes (e.g., impulsivity scores), which served as dependent variables.

To model these relationships while controlling for potential confounding factors, linear mixed effects modeling was employed. This model incorporated key demographic covariates, such as sex, age, and educational level, and accounted for hierarchical dependencies by specifying nested random effects through the term (1 | site_id 1:rel_family_id). These statistical procedures were carried out using MATLAB R2021b, resulting in t-values that represent the direction and magnitude of the effects, as well as p-values used to assess statistical significance for each brain–behavior relationship.

To address concerns about multiple comparisons in whole-brain analyses, False Discovery Rate (FDR) correction was applied across all 68 cortical regions, with a significance threshold set at $q < 0.05$. For visual representation of the results, parametric heatmaps were created, with color gradients

corresponding to the magnitudes of the t-values. Regions showing uncorrected significance ($p < 0.05$) were clearly marked with asterisks on the heatmaps, providing additional statistical context alongside the FDR-corrected results. Finally, publication-quality visualizations, at a resolution of 300 dpi, were exported to facilitate the neurobiological interpretation of the findings.

Through this analytical framework, the relationships between brain structure and behavior were thoroughly examined, while controlling for demographic confounds and the hierarchical structure of the data. This approach adhered to well-established conventions in neuroimaging analysis throughout the study.

2.9. Data preprocessing and analysis workflow

The data preprocessing and analysis were carried out in three main stages. The first step involved preprocessing the dataset by grouping participants based on the median of their total screen time. To achieve this, the dataset was arranged in ascending order according to the sumtime column, and the sample size along with the median position was determined. Participants who fell within the top 50% of the sorted data were categorized as the high-time group. In the second step, the sorted dataset was duplicated, and a new column was added to represent the grouping variable. This new dataset was then created for further analysis, and linear mixed models (LMMs) were applied, incorporating false discovery rate (FDR) correction to address multiple comparisons. Finally, the third step involved visualization. A table summarizing the statistical results was created, including significant p-values, and these results were mapped to corresponding brain regions using the Desikan-Killiany cortical parcellation, resulting in detailed brain maps that visually represented the findings. For color coding, red indicates positive correlations (high-time group $>$ low-time group), and blue indicates negative correlations. The overall data processing workflow is summarized in Figure 2.

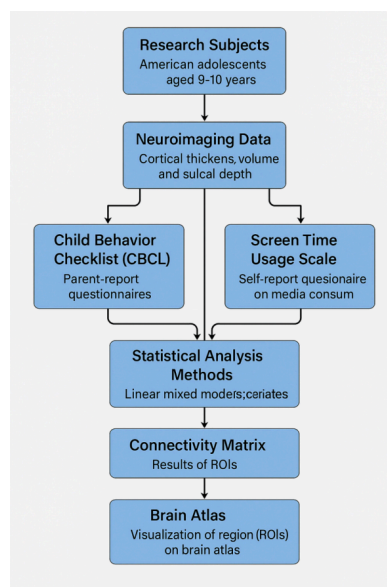


Figure 2. Overall data processing and analysis workflow

3. Results

3.1. Relationship between screen time and psychiatric symptoms

Greater daily screen exposure was strongly linked to a range of behavioral issues in children and adolescents. The most pronounced associations were observed within the externalizing domain, where higher levels of screen time were associated with increased instances of rule-breaking behaviors, attention problems related to ADHD, conduct difficulties, oppositional traits, as well as overt aggression and social conflict. Additionally, a more modest, yet statistically reliable, connection was found with internalizing distress, where heavier screen use was correlated with slightly higher levels of depressive symptoms.

As shown in Figure 3, a heatmap of t-values visually represents the statistical relationships between daily screen time and various psychiatric symptom dimensions. The corresponding p-values and t-values are detailed in Table 1. Statistically significant associations are highlighted with asterisks, with the most substantial effects consistently emerging in the externalizing symptom domains. Complementarily, Figure 4 displays a bar plot quantifying the strength of these associations across individual psychiatric symptoms. This plot underscores the most significant connections, particularly with rule-breaking behaviors, ADHD symptoms, and conduct problems, followed by issues like inattention, oppositionality, aggression, and social difficulties. While depressive symptoms showed a weaker effect size, they still demonstrated a significant positive association with screen time exposure.

Taken together, these results suggest that excessive daily screen time is more strongly linked to outward-directed behavioral dysregulation, while also showing early signs of mood disturbance. This pattern highlights the importance of considering both behavioral and emotional factors when assessing the potential risks associated with media use in pediatric populations.

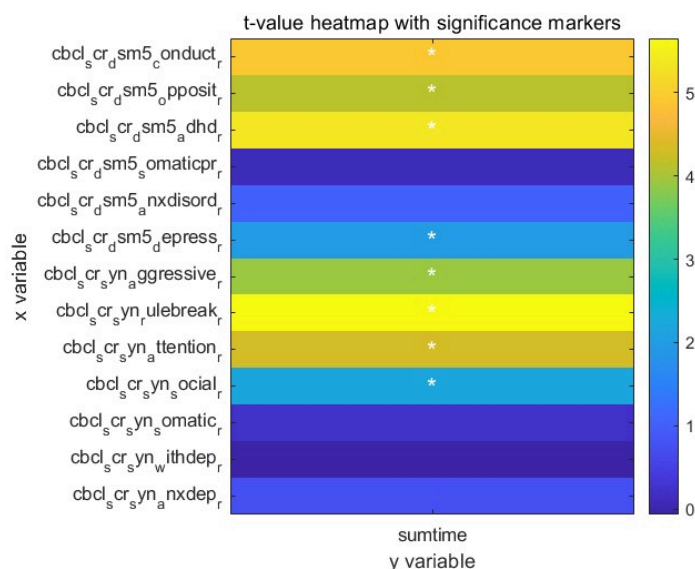


Figure 3. Heatmap of t-values illustrating the relationship between daily screen time and psychiatric symptoms, with significance markers

Table 1. Statistical results for the associations between screen time and psychiatric symptom dimensions

region	p	t
cbcl_scr_syn_rulebreak	1.67E-08	5.65
cbcl_scr_dsm5_adhd_r	7.85E-08	5.38
cbcl_scr_dsm5_conduct_r	9.09E-07	4.92
cbcl_scr_syn_attention_r	1.55E-05	4.33
cbcl_scr_dsm5_opposit_r	3.71E-05	4.13
cbcl_scr_syn_aggressive_r	8.59E-05	3.93
cbcl_scr_syn_social_r	2.73E-02	2.21
cbcl_scr_dsm5_depress_r	4.92E-02	1.97

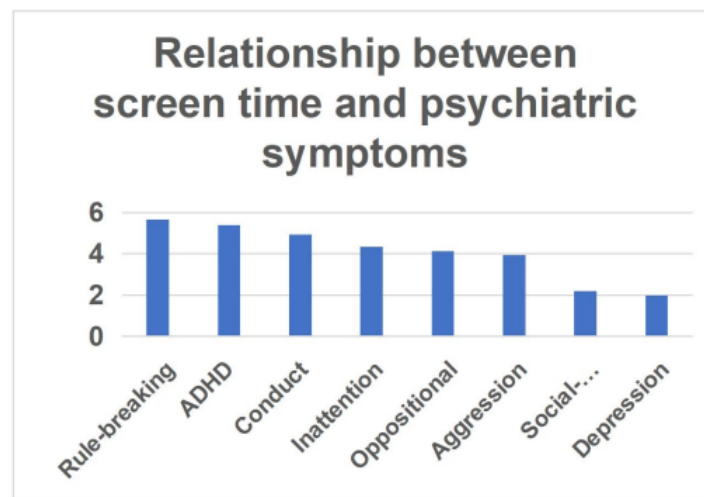


Figure 4. T-values of significant associations

3.2. Relationship between screen time, impulsivity, and rewards and punishments

Higher daily screen exposure was consistently linked to a behavioral profile that is characterized by increased impulsivity and a stronger tendency to seek out rewarding experiences. The most significant associations were found in the domains of drive and urgency: children and adolescents with more screen time reported a notably higher motivation to approach rewarding situations, as well as a greater tendency to act impulsively, particularly in emotionally charged contexts, whether positive or negative.

As shown in Figure 5, a heatmap of t-values visually represents the statistical relationships between daily screen time and the various subcomponents of impulsivity, along with sensitivity to rewards and punishments. The corresponding p-values and t-values are displayed in Table 2. Statistically significant associations, after appropriate corrections (e.g., false discovery rate (FDR) correction as described in the Methods section), are marked with asterisks. This visualization confirms that multiple impulsivity-related traits—especially drive, positive urgency, and negative urgency—show significant positive associations with higher screen exposure. Additionally, Figure 6 presents a bar chart that quantifies the magnitude of these significant t-values for each impulsivity-

related construct. The chart reveals that the most substantial effects were observed in traits like punishment sensitivity, reward responsiveness, and poor planning, followed by urgency-related characteristics and sensation-seeking behaviors.

Other noteworthy patterns were found for reward responsiveness, including higher levels of fun-seeking behavior and an increased sensitivity to incentives. Additionally, typical indicators of self-regulatory weaknesses, such as poor planning, decreased perseverance, and an overall composite of impulsivity, were all positively associated with screen time exposure. Taken together, these findings suggest that heavy screen users tend to be individuals who prioritize the pursuit of immediate rewards while struggling with inhibiting impulsive actions. This pattern highlights impulsivity and heightened reward sensitivity as key psychological mechanisms that may explain how excessive digital engagement could contribute to developmental risks.

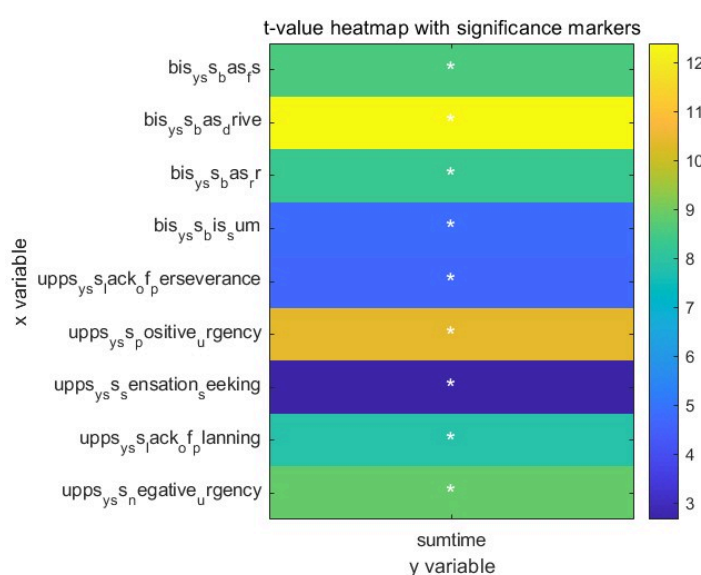


Figure 5. Relationship between screen time, impulsivity, and rewards and punishments

Table 2. Statistical results for the associations between screen time and impulsivity/reward-related traits

region	p	t
bis _y _ss_bas _{drive}	1.13E-34	1.24
upps _y _ss_positive_urgency	4.27E-25	1.04
upps _y _ss_negative_urgency	1.02E-18	8.87
bis _y _ss_bas _{fs}	1.23E-17	8.59
bis _y _ss_bas _{rr}	1.52E-16	8.29
upps _y _ss_lack_of_planning	5.39E-15	7.84
bis _y _ss_bis _{sum}	1.49E-06	4.82
upps _y _ss_lack_of_perseverance	3.06E-06	4.67
upps _y _ss_sensation_seeking	7.86E-03	2.66



Figure 6. T-values of significant associations

3.3. Relationship between screen time and cortical thickness

In a comprehensive whole-brain vertex-wise analysis, extended daily screen time was linked to significantly thinner cortical regions in 18 out of 19 suprathreshold areas ($p < 0.05$, FDR-corrected), forming a consistent anatomical network rather than isolated brain regions. As shown in Figure 7, negative associations (represented by cooler colors) were mainly observed in the lateral and medial orbitofrontal cortices, the ventral visual stream, and various paralimbic regions, pointing to widespread cortical thinning associated with increased screen exposure. The most pronounced effects were seen bilaterally in the lateral and medial orbitofrontal cortex, areas crucial for reward valuation, impulse regulation, and emotional control. Further cortical thinning was observed in the ventral visual stream, particularly in the fusiform and lingual gyri, as well as the cuneus, all regions that play vital roles in object and face recognition. In addition, a reduction in cortical thickness in the insula and parahippocampal cortex suggests altered integration of interoceptive functions and emotional memory processing. Thinning was also evident along the midline parietal surface, including the precuneus, posterior cingulate, and paracentral lobule—areas involved in self-referential thinking and sensorimotor integration.

Collectively, these regions form cortical hubs that undergo extended maturation during adolescence, influenced by experience-dependent synaptic pruning that underpins cognitive and emotional development. These results, as detailed in Table 3, underscore that screen time was most strongly linked to cortical thinning in the orbitofrontal cortex (e.g., *smri_thick_cdk_lobfrlh*, *mobfrlh*) and fusiform/lingual regions, with *t*-values surpassing -4 and *p*-values well below 0.001 . Interestingly, a positive association was found in the pericalcarine cortex, where a thicker cortex was observed with increased screen exposure ($t = 2.51$, $p = 1.22 \times 10^{-2}$), which may reflect use-dependent plasticity in the primary visual areas that receive prolonged stimulation from digital media. Therefore, the overall pattern indicates that excessive screen time may accelerate cortical thinning in higher-order regulatory networks while fostering cortical growth in sensory areas that are most directly involved in screen-based experiences.

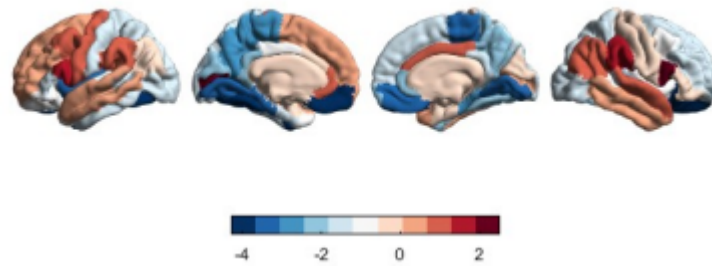


Figure 7. Relationship between screen time and cortical thickness

Table 3. Statistical results for the associations between screen time and cortical thickness

region	p	t
smri_thick_cdk_lobfrrh	1.87×10^{-5}	-4.28
mobfrrh	3.87×10^{-5}	-4.12
fusiformlh	1.60×10^{-4}	-3.78
lingualrh	2.82×10^{-4}	-3.63
insulalh	4.38×10^{-4}	-3.52
parahpallh	6.87×10^{-4}	-3.40
linguallh	6.89×10^{-4}	-3.4
mobfrrh	1.09×10^{-3}	-3.27
paracnrh	1.14×10^{-3}	-3.25
pclh	3.15×10^{-3}	-2.95
paracnlh	3.21×10^{-3}	-2.95
parahpalrh	5.69×10^{-3}	-2.77
pcrh	1.73×10^{-2}	-2.38
rracaterh	2.08×10^{-2}	-2.31
ihcatelh	2.15×10^{-2}	-2.3
frpolverh	2.55×10^{-2}	-2.23
fusiformrh	3.40×10^{-2}	-2.12
cuneuslh	4.63×10^{-2}	-1.99
pericclh	1.22×10^{-2}	2.51

3.4. Relationship between screen time and cortical surface area

A correlational analysis conducted in a cohort of children and adolescents revealed that prolonged daily screen exposure was associated with a consistent pattern of reduced cortical surface area, spanning several functional systems rather than being confined to isolated brain regions. As shown in Figure 8, widespread reductions in cortical surface area were observed across important association cortices, with the most significant effects concentrated in the lateral orbitofrontal cortex and anterior cingulate cortex—both of which play critical roles in reward processing, impulse control, and emotional regulation. The statistical details of these findings are presented in Table 2, where notable negative associations were found in regions such as the left superior temporal gyrus (t

= -4.21), the right inferior temporal gyrus ($t = -4.49$), the right middle temporal gyrus ($t = -3.85$), and the right posterior cingulate cortex ($t = -3.81$). These areas are involved in essential functions like language processing, social perception, and higher-order visual processing.

Additionally, the involvement of the precuneus, posterior cingulate, and supramarginal gyri—key hubs of the default mode and attention networks—suggests that prolonged screen exposure may be linked to reduced expansion of the association cortex, which is typically involved in self-referential thinking and cognitive flexibility. Taken together, these localized reductions in cortical surface area are consistent with earlier findings of cortical thinning in overlapping neural circuits, strengthening the idea that excessive screen time may disrupt neurodevelopmental processes in brain networks responsible for reward processing, executive control, and multimodal integration.

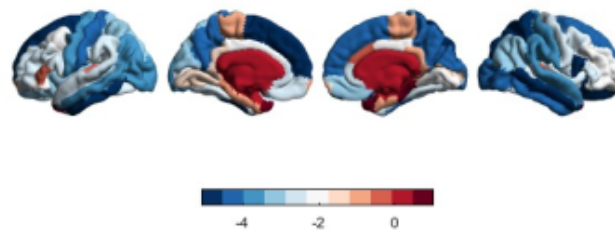


Figure 8. Relationship between screen time and cortical surface area

Table 4. Statistical results for the associations between screen time and cortical surface area

region	p	t
left lateral orbitofrontal cortex	$< 1.0 \times 10^{-4}$	-4.08
left superior temporal gyrus	$< 1.0 \times 10^{-4}$	-4.21
right inferior temporal gyrus	$< 1.0 \times 10^{-4}$	-4.49
right middle temporal gyrus	1.0×10^{-4}	-3.85
right posterior cingulate cortex	1.0×10^{-4}	-3.81
left precuneus	2.0×10^{-4}	-3.69
right lateral occipital cortex	3.0×10^{-4}	-3.65
left rostral middle frontal cortex	4.0×10^{-4}	-3.53
right supramarginal gyrus	4.0×10^{-4}	-3.52
bilateral fusiform gyri	5.0×10^{-4}	-3.48
left superior frontal gyrus	6.0×10^{-4}	-3.42
left precentral gyrus	7.0×10^{-4}	-3.39
right caudal anterior cingulate cortex	8.0×10^{-4}	-3.34
left transverse temporal gyrus	1.0×10^{-3}	-3.29

4. Discussion

From the standpoint of cognitive neuroscience and brain science, the observed positive associations between screen time and both externalizing and internalizing problems (as shown in Figure 1) can be understood through the ongoing development of neural circuits involved in behavioral regulation in children and adolescents. A substantial body of research emphasizes the essential role of the prefrontal cortex—particularly the dorsolateral prefrontal cortex and orbitofrontal regions—in

supporting executive functions, impulse control, and emotional regulation. During adolescence, the connections between the prefrontal cortex and limbic regions, such as the nucleus accumbens and amygdala, are still undergoing significant maturation. This stage of development renders the reward system more susceptible to external influences, including digital media exposure. Excessive screen time, especially when it involves highly stimulating content, could potentially disrupt or overwhelm these developing control mechanisms, leading to various negative outcomes. These include attentional deficits, disruptive or aggressive behaviors, and even the emergence of internalizing symptoms, such as depression.

In relation to Figure 2, the significant correlations between screen time and various measures of impulsivity, as well as reward and punishment sensitivity, suggest a potential imbalance in the Behavioral Inhibition System (BIS) and the Behavioral Activation System (BAS). Dual systems models propose that the BAS plays a central role in reward-seeking and drive, while the BIS is associated with sensitivity to punishment cues and inhibitory control. High sensitivity to rewards (e.g., positive urgency, sensation seeking) is often linked to increased impulsivity and a reduced capacity for self-regulation, which makes it more difficult to resist immediate gratification [17-20]. For adolescents, frequent and prolonged screen use may enhance dopamine-driven reward pathways, reinforcing the craving for immediate and diverse digital stimuli, thereby weakening the ability to engage in delayed gratification and self-regulation. Therefore, intervention strategies should leverage insights from brain science to help adolescents moderate their screen usage, while also focusing on strengthening impulse control and emotional regulation skills.

The notable associations between screen time and cortical thickness in key regions, including the fusiform gyrus, lingual gyrus, cuneus, parahippocampal gyrus, medial orbitofrontal cortex, insula, and posterior cingulate cortex, suggest that prolonged exposure to digital media could be linked to structural changes in brain areas involved in visual processing, memory, and emotional regulation. For example, the fusiform gyrus and lingual gyrus are essential for higher-order visual processing, such as object and pattern recognition, and structural changes in these areas may reflect the intense and repetitive visual stimulation inherent in screen-based activities. Similarly, alterations in the parahippocampal cortex—an area involved in memory encoding and contextual association—may suggest that extensive screen time influences how environmental cues are processed and integrated into memory. Significant associations were also observed in the orbitofrontal cortex and insula, both of which are critical for emotion regulation and decision-making. These changes may reflect the impact of frequent engagement with digital rewards (e.g., social media feedback or online gaming reinforcement) on neural circuits involved in affective regulation and interoceptive awareness. Furthermore, the posterior cingulate cortex, which is often linked to internally directed cognition and the default-mode network, showed significant relationships with cortical thickness, suggesting that prolonged screen immersion may influence self-referential thinking or mind-wandering processes.

In parallel, surface area analyses further support the idea that screen time may be linked to structural differences within similar functional brain domains, with significant effects observed in regions such as the insula, orbitofrontal cortex, parahippocampal areas, and the cuneus, among others. The insula's role in interoception and emotional awareness, combined with the orbitofrontal cortex's involvement in reward processing and decision-making, highlights how digital media use could potentially shape or reflect changes in networks responsible for emotional regulation and reward valuation. Additionally, significant surface area alterations in the parahippocampal cortex reinforce the possibility that screen exposure might impact memory and contextual processes, while changes observed in primary and secondary visual regions, like the cuneus, suggest that repetitive,

visually-driven engagement typical of screen-based platforms could influence cortical organization [21,22].

Taken together, the results from both cortical thickness and surface area analyses underscore a complex interaction between frequent screen use and neurodevelopmental trajectories. They suggest that neural structures involved in visual processing, emotional regulation, reward responsiveness, and memory may be especially sensitive to the duration and intensity of digital media exposure. Given these findings, further longitudinal and mechanistic research is needed to determine whether these structural variations precede, result from, or develop in parallel with increased screen time [23].

Overall, the combined evidence from analyses of cortical thickness and surface area—along with the associations between screen time, psychiatric symptoms, impulsivity, and reward/punishment sensitivity—points to a multifaceted relationship between digital media use and neurobiological development. Although the exact mechanisms behind these associations remain unclear, it is plausible that intensive screen-based stimulation could influence the maturation of critical neural circuits responsible for attention, emotional processing, reward sensitivity, and higher-order visual functions. On the other hand, adolescents and children who already display certain cognitive or emotional traits, such as heightened reward sensitivity or difficulties with impulse control, may be more inclined to engage with digital media. Therefore, future studies using longitudinal designs, diverse neuroimaging methods, and targeted interventions are crucial to better understand the directionality and causality of these effects. Such studies should also explore potential moderating factors (e.g., type of content, context of use) and aim to develop strategies that help optimize technology use while minimizing adverse developmental consequences.

As a practical application of these findings, we developed a prototype application (illustrated in Figure 9) designed to assist our peers in regulating their smartphone usage. The app integrates two primary functions: ① lock-screen modifications and screen-time monitoring, paired with science-based prompts aimed at encouraging users to reduce their screen time (Figure 9A), and ② selective blocking of specific sub-pages within apps while still allowing access to essential functions (Figure 9B & 9C). This design is particularly beneficial for social networking apps (e.g., WeChat), where adolescents frequently rely on timely notifications for academic or group-related updates. By allowing users to target specific restrictions rather than imposing a blanket block, the prototype aims to strike a balance between preventing excessive screen use and preserving access to necessary communication. Although this design is still in its preliminary stages, it demonstrates how insights from neuroscience can be applied to create practical tools that promote healthier digital habits and support more balanced screen time among adolescents.



Figure 9. Prototype design of the smartphone application for regulating screen use. (A) Lock-screen interface displaying daily screen time and usage statistics, accompanied by reminders to encourage reduced exposure. (B) Selective blocking function allowing users to choose specific applications or sub-pages for restriction. (C) Blocking notification window that prevents access to selected apps or pages during focus periods, while preserving essential communication functions

5. Conclusion

This study provides extensive evidence linking excessive screen time during early adolescence to behavioral dysregulation and structural changes in brain regions that are crucial for reward processing, impulse control, emotional regulation, and visual cognition. By utilizing the robust ABCD dataset, our findings offer insight into how frequent exposure to digital stimuli may influence ongoing neurodevelopmental processes, enhancing reward-driven behaviors while diminishing self-regulation mechanisms. These results emphasize the heightened neurobiological vulnerability of early adolescence to external influences and highlight the need for evidence-based guidelines that help balance technology use with healthy brain development. While the prototype application presented here represents a practical and behaviorally informed approach, the primary contribution of this research lies in enhancing our understanding of the brain mechanisms affected by screen exposure. It also identifies potential targets for future interventions designed to mitigate psychopathology risk and foster healthy cognitive and emotional development.

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