

Youth screen use in the ABCD® study^{☆,☆☆,★}

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ABSTRACT

Adolescent screen usage is ubiquitous and influences development and behavior. Longitudinal screen usage data coupled with psychometrically valid constructs of problematic behaviors can provide insights into these relationships. We describe methods by which the screen usage questionnaire was developed in the Adolescent Brain Cognitive Development (ABCD) Study, demonstrate longitudinal changes in screen usage via child report and describe data harmonization baseline-year 2. We further include psychometric analyses of adapted social media and video game addiction scales completed by youth. Nearly 12,000 children ages 9–10 years at baseline and their parents were included in the analyses. The social media addiction questionnaire (SMAQ) showed similar factor structure and item loadings across sex and race/ethnicities, but that item intercepts varied across both sex and race/ethnicity. The videogame addiction questionnaire (VGAQ) demonstrated the same configural, metric and scalar invariance across racial and ethnic groups, however differed across sex. Video gaming and online social activity increased over ages 9/10–11/12 (p 's < 0.001). Compared with boys, girls engaged in greater social media use (p < .001) and demonstrated higher ratings on the SMAQ (p < .001). Compared with girls, boys played more video games (p < .001) and demonstrated higher ratings on the VGAQ (p < .001). Time spent playing video games increased more steeply for boys than girls from age 9/10–11/12 years (p < .001). Black youth demonstrated significantly higher SMAQ and VGAQ scores compared to all other racial/ethnic groups. These data show the importance of considering different screen modalities beyond total screen use and

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point towards clear demographic differences in use patterns. With these comprehensive data, ABCD is poised to address critical questions about screen usage changes across adolescence.

1. Introduction

By 12 years of age, 69 % of children have their own smartphone and approximately 85 % of children and adolescents engage in recreational screen usage behaviors, with escalating use throughout adolescence (Rideout and Robb, 2019a). Here screen usage is defined as activities done in front of, and/or with the assistance of a digital device with a screen. This includes, but is not limited to, gaming, texting, social media use, video chatting and watching/streaming TV/videos for recreational purposes. While screen usage is associated with passive or sedentary activities, some screen modalities may allow for moderate to vigorous physical activity (MVPA) such as certain games/gaming platforms, and fitness applications (apps). There are no specific current time recommendations for screen exposure for school-age children or adolescents by government or federal health intuitions or medical societies such as the American Academy of Pediatrics and the American Academy of Child & Adolescent Psychiatry, (Pediatrics, A. A. o. Council on Communications and Media, 2016; Organization, 2019; American Academy of Child and Adolescent Psychiatry) however most organizations suggest tailoring screen usage based on screen modality, family or child needs or motivations and developmental stage (Reid Chassiakos et al., 2016). It is estimated that screen usage is 4 h/day in pre-adolescence, and 7 h/day in adolescence, (Rideout and Robb, 2019a) and that only 5 % of children and adolescents meet all physical activity (≥ 1 h/day), sleep (turn off screens 30–60 min prior to bedtime and remove them from the bedroom), and screen usage guidelines (Knell et al., 2019). Variation also seems to exist in average duration of screen exposure by socio-demographic factors, with white youth from higher socioeconomic backgrounds engaged in lower amounts of daily screen use; engaging in screen-related activity an estimated hour and 50 min less per day than those from lower-income and underrepresented racial/ethnic minority households (Reid Chassiakos et al., 2016). However, underrepresented minority youth are highly likely to own smartphones and engage in screen usage activities regardless of socioeconomic background (Hunt et al., 2019). Evidence also exists for variation in types of screen usage by sex. Girls have been shown to spend more time on social media, (Pew Research Center, 2018) whereas boys are more likely to play video games (Pew Research Center, 2018). Further, age and socioeconomic status appear to affect screen usage. Young children under age 8 mostly engage in passive streaming, (Kabali et al., 2015) whereas older adolescents engage in more media multi-tasking, using multiple devices or platforms simultaneously (Moreno et al., 2012; Brasel and Gips, 2011). Children from high socioeconomic backgrounds are nearly twice as likely to view or engage with educational content as those from low socioeconomic backgrounds (Rideout and Robb, 2019a). Thus youth with varying sociodemographic characteristics may utilize screens differentially to meet different needs, ultimately impacting developmental health trajectories in diverse ways.

Child and adolescent use of technology far outpaces our understanding of the impact of different screen modalities and technology, and modality-based content on growth and development in the long term. Much of the work in this field done thus far has been cross-sectional, limiting our ability to draw conclusions about temporal relationships between psychosocial, health and cognitive factors leading to, and resulting from screen usage in youth. Further, while gross measures of screen usage at a single time-point may be able to index some aspects of addictive or harmful patterns of device use, the widely varied online activities that youth participate in across, and within, specific devices and apps are so diverse that they are likely to have a wide range of effects on health over the course of development. It is important to measure perceived consequences of screen usage and

indicators of screen usage beyond total screen duration, to evaluate different screen modalities (e.g., social media, gaming), as well as timing of use, and problematic use (use that interferes with social or interpersonal aspects of life). A recent review identified 145 distinct screen use measures, of which many have been found to be valid and reliable for measurement of distinct modalities of screen use (Browne et al., 2021). However, to-date, there is limited literature on nuanced (i.e. not just time spent, but also motivation for, and context of use and other related contextual factors) and/or validated methods of assessment for evaluation of the aforementioned factors particularly among racially/ethnically diverse youth across development. In large studies of screen usage in particular, investigators have typically relied on gross measurements of hours spent on screens in general, failing to examine various modes of screen exposure in isolation, and they have examined these screen-related data cross-sectionally (Browne et al., 2021; Lenhart et al., 2010; Houghton et al., 2015) or within-subject, (Rosenberg et al., 2018) not accounting for context or changes in screen use within person across neurodevelopmental stage, and/or have focused on only on one mode of exposure (e.g. smartphone) (Browne et al., 2021; Lenhart et al., 2010).

An accelerated longitudinal cohort study linking 2 year longitudinal data across cohorts (Rosenberg et al., 2018) began addressing many of the aforementioned issues with the extant methods. The authors demonstrated greatest fluidity in screen exposure grades 7–11, and that over the course of 2 years, time spent on an individual's main screen-related activity remained relatively stable (social networking, gaming, web use, passive screen use). However, even this most comprehensive effort to date failed to examine addiction, while acknowledging the need for such assessment. Further, cohort effects in this study likely reflected changing technologies over the course of the 2-year trial which may have differentially impacted some age groups rather than others given differences in age, and age-related access and/or use. Others have examined addiction to various screen modalities, including social media, internet and gaming, using reliable and valid measures, many adapted from the same base measures, however are limited by the use of specific sub-populations of youth based on region or culture, (Barbosa Filho et al., 2021) associated factors such as physical activity, (Vaughn et al., 2019) small sample size and cross-sectional methodology. Further, less than 2 % of these scales assess potential clinical significance of screen use (Browne et al., 2021).

The Adolescent Brain Cognitive Development (ABCD) Study® is a 10-year longitudinal study of brain development and child health in the U.S. The Novel Technology Workgroup is a group of ABCD investigators, consultants, and staff tasked with determining best practices for measuring screen usage and use of novel mobile and digital technologies for measuring behaviors of interest in this cohort. Here we describe efforts to begin to address the limitations of the current screen usage literature by describing development of comprehensive youth self-report and parent report (of youth behavior) surveys based on extant measures, previous research and a rigorous internal process, administered annually over the 10-year lifespan of ABCD to assess screen use longitudinally and the impact on development and health and vice versa. Adaptations made to the screen use questionnaire from baseline to year two were due to recognition of changes in and increasing screen use based on evolving developmental stage of participants.

We describe screen usage questionnaires completed by both youth and parent developed by ABCD investigators for the purpose of the study to assess types, timing, and duration of screen exposure in the nearly 12,000 child sample, and harmonization of data across study years given improvements made in the questionnaire after baseline. We also present data showing longitudinal changes in child self-reported screen usage in participants across the first 3 years of the ABCD Study® (baseline, Year

1, Year 2), and compare child self-report to parent report of child screen use. Finally, as we adapted the Bergen Facebook Addiction Scale to measure social media and video game addictions in the ABCD sample, (Andreassen et al., 2012a) we present psychometric analyses of these questionnaires to demonstrate validity of these scales for measurement of these addictions in youth (Neimeyer, 2019).

2. Methods

2.1. Participants

The ABCD Study® is a longitudinal study following a cohort of 11,878 9–10-years-olds from 21 research sites within the United States beginning in 2016. The child and a participating parent/caregiver complete a comprehensive assessment once per year, with neuroimaging data collection occurring every other year. Full details regarding the larger ABCD Study® design are provided elsewhere (Garavan et al., 2018). The intention is to follow the cohort until at least age 19–20 (2026–2028). At the time of this report, youth are completing their Year 4 follow-up (age 13–14) and data have been released for the full cohort up to Year 2 follow-up (age 11–12; ABCD Data Release 3.0 includes data collected until 12–31–2019). Eleven thousand eight hundred and seventy-one participants are included in these analyses. Nearly half are female (48%) and 63% identified as white (Table 1). Time points and measures relevant for screen usage assessments are outlined in Table 2.

2.2. Measures

2.2.1. Screen usage survey

Child screen usage was assessed via youth self-report and parent report at all annual visits, starting at baseline. Screen usage was assessed separately for weekdays and weekends. Weekday was specifically defined as Monday through Friday during the school year and holiday/school breaks. Weekend was defined as Saturday and Sunday.

Parent report. Parents were asked, “On a typical WEEKDAY [or WEEKEND] how much TIME per day does your child spend in TOTAL on a computer, cell phone, tablet, iPod or other electronic device?”, not including school-related activities. Parents reported total screen usage in terms of average number of hours and minutes. Beginning in Year 2,

Table 1
Baseline demographics for youth participants of the Adolescent Brain Cognitive Development (ABCD) Study in the current analyses.

	Sample (%)
Sex	
Male	6193 (52.2%)
Female	5678 (47.8%)
Families' Income Bracket	
< \$50 K (Low)	2956 (24.9%)
\$50–100 K (Mid)	3027 (25.5%)
> \$100 K (High)	5482 (46.2%)
Missing/Undefined	406 (3.4%)
Race	
American Indian / Alaska Native	62 (0.5%)
Asian	276 (2.3%)
Black	1868 (15.7%)
Native Hawaiian / Pacific Islander	16 (0.1%)
Other	1959 (16.5%)
White	7520 (63.3%)
Missing/Undefined	170 (1.4%)
Ethnicity	
Hispanic	2409 (20.3%)
Not Hispanic	9309 (78.4%)
Missing/Undefined	153 (1.3%)
Total	11,871 (100%)

Note. Because household incomes (Income Bracket) may change over time, these data are based on each participant’s maximum household income for this sample.

Table 2
Timeline of Screen Usage Assessments with questionnaires in the ABCD Study®.

Assessment	Time Point of Administration				
	Baseline	1-Year Follow-Up	2-Year Follow-Up	3-Year Follow-Up	4-Year Follow-Up
<i>Screen usage/mobile device usage</i>					
Screen usage Questionnaire	P, C	P, C	P, C	P, C	P, C
Online Dating Questionnaire			C		
Sleep and Screen usage			C	C	C
Social Media Addiction Questionnaire			C	C	C
Video Game Addiction Questionnaire			C	C	C

Note. “P”=parent report, “C”=child report,

parents were asked to report hours from a drop-down list (0–23) and report minutes rounded to the nearest 15-minute interval (0, 15, 30, 45) to minimize out-of-range responses and implausible values. In addition to estimating their child’s total screen usage, parents complete questions about whether the child has their own mobile device (and the type of devices they possess), whether any devices in the child’s possession has WIFI access, and age when the child received a cell phone (if applicable). The parent’s oversight of the child’s social media use is also assessed [e.g., Are you following, or friends with, your child on any social media sites (e.g., Facebook, Instagram, Snapchat)].

Youth report. Youth are asked about their own total weekday and weekend screen usage and are also asked to report their screen usage by device, media platform, or activity (see Table 3). Specifically, youth were asked how much time they spent a) watching TV shows or movies (in Year 2, this was modified to include streaming TV shows, movies, or videos), b) watching videos (such as YouTube), c) playing video games, d) texting on a cell phone, tablet, or computer, e) social networking [encompassing visiting social networking sites (baseline)/apps (Year 2); not including time spent editing videos of photos to post (Year 2)], f) editing social media photos (Year 2 only), g) browsing the internet (beginning in Year 2) or h) engaging in video chat. When reporting on total screen usage, youth were instructed not to include time spent on school related work. At baseline and Year 1, youth were provided with categorical response options to estimate the amount of screen usage they spent on each device, media platform, or activity. These options included: none (0), < 30 min (0.25), 30 min (0.5), 1 h (1), 2 h (2), 3 h (3), or 4 + hours (4). Beginning in Year 2, the activities listed were changed slightly to reflect the increase in video streaming: watching TV shows or movies changed to “watching or streaming TV shows or movies”; watching videos (such as YouTube) changed to “watching or streaming videos or live streaming (such as YouTube, Twitch)”; time spent playing videogames was broken down into “time spent on single player” and “multiplayer gaming”; editing photos or videos to post on social media was added; “searching or browsing the internet that is not for school” was added; and total time spent on all non-school related screen usage activities was added. Importantly, the response format in Year 2 was changed from categories to open format, where individuals input the hours and minutes, they estimated spending on each screen usage activity.

2.2.2. Additional screen usage items (Year 2 onwards)

Surveys were updated based on emerging literature on relationships between screen use and health in children, to take account of age-related changes in screen use (e.g., more mobile phone usage), and to address limitations in the baseline survey (e.g., lack of measures of problem use of screens or use around bedtime). Changes to the measure were

Table 3
Youth Screen usage Self-Report Questionnaire, developed for the ABCD Study®, showing modifications made by Year.

Youth Questions	Baseline	1-Year Follow-Up	2-Year Follow-Up	3-Year Follow-Up
Watch “or stream” TV shows or movies? (such as Hulu, Netflix or Amazon, not including videos on YouTube)	✓ ^a	✓ ^a	✓	✓
Watch or stream videos or live stream (such as YouTube, Twitch)?	✓ ^b	✓ ^b	✓	✓
Play video games on a computer, console, phone or other device (Xbox, Play Station, iPad)?	✓	✓		
Play single-player video games on a computer, console, phone or other device (Xbox, Play Station, iPad, AppleTV)?			✓>	✓
Play multiplayer video games on a computer, console, phone, or other device (Xbox, Play Station, iPad, AppleTV) where you can interact with others in the game?			✓	✓
Text on a cell phone, tablet, computer, iPod, or other electronic device (e.g., GChat, WhatsApp, Kik etc.)?	✓ ^c	✓ ^c	✓	✓
Visit social networking sites like Facebook, Twitter, Instagram, etc.?	✓	✓		
Visit social media apps (e.g., Snapchat, Facebook, Twitter, Instagram, TikTok, etc.? (Do not include time spent editing photos or videos to post on social media.)			✓	✓
Edit photos or videos to post on social media.			✓	
Video chat (Skype, FaceTime, VRchat, etc.)	✓ ^d	✓ ^d	✓	✓
Searching or browsing the internet (e.g., using Google) that is NOT for school.			✓	✓
Spend in TOTAL on a computer, phone, tablet, iPod, or other device or video game? Please do NOT include time spent on school related work, but do include watching TV, shows or videos, texting or chatting, playing games, or visiting social networking sites (Facebook, Twitter, Instagram).			✓	✓
Spend in TOTAL on school-related work on a phone, tablet, computer, or other computerized device? Please do not include time during school.			✓	✓

Note. ^aEarlier version read, “Watch TV shows or movies?”; ^bEarlier version read, “Watch videos (such as YouTube)?”; ^cEarlier version read, “Text on a cell phone, tablet, or computer (e.g. GChat, WhatsApp, etc.)?”; ^dEarlier version read, “Video chat (Skype, Facetime, etc.)?”; ^eAsked only for weekend days in Year 4

determined by the Novel Technology Workgroup and were informed by the continually changing digital landscape. Additions and changes were thoroughly discussed by the workgroup and piloted before being implemented. Through this process, screen usage assessments were expanded to also include questions about mobile phone ownership and usage, social media accounts, and online dating, and timing of screen

usage around bedtime. These questions are briefly described here but are not presented in the results. The Social Media Addiction Questionnaire (SMAQ) and Video Game Addiction Questionnaire (VGAQ) were also introduced at Year 2.

2.2.3. Mobile phone involvement questionnaire (MPIQ)

Walsh et al. (2010) This is an 8-item questionnaire designed to assess problematic mobile phone usage, beginning in Year 2. Youth are asked to report how much they agree with various statements using a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Example statements include “I lose track of how much I am using my phone” and “I interrupt whatever else I am doing when I am contacted on my phone.”

2.2.4. Mobile PHone Attachment

Beginning in Year 2, youth were asked the following question: “on a scale of 1–10 (with 1 =barely check it/can go days without it, and 10 =check at least hourly when awake), how attached are you to your phone?”.

2.2.5. Online dating questionnaire

In Year 2, youth were asked whether they had ever used a dating app, whether they currently are using a dating app, how much time per week they spend on online dating apps, and whether they have ever arranged an in-person meeting with someone they met through a dating app.

2.2.6. Social media accounts

Beginning in Year 2, youth were asked which social media site (Facebook, Instagram, Snapchat, Twitter, YouTube, Pinterest, Tumblr, Reddit, Multiplayer Videogame Online Chatting Platforms, TikTok, other) that they used the most, whether their accounts were public or private, and whether they had accounts that their parents did not know about.

2.2.7. Social media addiction questionnaire (SMAQ)

This 6-item questionnaire was adapted from the Bergen Facebook Addiction Scale (Andreassen et al., 2012b). This questionnaire was added in Year 2, to assess problematic social media use. Example statements included: “I feel the need to use social media sites/apps more and more” and “I use social media sites/apps so much that it has had a bad effect on my schoolwork or job.” Responses were on a Likert-type scale, ranging from 1 = Never to 6 = Very often. These items were asked only for a subsample of participants, who reported having at least one social media account. See Appendix 1.

2.2.8. Videogame addiction questionnaire (VGAQ)

This 6-item questionnaire was added in Year 2 to assess problematic video game use, as reported by the child. It was also modeled after the Bergen Facebook Addiction Scale (Andreassen et al., 2012b). Example statements include: “I feel the need to play video games more and more” and “I play video games so much that it has had a bad effect on my schoolwork or job.” Responses were on a Likert-type scale, ranging from 1 = Never to 6 = Very often. These items were asked only for a subsample of participants, who reported any video game use on weekdays or weekends. See Appendix 1.

2.2.9. Screen usage around bedtime

A 9-item measure was administered to youth to assess engagement in activities, including screen time activities, prior to sleeping. Items were modified from Lemola et al. (2015) and Arora et al. (2014). On a 5-point Likert scale ranging from 1 (never) to 5 (every night), youth reported how often (in the past week) they engaged in the following activities while already in bed before going to sleep: watch TV or movies, play video games, play music, talk on the phone or text, spend time online on social media, browse the internet, use a computer/laptop for studying. Four additional items were asked related to sleep and media use which

Table 4
Comparison of factor analysis models applied to the SMAQ.

Model	χ^2 (df)	P-value	RMSEA (90% CI)	BIC	CFI	SRMR	Δ BIC	Δ CFI
Sex*		0.000						
Configural	613.69 (18)	0.000	0.109 (0.101, 0.116)	98433	0.942	0.036		
Metric	627.65 (23)	0.000	0.097 (0.090, 0.103)	98404	0.942	0.039	29	0.000
Scalar	660.90 (28)	0.000	0.096 (0.084, 0.096)	98394	0.939	0.040	10	0.003
Race**								
Configural	676.37 (54)	0.000	0.112 (0.104, 0.119)	96524	0.939	0.039		
Metric	760.82 (79)	0.000	0.097 (0.091, 0.103)	96393	0.933	0.048	131	0.006
Scalar	832.95 (104)	0.000	0.087 (0.082, 0.093)	96250	0.928	0.050	143	0.005
Income***								
Configural	588.57 (27)	0.000	0.111 (0.103, 0.118)	88460	0.940	0.038		
Metric	607.81 (37)	0.000	0.095 (0.089, 0.102)	88394	0.939	0.041	66	0.001
Scalar	662.75 (47)	0.000	0.088 (0.082, 0.094)	88363	0.934	0.043	31	0.005

*Sex (female, male)

**Race (white, black, AIAN, Asian, mixed, other)

***Income (<\$50,000, \$50,000-\$100,000, >\$100,000)

Table 5
Comparison of factor analysis models applied to the VGAQ.

Model	χ^2 (df)	P-value	RMSEA (90% CI)	BIC	CFI	SRMR	Δ BIC	Δ CFI
Sex*		0.000						
Configural	741.21 (18)	0.000	0.103 (0.097, 0.110)	135492	0.955	0.034		
Metric	824.96 (23)	0.000	0.096 (0.091, 0.102)	135531	0.950	0.045	39	0.005
Scalar	998.07 (28)	0.000	0.096 (0.091, 0.101)	135659	0.939	0.053	128	0.011
Race**								
Configural	420.07 (54)	0.000	0.104 (0.095, 0.114)	68714	0.961	0.032		
Metric	450.48 (79)	0.000	0.087 (0.079, 0.095)	68539	0.961	0.038	175	0.000
Scalar	500.16 (104)	0.000	0.078 (0.072, 0.085)	68383	0.958	0.041	156	0.003
Income***								
Configural	738.43 (27)	0.000	0.107 (0.100, 0.113)	125547	0.957	0.033		
Metric	758.42 (37)	0.000	0.092 (0.086, 0.098)	125479	0.956	0.037	68	0.001
Scalar	807.85 (47)	0.000	0.084 (0.079, 0.089)	125440	0.954	0.038	39	0.002

*Sex (female, male)

**Race (white, black, AIAN, Asian, mixed, other)

***Income (<\$50,000, \$50,000-\$100,000, >\$100,000)

were adapted from questions in a National Sleep Foundation poll (Gradisar et al., 2013). Youth were asked whether there was a TV set or an internet connected device in their bedroom (yes/no), what they do with their phone when they are ready to go to sleep (e.g., turn the phone off, leave the ringer on), how often they had phone calls, text messages, or emails that awake them after trying to go to sleep, and how often they used their phone or other device when they woke up during the night.

Data Analysis of Self-Reported Screen Usage and Problematic Usage (Across 3 Years of the ABCD Study®).

2.2.10. Self-reported screen usage

As described above, self-reported screen usage data at baseline and Year 1 were collected as yes-no responses; at Year 2, open-ended responses.

To harmonize screen usage data across Baseline, Year 1, and Year 2 for analyses here, it was necessary to transform Year 2 open responses to categories consistent with Baseline and Year 1. This was done by summing hours and minutes for each activity in Year 2 and recoding it to the categories (with anything above 4 h recoded as ‘4 + hours’), according to a 6-point scale: 0 h, < 1 h, 1–2 h, 2–3 h, 3–4 h, and > 4 h. For analyses, these were coded as 0–5, respectively. Furthermore, ‘editing photos and videos’ and ‘searching or browsing the internet’ were omitted as these items were not queried at previous assessments. Time spent on single player and multiplayer gaming was collapsed into a single category of “video games” (by summing them) to be consistent with previous assessments. We further reduced the number of categories by summing “watching TV or shows” and “watching videos” into a combined category of “screen watching” and collapsed “texting”, “visiting social networking sites” and “video chatting” into a combined category of “online social activity”.

Linear mixed-effects models via MATLAB’s Statistics and Machine Learning Toolbox (2020a, Version 11.7) were used to evaluate the extent to which screen time usage changed from baseline to Year 2 as a function of sex at birth (male, female) and day (weekend, weekday). Separate analyses were conducted for “screen watching”, “video games”, and “online social activity”. The fixed-effects structures included sex at birth, age (in months), day, assessment (baseline = 0, Year 1 = 1, Year 2 = 2), and interactions to determine whether the associations between screen usage duration and assessment (for each usage type) were moderated by sex and day (i.e., Sex \times Assessment, Day \times Assessment). The random-effects structures included random intercepts of participant and study site. Data from 11,871 participants were included in analysis, with some participants not having data at all three assessments (screen-watching: 59,114 total observations; video games: 59,131 total observations; online social activity: 59,109 total observations). The categorical factors of sex and day were effects-coded, with Male/Female as $-1/+1$ and weekend/weekday as $-1/+1$; the continuous factor of time-point was centered with respect to Year 1 (baseline = -1 , Year 1 = 0, Year 2 = 1), and the continuous factor of age was mean-centered. Results are presented in the main text in the form of F tests using MATLAB’s *anova* function, and effect sizes for these analyses are presented as partial eta-squared (η_p^2). Finally, parent versus child report of total screen time usage was compared at Year 2 using a pairwise comparison.

Problem. Screen Usage. To evaluate the psychometric validity of the SMAQ and VGAQ, each of these questionnaires was fitted in a single-factor confirmatory factor analysis (CFA) and their model fit was estimated. They were then tested for invariance (configural, metric, scalar) across sex, race, and income. The CFA models were estimated in R Studio 4.1.2 with the “lavaan” function, using maximum likelihood with

robust errors (MLR) as the estimator. Satorra-Bentler adjusted χ^2 was used for all comparisons of nested models (Satorra and Bentler, 2010). Given that the χ^2 statistic is known to be affected by large sample sizes, alternative fit indices were employed for estimating model fit. For absolute model fit, the cut-off values of CFI > 0.90 and RMSEA < 0.08 were considered. Similarly, to compare relative change in model fit, the cutoff values of Δ CFI < 0.01 and Δ RMSEA < 0.01 were used (Chen, 2007; Cheung and Rensvold, 2002).

3. Results

3.1. Psychometric properties of SMAQ and VGAQ

SMAQ was fitted as a single-factor model with items as indicators. The results showed adequate fit, $\chi^2(9) = 597.23, p < .001$, CFI = 0.943, RMSEA = 0.108, 90% RMSEA CI [0.101,0.115]. The modification indices for both the SMAQ and VGAQ suggested a substantial covariance for the residual variance of items 1 (I spend a lot of time thinking about social media apps/planning my use of social media apps/playing video games) and 2 (I feel the need to use social media apps/play video games more and more). Adding this covariance to SMAQ improved the model fit substantially, $\chi^2(8) = 119.98, p < .001$, CFI = 0.989, RMSEA = 0.050 [0.042,0.058]. The fit of the original single-factor VGAQ model was mediocre, $\chi^2(9) = 753.84, p < .001$, CFI = 0.959, RMSEA = 0.105, 90% RMSEA CI [0.098,0.111] but was also improved by adding the residual covariance, $\chi^2(8) = 223.80, p < .001$, CFI = 0.988, RMSEA = 0.060 [0.053,0.067]. The internal consistency reliability indexed by McDonald's ω was .86 for SMAQ and .90 for VGAQ.

In the next step, we tested the measurement invariance by sex. Invariance tests failed to show substantial divergences in sex-, age-, or time point-specific models for SMAQ and VGAQ. Invariance by sex, race, and income were evaluated in multiple-group CFA models. In all models, adding invariance constraints (metric and scalar) resulted in worsening of the models. Changes from configural to metric models showed decreases in RMSEA values that were greater than 0.01. However, in the change from metric to scalar, the change in RMSEA was less than or equal to 0.01. There were not substantial differences in CFI between models (≤ 0.006).

The fit of the configural model for SMAQ was $\chi^2(18) = 613.69, p < .001$, CFI = 0.942, RMSEA = 0.109 [0.101,0.116]. Then, metric model (all loadings set to equality) was fit and its fit was compared to the configural model. The metric model showed a worse fit from the configural model, $\Delta\chi^2(23) = 627.65, p = .000$, but with no change in CF and a larger change in RMSEA (Δ CFI = -0.000 , Δ RMSEA = 0.012). Next, we fit the scalar model (all loadings and intercepts set to equality) and compared its fit to the metric model. While the scalar model showed significantly worse fit than the configural model, $\Delta\chi^2(28) = 660.90, p = .000$, the difference with regards to change in CFI and RMSEA was small, Δ CFI = -0.003 , Δ RMSEA = 0.001.

Next, we tested VGAQ for invariance by sex. The fit of the configural model for VGAQ was $\chi^2(18) = 741.21, p < .001$, CFI = 0.955, RMSEA = 0.103 [0.097,0.110]. The VGAQ metric model showed significantly worse fit than the configural model, $\Delta\chi^2(18) = 741.21, p = .000$. The scalar model, when compared to the metric model, showed significantly worse fit, $\Delta\chi^2(28) = 998.07, p = .000$, Δ CFI = -0.006 , Δ RMSEA < 0.001.

In the next step, we tested measurement invariance of SMAQ and VGAQ by race. The fit of the configural model for SMAQ was $\chi^2(54) = 676.37, p = .000$, CFI = 0.939, RMSEA = 0.112 [0.104,0.119]. The metric model showed a significantly worse fit than the configural model, $\Delta\chi^2(79) = 760.82, p = .000$, and the scalar model showed worse fit than the metric model, $\Delta\chi^2(104) = 832.95, p = .000$, with minimal difference in Δ CFI (-0.005) and a slightly larger difference in Δ RMSEA (0.010). For the invariance testing of VGAQ by race/ethnicity, the fit of the configural model was $\chi^2(54) = 420.07, p = .000$, CFI = 0.961, RMSEA = 0.104 [0.095,0.114]. The metric and scalar models had significant

differences with small change in CFI respectively ($\Delta\chi^2(79) = 450.48, p = .000$; $\Delta\chi^2(104) = 500.16, p = .000$).

Measurement invariance of SMAQ and VGAQ by income was also tested. As was the case for the different race and sex invariance models, the scalar models had the worst fit and the metric models had a worse fit than the configural models for both SMAQ and VGAQ.

Girls reported significantly higher values of SMAQ ($M = 6.35$) as compared to boys ($M = 4.96$), $t(6301) = 8.74, p < .001$. On the other hand, boys reported significantly higher endorsement of VGAQ items ($M = 11.17$) as compared to girls ($M = 5.06$), $t(6312) = 35.58, p < .001$. Further, the highest levels of SMAQ were reported by Black participants ($M = 7.75$), followed by Hispanic ($M = 6.69$), Other ($M = 6.27$), White ($M = 4.73$) and Asian ($M = 4.65$; all pairwise comparisons significant after Bonferroni correction except for Asian and Other, Asian and White, and Other and Hispanic). Similarly, highest values of VGAQ were reported among Black participants ($M = 10.23$), followed by Hispanic ($M = 9.10$), Other ($M = 8.80$), Asian ($M = 7.88$) and White ($M = 7.54$). The mean for Black participants was significantly higher as compared to other four groups; the mean level for Hispanic participants was higher than for White participants; Other reported significantly higher levels than White participants.

3.2. Self-reported screen usage

For all types of screen usage activities, screen usage increased over the three assessments (Figs. 1–3): screen-watching, $F(1, 59107) = 4.04, p = .044, \eta_p^2 = 0.0001$; video games, $F(1, 59124) = 65.43, p < .001, \eta_p^2 = 0.001$; online social activity, $F(1, 59102) = 104.10, p < .001, \eta_p^2 = 0.002$. Across all assessments, boys spent more time screen-watching, $F(1, 59107) = 46.48, p < .001, \eta_p^2 = 0.001$, and playing video games, $F(1, 59124) = 3315.90, p < .001, \eta_p^2 = 0.053$, and girls spent more time on online social activities, $F(1, 59102) = 643.23, p < .001, \eta_p^2 = 0.011$. Time spent playing video games increased more steeply for boys than girls over the three assessments (Sex \times Assessment), $F(1, 59124) = 474.77, p < .001, \eta_p^2 = 0.008$. In contrast, the significant positive association between assessment and time spent engaging in online social activity was more pronounced in girls than boys (Sex \times Assessment), $F(1, 59102) = 485.71, p < .001, \eta_p^2 = 0.008$. There was no Sex \times Assessment interaction on time spent screen-watching, $F(1, 59107) = 0.58, p = .448$. Lastly, for all types of screen usage activities, the increase in usage with assessment was more pronounced on weekends than weekdays (Day \times Assessment), $F_s \geq 12.84, p/s < 0.001, \eta_p^2s \geq 0.0002$.

Direct comparisons of parent and child total screen time usage in Year 2 showed that usage was significantly higher for child vs parent report for both weekdays [$M_{\text{child}} = 196.97$ min, $M_{\text{parent}} = 182.57$ min, $t(11,812) = 4.58, p < .001$] and weekends [$M_{\text{child}} = 310.43$ min, $M_{\text{parent}} = 274.26$ min, $t(11,812) = 9.30, p < .001$].

4. Discussion

While screen-related activities are highly diverse, and likely to change over time, and as such, likely result in differential impact on the neurodevelopmental and behavioral trajectory over the course of childhood and adolescence, studies-to-date are largely cross-sectional, limiting our ability to make causal inferences. These longitudinal screen use data collected in ABCD may begin to address these limitations. Further, by linking screen use data to the wealth of longitudinal neurobehavioral and psychosocial data being collected in ABCD, we may be able to examine short and long term developmental, health and psychosocial outcomes of screen usage in youth. Fig. 4.

4.1. Measures

Given that screen usage questions and response options varied across years of assessment, efforts to harmonize the data to allow for interpretation of longitudinal changes over time were necessary. Harmonized

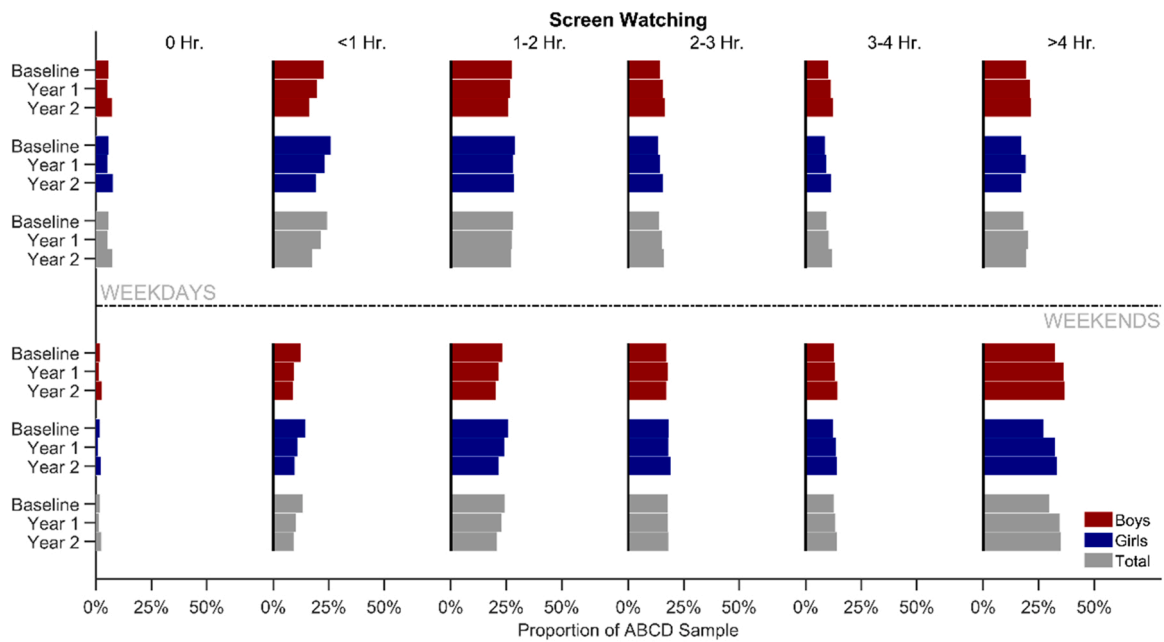


Fig. 1. Proportion of time spent on screen watching across three annual assessments during weekdays and weekends, plotted separately for boys and girls in the ABCD Study®.

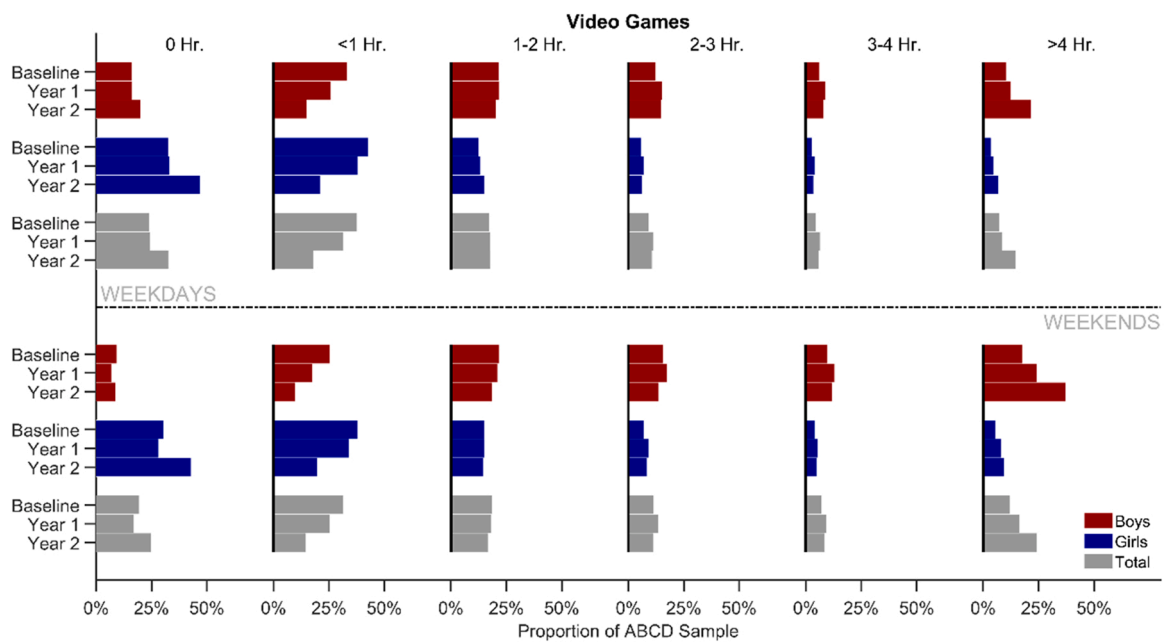


Fig. 2. Proportion of time spent on video gaming across three annual assessments during weekdays and weekends, plotted separately for boys and girls in the ABCD Study®.

youth screen usage variables were created by re-coding the more precise response options beginning in Year 2 to correspond to the categorical response options at baseline and Year 1 assessments. For example, if a child reported that he/she/they spent an average of 2 h and 15 min watching TV or movies in Year 2, for longitudinal analyses comparing baseline, Year 1, and Year 2, this response was recoded to 2 h to fit the earlier categorical response options. We strongly encourage researchers examining ABCD screen usage data to consider assessment changes over time when interpreting their data. We present basic metrics of screen time usage by weekday/weekend and by gender here as an illustrative example. However, we encourage researchers to use the rich, available dataset to examine nuanced associations between screen usage (both

subjective and objective measures) and youth mental and physical health. Consistent with recommendations that any guidelines should account for screen modality and purpose, detailed information about different screen usage categories reported by youth in the ABCD sample will allow researchers to explore more nuanced associations between mental and physical health and screen time usage. [Fig. 5.](#)

4.1.1. Self-reported screen usage

Preliminary analysis of screen usage data from the first three ABCD assessments shows a steady increase in usage for the three modalities examined, screen watching, video gaming, and online social activity, consistent with expected trajectories of increasing use with age across

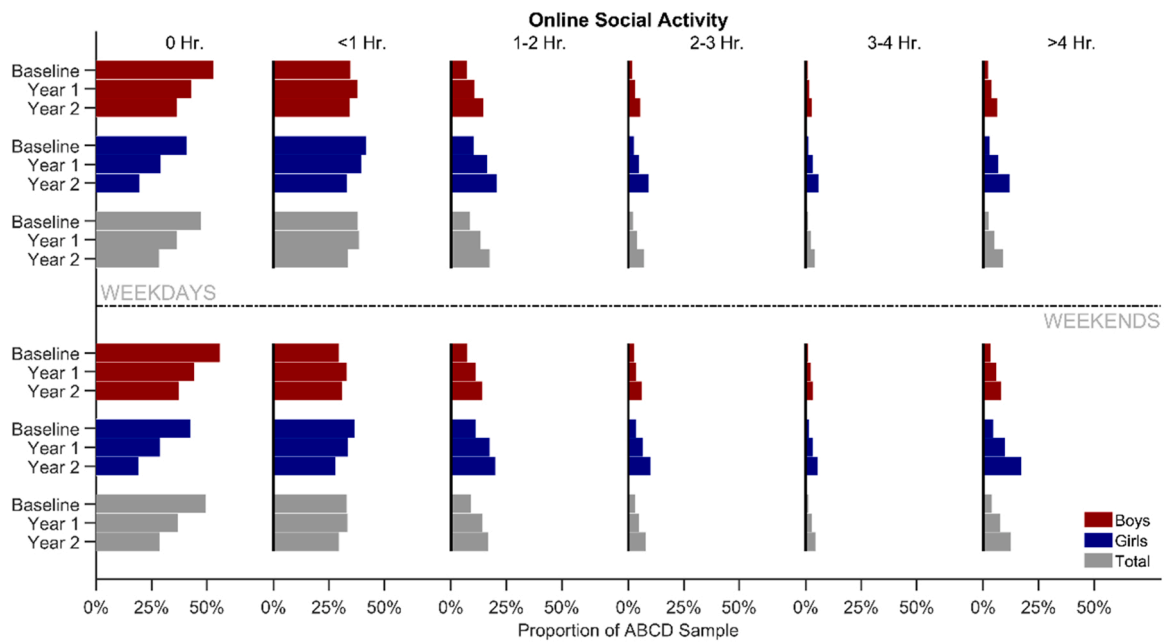


Fig. 3. Proportion of time spent engaged in online social activity across three annual assessments during weekdays and weekends, plotted separately for boys and girls in the ABCD Study®.

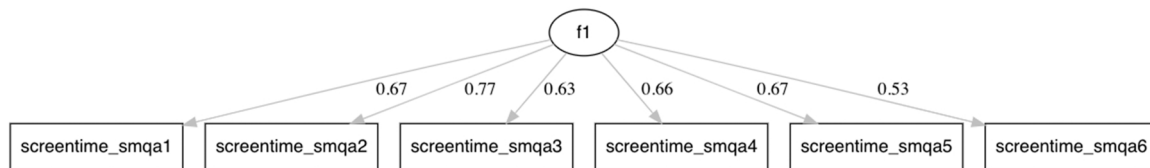


Fig. 4. One Factor Analysis for the Social Media Addiction Questionnaire (Appendix I).

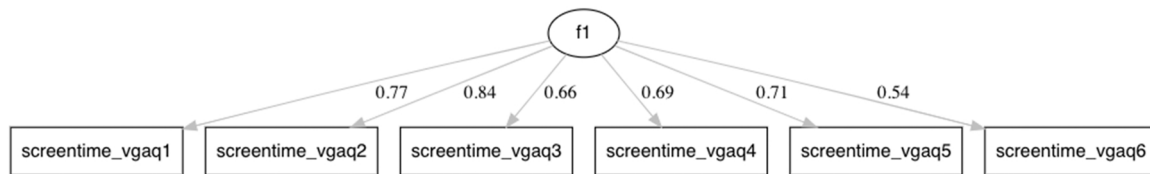


Fig. 5. One Factor Analysis for the Videogame Addiction Questionnaire (Appendix I).

the child and adolescent period (Rideout and Robb, 2019a, 2018).

Total screen usage was significantly higher on weekends versus weekdays, and the increase in usage over time was steeper for weekends than weekday usage. Children and adolescents typically spend more time on screen usage activities on school-free days, like weekends, as supported by our data. Consistent sex differences emerged in screen usage and trajectories over time, which varied depending on the screen usage modality examined. Girls reported greater online social activity and showed a steeper increase in online social activity over assessments than boys. These findings are consistent with prior work among 13–18 year-olds that suggested girls spend more time on social media than boys (Twenge and Martin, 2020). We also found that girls demonstrated higher SMAQ scores, than boys reflecting potential addiction and related consequences. Because girls’ use of social media has also been more strongly linked to negative mental health outcomes such as depressive symptoms and self-harm, this sex difference may have significant implications on the mental health of girls as they reach mid-adolescence (Twenge and Martin, 2020; Twenge and Farley, 2021). In contrast, screen watching and video gaming was higher for boys than for girls consistently across assessment periods. Further, the increase in video

game usage across assessments was steeper in boys than in girls, and boys demonstrated higher VGAQ scores than girls. These data are consistent with literature that adolescent boys are more likely to use video games than girls (Lenhart et al., 2015). Racial and ethnic differences were also found such that Black and Hispanic girls demonstrated significantly higher scores on the SMAQ, and black males had significantly higher scores on the VGAQ. While previous studies have shown higher overall screen use among Black youth, (Magid et al., 2021; Sousa and Silva, 2017) there are a lack of data on racial and ethnic differences in propensity for addiction to social media and video gaming. These are important, as again extrapolating from the youth substance addiction literature, underrepresented minority youth have the poorest addiction-related psychosocial and health outcomes and poorest access to care (Cook et al., 2013; Marrast et al., 2016; Alegria et al., 2011; Foster et al., 2018; Wu et al., 2016; Floyd, 2020). Given that there is increasing acceptance of technology-based behavioral addictions as addictions similar to substance use disorders, (Neimeyer, 2019) this suggests increased health disparities among already at-risk populations.

Finally, in the ABCD Study®, youth reports of their own screen usage are, on average, higher than parent reports of their child’s screen usage,

which may reflect low parental monitoring with regard to mobile and digital device use. Extrapolating from the substance addiction literature, (Fay et al., 2020; Keogh-Clark et al., 2021; Kuntsche and Kuntsche, 2016) this finding may portend poor behavioral and health outcomes for youth. This finding also supports prior literature that parent reports of their child's screen usage have low-moderate concordance with the child's report (Radesky et al., 2020; Ramirez et al., 2011). In studies examining reliability of parent report of adolescent sedentary screen use, parent-adolescent agreement ranged from 0.41 to 0.60 for weekday behavior items and .46 to .66 for weekend behavior items, with greater concordance in dyads where adherence to screen-related rules is higher (Ramirez et al., 2011). In summary, these data from the ABCD Study® show that patterns of self-reported usage increase over time, with divergences in patterns according to weekday and weekend, and that there are notable sex differences, dependent on specific screen modality examined.

4.1.2. Psychometrics of social media and video game addiction questionnaires

Screen time duration is not a direct indicator of problematic social media or video game usage and other measures are necessary to capture compulsory or problematic screen time use. A measure of problematic Facebook use was broadened to assess problematic social media use (SMAQ). This same measure was adapted for problematic video game use in the ABCD sample (VGAQ). We conducted initial tests of measurement invariance across sex, race, and income for both scales. Results suggested that the SMAQ showed similar factor structure and item loadings across sex and race/ethnicities, but that item intercepts varied across both sex and race/ethnicity (scalar invariance not supported). Researchers are encouraged to use caution when comparing group means on the SMAQ across different demographic groups as differences in mean levels may not be meaningfully interpreted. The VGAQ can be used across race/ethnicity, as full configural, metric, and scalar invariance was found supporting the notion that problematic video game use has the same factor structure (configural invariance), item loadings (metric invariance), and intercepts (scalar invariance) across racial and ethnic groups. However, the item loadings and intercepts of the VGAQ differed across sex suggesting that the items of the scale may not measure identical constructs across girls and boys. A reduced or modified version of the scale may be considered. However, it is also possible that problematic video game use looks different for girls and boys and mean comparisons of the VGAQ across sex may not be meaningful.

4.1.3. Limitations and strengths

We are unable to objectively assess screen content using these self-report data. However, as an enhancement compared with much of the extant literature, we capture duration of specific activity by screen modality. For example, not only are we measuring duration of time on social media, but also active (i.e., posting, editing pictures/videos to post) and passive engagement (scrolling). We also capture social aspects of video gaming contributing, measuring a unique and under recognized method of social networking, particularly in boys, by including domains of single and multiplayer video gaming. We also collect contextual data including weekday/weekend screen use and recreational versus school use and parental monitoring, which extrapolating from the substance use literature, likely has a significant impact on addiction and other screen use-related consequences.

The COVID pandemic has had an impact on screen use trajectories in this large, nationally representative sample, as tracked with COVID-focused surveys in the ABCD sample (Nagata et al., 2021). While trajectories of recreational and educational screen usage have escalated during the pandemic, the modes and methods of screen exposure remain largely unchanged and thus captured by the extant screen use survey.

4.1.4. Future directions

There have been many technological advances allowing objective

measurement of health behaviors in youth, which can address over-reliance on self-reported measures of device use and behavior. Self-reported retrospective recall of device use is likely to co-vary with self-reported estimates of mental health symptoms because of overlapping methods and rater bias (Podsakoff et al., 2003). Therefore, there may be inflation of the apparent association between these variables (Kaye et al., 2020). Ideally, to accurately capture how and why people are using different modalities, objective measurement of behavior is useful.

Linking screen usage with other behaviors, like physical activity and sleep, can also be advanced through the application of objective measures of these behaviors. Starting in Year 2 of the ABCD Study®, a commercial activity tracker (Fitbit Charge 2) was added to the protocol and is used to collect data biannually (even years only). Longitudinal monitoring of physical activity and sleep allows examination of patterns over development, seasonal changes and biopsychosocial determinants of healthy, activity and sleep, and examination of relationships between physical activity, sleep, screen usage behaviors, developmental, and mental and physical health in youth. Detailed descriptions of Fitbit data and EARS app data are beyond the scope of this paper and are described elsewhere in relation to pilot data collected in the ABCD sample (Wade et al., 2021; Godino et al., 2020; Wing, et al.).

Finally, (Ramirez et al., 2011) beginning at the Year 4 assessment (End of 2020), the ABCD Study® implemented a smartphone App, Effortless Assessment of Risk States (EARS) (Lind et al., 2018), to passively collect objective smartphone data on duration and time of day of specific app use. The use of EARS may provide important information about digital behaviors, especially as smartphones are the primary source of access to the internet and app-based platforms among youth (Rideout and Robb, 2019b). These data can be used to address critical public health question of the associations between digital device use and developmental outcomes. In addition to individual application use information (to be accessible through the NIMH Data Archive when Year 4 data are available, <https://nda.nih.gov/abcd>), category summaries will also be made publicly available. Readers are referred to a description of the EARS application as applied within the ABCD study, recently published by Wade and colleagues (Wade et al., 2021).

Screen usage data can also be coupled with geospatial, biological, neurocognitive, psychosocial and neuroimaging data, to link behaviors and activity at specific locations or contexts to psychological health and well-being. Prospective study of these reciprocal relationships highlights the potential contribution of ABCD to our understanding of the bidirectional relationships between behavior and health.

5. Conclusion

Here we describe development and evolution of screen use measures in the ABCD study, and validity of measures used to examine potential addiction to social media use and video gaming among children and adolescents in the ABCD cohort. Due to the pace at which technology advances, and differing use by developmental stage, the Novel Technology Workgroup has and will continue to re-evaluate and update as needed the screen use survey to accurately reflect the modes and methods of mobile and digital technology access and use throughout the duration of the ABCD study. We found escalating screen use across modalities over the three-year assessment period, particularly on weekends. Boys demonstrated steeper escalation of video gaming over time, and correspondingly higher scores on the VGAQ for boys compared to girls. We also found more pronounced social media escalation for girls, and correspondingly higher scores on the SMAQ for girls as compared to boys. Racial/ethnic differences in SMAQ and VGAQ were found, such that Black youth had higher scores on addiction questionnaires than all other racial/ethnic groups. Finally, parents underestimated duration of their child/children's screen use.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Nicholas Allen and Ryann Crowley hold equity interests in Ksana Health Inc., a company that has the sole commercial license for certain versions of the Effortless Assessment Research System (EARS) mobile phone application and some related EARS tools.

Data Availability

The ABCD Data Repository stores all data generated by the study. Access can be requested by all qualified researchers via NIMH Data Archive.

Appendix I

Social media addiction questionnaire

Never – Very Rarely – Rarely – Sometimes – Often – Very often.

1. I spend a lot of time thinking about social media apps or planning my use of social media apps.
2. I feel the need to use social media apps more and more.
3. I use social media apps so I can forget about my problems.
4. I've tried to use my social media apps less but I can't.
5. I've become stressed or upset if I am not allowed to use my social media apps.
6. I use social media apps so much that it has had a bad effect on my schoolwork or job

Videogame addiction questionnaire

Never – Very Rarely – Rarely – Sometimes – Often – Very often.

1. I spend a lot of time thinking about playing video games.
2. I feel the need to play video games more and more.
3. I play video games so I can forget about my problems.
4. I've tried to play video games less but I can't.
5. I've become stressed or upset if I am not allowed to play video games.
6. I play video games so much that it has had a bad effect on my schoolwork or job.

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