Current Psychology (2026) 45:657
https://doi.org/10.1007/s12144-026-09093-7

Adolescent screen use in the pre-internet era and subsequent health and well-being: an outcome-wide longitudinal study

Pedro Antonio de la Rosa Fernández-Pacheco[1,2] · Renae Wilkinson[2,3] · Richard G. Cowden[2] · Ying Chen[2,3] · Brendan Case[2] · Etsuji Suzuki[3,4] · Tyler J. VanderWeele[3,4,5]

Received: 4 March 2025 / Accepted: 18 January 2026

Abstract

This study used data from the National Longitudinal Study of Adolescent to Adult Health (Add Health, N=11,054) to assess whether increases in screen-based leisure during adolescence (Wave II, from 1996) predicted adult well-being (Wave IV, from 2008-09), adjusting for a wide range of covariates (Wave I, from 1995). Using an outcome-wide analytic approach, we examined associations between screen time and 38 adult outcomes, adjusting for prior screen time, values of most outcomes, and confounders. Most associations were null. Modest evidence was found for links between screen time (continuous) and reduced sense of control, illicit drug use, and allostatic load. High screen time (14 h/week) or more also showed weak associations with lower depression and preventive care use. Because the data predate widespread internet use, the findings help establish a baseline for the long-term effects of non-internet screen activities, which appeared to behave had limited impact on adult health and well-being.

Keywords Leisure · Television · Outcome-wide epidemiology · Video games · Adolescence · Well-being.

Introduction

Adolescence is a critical period for personal development marked not only by rapid physical, cognitive, and socioemotional changes but also by significant disruptions compared to earlier life experiences. These disruptions may occur at different times, creating developmental turning points that reshape previous trajectories through the interaction with the changes at individual, family, friendships, and school contexts (Chaku & Davis-Kean, 2024).

One major disruption which adolescents increasingly face is the shift from traditional leisure activities to screen-based leisure, which tends to increase and change in nature during adolescence (Zhu et al., 2023). However, due to the neurological changes that take place during adolescence, adolescents might be more vulnerable to the effects of screen leisure than adults or even kids (Marciano et al., 2021).

To date, empirical evidence has generally shown that higher screen-based leisure time is linked to health issues such as obesity (Biddle et al., 2017), symptoms of anxiety and depression (Keles et al., 2020) and suicidal behavior (Twenge et al., 2018). Moreover, cognitive development during adolescence may be disrupted by excessive screen time, which is associated with decreased attention spans (Morita et al., 2022) and lower academic performance (Adelantado-Renau et al., 2019). Furthermore, adolescents may engage in risky behaviors portrayed through media content, such as early sexual activity (Dajches et al., 2021) and substance use (Kelleghan et al., 2020). Additionally, idealized media portrayals may negatively affect adolescents' self-concept, body image, and perceptions of reality, especially when they lack sufficient media literacy (Lemenager

✉ Pedro Antonio de la Rosa Fernández-Pacheco
pdelarosa@alumni.unav.es

1 Youth in Transition, Institute for Culture and Society, Universidad de Navarra, Pamplona, España

2 Human Flourishing Program, Institute for Quantitative Social Science, Harvard University, Cambridge, MA, USA

3 Department of Epidemiology, Harvard T.H. Chan School of Public Health, Boston, MA, USA

4 Department of Epidemiology, Graduate School of Medicine, Dentistry and Pharmaceutical Sciences, Okayama University, Okayama, Japan

5 Department of Biostatistics, Harvard T.H. Chan School of Public Health, Boston, MA, USA

Published online: 09 March 2026

et al., 2020; Owens et al., 2012). The constant availability of digital devices can further amplify these disruptive effects, potentially impairing interpersonal connections and overall well-being (Mérelle et al., 2017).

These immediate effects of screen-based leisure during adolescence could eventually become long-term disruptions within development, acting as turning points with cascading consequences. According to developmental cascade theory, developmental processes function as complex, interconnected systems in which events or disruptions in one domain can propagate effects across other developmental domains, generating cumulative, iterative impacts over time. To robustly capture these cascading effects, it is crucial to employ longitudinal studies with at least three measurement points, clearly defined endpoints, and a suitable timescale to measure developmental trajectories meaningfully (Chaku & Davis-Kean, 2024).

Despite existing research on screen-based leisure, significant gaps remain. First, many existing studies in this area rely on cross-sectional data or are unable to mitigate reverse causation bias because their models typically do not adjust for prior values of the outcome. Second, most studies have focused on the effects of a specific screen time activity or on the combination of several activities. There is a need for more studies that compare the effects of different screen-based activities, which could serve to generate hypotheses about the possible mechanisms that explain the associations between screen-based leisure time and a given outcome (Adelantado-Renau et al., 2019). Third, most research has focused on a single outcome per study, which poses challenges for making meaningful comparisons across studies due to differences in methodology (Odgers & Jensen, 2020). A significant new complexity in interpreting the study's findings arises from the pervasive adoption of smartphones and social media, leading to challenges in determining whether observed effects are uniquely attributable to social media use or reflect a general consequence of broader screen-based activities. In order to address these gaps and enhance the reliability of findings, it is crucial to conduct cohort studies that encompass various types of screen-based activities and examine their associations with a wide range of health and well-being outcomes, while taking steps to mitigate concerns about reverse causality.

To address these limitations, the National Longitudinal Study of Adolescent to Adult Health (Add Health) provides a unique methodological advantage. First, Add Health includes data from multiple waves, enabling examination of how changes in screen-based leisure time between waves influence subsequent outcomes in the long term. Second, given that it started in 1995, Add Health allows exploration of screen-based leisure effects independent of current widespread social media and smartphone use. Thus, this study offers foundational insights for comparative assessment of future research specifically investigating the impacts of social media and smartphones on adolescents.

The primary aim of this study is to investigate associations between adolescents' total screen-based leisure time—including watching TV, video watching videos, and playing video games—and 38 distinct adulthood outcomes across physical health, health behaviors, mental health, psychological well-being, social factors, and civic and prosocial behaviors. A secondary objective is to explore associations between specific screen-based activities and individual outcomes. Based on prior research, we hypothesize that increases in screen-based leisure time during adolescence will be associated with reduced psychological well-being and negative mental and physical health outcomes in adulthood.

Method

Sample

This study utilizes data from Waves I, II, and IV of Add Health, a school-based longitudinal study following a representative sample of adolescents in the United States. The dataset provides extensive information gathered from adolescents, their parents, and additional sources to examine determinants of adolescent development. Detailed protocols and study descriptions are available at https://addhealth.cpc.unc.edu/documentation/. Below is a brief summary.

Interviews (Wave I) were conducted with 20,745 American adolescents in grades 7–12 (ages 12–21) and their parents (typically the mother) in their homes between April and December 1995. A follow-up interview (Wave II) was carried out approximately one year later in 1996 (N=14,738), and additional interviews were conducted in 2000–2001 (Wave III) and 2008 (Wave IV) when participants were 18–26 and 24–32 years old, respectively. The final analytic sample for this study included respondents who completed the Wave II survey (when the screen time exposure was measured) and had a valid sampling weight at Wave IV (N=11,054).

Measures

Exposure

The primary exposure variable was the total amount of screen time in adolescence (Wave II). Participants reported the number of hours per week they spent engaging in three types of screen-based activities: watching TV ("*How many hours a week do you watch television*?"), watching videos

("*How many hours a week do you watch videos?"*), and playing video games ("*How many hours a week do you play video or computer games?*"). The total screen time variable was created by summing the hours spent on these activities.

To facilitate comparisons with prior studies and explore potential threshold effects, the continuous screen time variable was additionally categorized into two groups: screen time usage of fewer than 14 hours per week (approximately equivalent to an average of two hours per day) and 14 or more hours per week (Strasburger et al., 2013). We selected the 14-hour threshold based on international recommendations that limit recreational screen time—including watching TV and playing video games—to no more than 2 hours per day for children and adolescents (Carson et al., 2016). For interpretability, these categories are labeled as 'low' and 'high' screen time usage. Both the continuous and categorical screen time variables were used in the main analyses and assessed separately.

Outcomes

All outcomes were assessed at Wave IV. A comprehensive description of these variables and their coding is provided in Supplemental Text S1. A total of 38 outcomes across multiple domains of health and well-being were analyzed, including:

- ***Physical health***: Number of diagnosed physical health conditions, allostatic load, functional limitations, cognitive health, self-rated health.
- ***Health behavior***: Sleep disturbance, physical inactivity, cigarette smoking, binge drinking, marijuana use, prescription drug misuse, illicit drug use, history of sexually transmitted infections (STIs), preventive healthcare use.
- ***Mental health***: Depressive symptoms, depression diagnosis, anxiety diagnosis, post-traumatic stress disorder (PTSD) diagnosis, attention-deficit/hyperactivity disorder (ADHD) diagnosis, suicidal ideation, perceived stress.
- ***Psychological well-being***: Happiness, job satisfaction, optimism, sense of control.
- ***Social factors***: Loneliness, romantic relationship quality, parenting satisfaction, relationship quality with a parent.
- ***Civic and prosocial behavior***: Voting, volunteering.

Covariates

All models in the main analysis controlled for 37 covariates measured at Wave I. Following the modified disjunctive cause criteria (VanderWeele, 2019), these covariates were selected as they might influence screen time at Wave II, subsequent outcomes at Wave IV, or both, either directly or through proxy measures. Examples of covariates included:

- ***Sociodemographic and family factors*** (e.g., age, race/ethnicity, family structure, number of siblings).
- ***Psychosocial and academic factors*** (e.g., delinquency, grade point average).
- ***Health status and behaviors*** (e.g., pubertal development, somatic symptoms).

Additionally, models for our main analyses accounted for pre-baseline (Wave I) measures of total screen time and available outcome variables from Wave I to control for potential confounding and mitigate bias arising from reverse causality. All continuous measures for exposures, outcomes, and covariates were standardized (mean = 0, SD = 1) before analysis.

Missing data

To address missing data on covariates and outcome variables, we employed multiple imputation using the chained-equations method with five imputed datasets (Azur et al., 2011). In our dataset, the percentage of missing data varied across variables, ranging from 0 to 26%, with the highest proportion of missingness for Wave I household income (26%) and mother's race/ethnicity (25%).

Statistical analysis

Outcome-wide framework

This study adopted an outcome-wide framework, a novel methodological framework that extends traditional causal inference approaches by simultaneously examining the effects of a single exposure (screen time) on multiple outcomes rather than focusing on a single exposure-outcome relationship. This design applies established principles of confounding control across numerous temporally subsequent outcomes, offering several advantages over conventional single-outcome studies, including reduced investigator subjectivity in covariate selection, greater potential for reporting null effects, enhanced capacity for comparing effect sizes across outcomes, and more rapid advancement of knowledge (VanderWeele, 2020).

To mitigate reverse causality and overadjustment bias, outcome-wide studies follow specific temporal and confounding control principles. Covariates are selected using the modified disjunctive cause criterion, controlling for variables that are associated with either the exposure or any of the outcomes, while excluding instrumental variables and including proxies for unmeasured confounders (VanderWeele, 2019). Crucially, all covariates must be measured prior to the exposure (baseline), and pre-baseline outcome measures are also adjusted for to reduce reverse causation (VanderWeele et al., 2020).

Associations between the exposure and each outcome can be directly compared through standardized effect size metrics (standard deviation units) for continuous outcomes, or risk ratios (RRs) for dichotomous outcomes. Using a common scale facilitates direct comparison of effect magnitudes across diverse physical, psychological, and social domains, thereby informing policy discussions with a holistic view of the exposure's potential impact (VanderWeele et al., 2020).

Main analyses

For our main analyses, we conducted a series of multivariable regression models to assess the relationship between total and categorical screen time usage at Wave II and each of the 38 outcomes measured at Wave IV. These models adjusted for the full set of covariates, including pre-baseline measures of the exposure and outcomes (where available) from Wave I. Due to the changing nature of the Add Health questionnaires, our data did not have information about the pre-baseline levels of the following 11 outcomes: allostatic load, cognitive health, prescription drug misuse, perceived stress, job satisfaction, sense of control, loneliness, romantic relationship quality, parenting satisfaction, voting and volunteering.

The analytical approach varied by outcome type:

- Logistic regression was used for binary outcomes with a prevalence below 10%.
- Generalized linear models with a log link and Poisson distribution were applied for binary outcomes with a prevalence of at least 10%.
- Linear regression was employed for continuous outcomes, which were standardized for comparability, as stated above.

Since our models adjusted for pre-baseline screen time levels, the estimated effects of the continuous screen time variable can be interpreted as the impact of a one-standard-deviation increase in screen time (VanderWeele et al., 2020).

The analyses using the dichotomous screen time variable examined differences between low- and high-screen time groups. In these models, the estimated effects reflect the change from low (<14 h/week) to high (≥ 14 h/week) screen time over a one-year period. All analyses are weighted and clustered by school ID to account for the complex sampling design.

To account for multiple testing, we report *p*-values both before and after applying a Bonferroni correction. The adjusted significance threshold was set at 0.05/38 outcomes = 0.0013. All statistical analyses were conducted using STATA 17.

E-values

To evaluate the robustness of our findings to potential unmeasured confounding, we calculated *E*-values. This metric estimates the magnitude of the minimum association that an unmeasured confounder would need to have with both the exposure and outcome, beyond the measured covariates, to fully explain away the observed associations (VanderWeele & Ding, 2017). Researchers can then compare these *E*-values with associations reported in previous literature where such confounders have been measured. This helps determine whether plausible unmeasured confounders are likely to alter the findings substantially, providing valuable context for interpreting the robustness of the results.

Other sensitivity analyses

Four sensitivity analyses were conducted. First, we replicated our models in our main analysis with a more conventional array of eight covariates, replacing the full covariates list with only the pre-baseline sociodemographic variables (omitting pre-baseline levels of the exposure, outcomes, and other family, psychosocial, and academic factors). This allowed us to explore whether differences between our results and those obtained in previous studies might be explained by our method of more extensive confounding control. Second, we replicated the models in our main analysis without controlling for the pre-baseline values of the exposure. This analysis provides an opportunity to assess whether observed associations stem from the disruption of increasing screen time—aligning with developmental cascade theory—or from established habits. Third, all models were replicated with complete-case data instead of imputing missing observations. Fourth, to examine the associations of the three screen-based activities individually with health and well-being in adulthood, we replicated all models of our main analysis by using each specific type of screen time (watching TV, watching videos, or playing video games) as the exposure (one set of analyses per activity), while adjusting for the pre-baseline value of the respective type of media. This last sensitivity analysis helps to infer potential mechanisms of action based on the different characteristics and contexts of these screen behaviors.

Results

The distribution of participants' pre-baseline characteristics by levels of total screen time is shown in Table 1. Compared with the low screen time group, participants with high screen time were more likely to be younger, male, of lower socioeconomic status, and come from single-parent households and households in which someone smoked cigarettes. Their parents were more likely to be Black or Hispanic and reported lower self-rated health. Participants with high screen time had slightly higher levels of parental control and relationship quality with a parental figure, and they were less likely to report having a romantic partner than those with lower screen time.

Main analyses

In our multivariable analyses with total screen time assessed as a continuous or dichotomous variable (Table 2), our models provided evidence of weak associations between total screen time and up to 5/38 of the outcomes examined (four with the continuous measure of screen time and another one with the dichotomous measure) before Bonferroni correction, but not after it; the remaining associations had confidence intervals that did not exclude the null. We summarize the main results below.

Associations between total screen time and health and well-being

A standard deviation increment in total screen time (SD = 20.14 h per week) was associated with an increase in allostatic load (beta: 0.04; 95% CI: 0.00, 0.07), a greater likelihood of illicit drug use (RR: 1.06; 95% CI: 1.02, 1.10), a decrease in sense of control (beta: −0.05; 95% CI: −0.08, −0.02), and a lower likelihood of preventative health care use (RR: 0.97, 95% CI: 0.95, 1.00). None of these associations passed the $p < 0.05$ threshold after Bonferroni correction.

When modeling total screen time as a dichotomous variable, moving from low to high screen time (14 or more hours per week) was associated with lower likelihood of preventative health care use (RR: 0.95, 95% CI: 0.92, 0.99) and a lower likelihood of depression diagnosis (RR: 0.90, 95% CI: 0.81, 1.00), although neither association passed the $p < 0.05$ threshold after Bonferroni correction.

Other analyses

E-values of the associations found

Table 3 shows the *E*-values for assessing the robustness of the assessed associations to potential unmeasured confounding. *E*-values for the associations that excluded the null ranged from 1.19 to 1.47, with their lower confidence intervals ranging from 1.05 to 1.16. These findings suggest that relatively modest unmeasured confounding, above and beyond all the measured covariates, could suffice to shift the observed associations or confidence intervals to include the null.

Sensitivity analyses

Results from all sensitivity analyses are presented in Supplement Text S2. Our sensitivity analyses generally yielded similar effect sizes and association directions, with a few exceptions. For example, in the conventionally adjusted multivariable models (Supplementary Table S1), associations with allostatic load, self-rated health, perceived stress, optimism, volunteering, and illicit drug use met the $p < 0.05$ threshold after Bonferroni correction. Effect sizes from the sensitivity analysis that did not control for pre-baseline values of screen time (Supplementary Table S2) generally fell somewhere in between the effect sizes observed in the main analysis and those observed in the conventionally-adjusted sensitivity analysis (Supplementary Table S1), and most effect sizes were only slightly different from those observed in the main analysis. Associations were similar in magnitude when complete-case analysis was performed (Supplementary Table S3); the association between total screen time and subsequent illicit drug use was the only one that passed the $p < 0.05$ threshold after Bonferroni correction.

When total screen time was replaced by one of the three different screen activities (watching TV, watching videos, or playing video games), effect sizes were generally similar to those found for total screen time. However, there was some variation in the pattern of associations across activity types. For example, watching TV had associations with allostatic load and preventive healthcare use that were similar to those for total screen time, whereas the associations were lower for the other two activities. Sense of control was similarly negatively associated with watching TV and playing video games as it was with total screen time, but the association was slightly weaker for watching videos. Illicit drug use was positively associated with playing video games and watching videos, with the former also showing evidence of association with higher cannabis use. Only the association of playing video games with illicit drug use passed the $p < 0.05$ threshold after Bonferroni correction.

Table 1 Characteristics of participants at baseline by screen time (National longitudinal study of adolescent to adult health [Add health]: N = 11,054)

	Screen time over the past week	
Characteristic	< 14 h of screen time (*n* = 4,984)	≥ 14 h of screen time (*n* = 6,070)
Sociodemographic and family factors		
Age (range: 1–21), mean (*SD*)	15.22 (1.64)	14.90 (1.65)
Female, %	56.82	43.88
Race/ethnicity, %		
White	70.02	62.69
Black	11.70	17.43
Hispanic	11.08	13.01
Asian	3.56	3.27
Other	3.63	3.60
Born in the U.S., %	94.41	94.74
Geographic region, %		
Northeast	17.45	15.80
Midwest	32.88	31.25
South	34.55	40.56
West	15.12	12.38
Two-parent household, %	71.02	67.32
Number of siblings (range: 0–12), mean (*SD*)	1.48 (1.20)	1.44 (1.25)
Household income, %		
1 st quintile	17.72	23.74
2nd quintile	17.55	20.74
3rd quintile	20.36	20.49
4th quintile	22.05	20.62
5th quintile	22.32	14.41
Household welfare receipt, %	18.59	25.06
Has health insurance, %	89.51	87.05
Smoker in household, %	43.83	50.32
Mother age (range: 23–81), mean (*SD*)	40.93 (5.50)	40.44 (5.68)
Mother race/ethnicity, %		
White	73.49	64.53
Black	11.36	16.77
Hispanic	9.36	11.95
Asian	3.50	3.49
Other	2.30	3.26
Parents born in the U.S., %	83.97	83.61
Parental education, %		
Less than high school	9.12	12.36
High school equivalency	26.13	29.89
Some college	25.80	27.48
College degree or higher	38.96	30.26
Mother employed full-time, %	54.30	57.40
Mother religious service attendance, %		
Never or seldom	20.01	20.46
Less than once a week	43.00	43.76
At least once a week	36.99	35.80
Mother self-rated health (range: 1–5), mean (*SD*)	3.71 (1.02)	3.56 (1.03)
Mother happy, %	89.60	88.16
Parent has a disability, %	11.42	13.87
Parent has obesity, %	23.99	23.40
Parent has alcoholism, %	16.94	17.68
Childhood maltreatment by parents, %	18.71	19.70
Psychosocial and academic factors		
Mental health condition diagnosis[a], %	5.73	6.23
Depressive symptoms[a] (range: 0–3), mean (*SD*)	1.69 (0.47)	1.70 (0.46)

Table 1 (continued)

	Screen time over the past week	
Happiness[a] (range: 0–3), mean (*SD*)	3.14 (0.80)	3.12 (0.81)
Self-esteem (range: 1–5), mean (*SD*)	4.10 (0.60)	4.13 (0.59)
Life expectancy (range: 1–5), mean (*SD*)	4.38 (0.67)	4.38 (0.68)
Parental control (range: 0–7), mean (*SD*)	1.91 (1.60)	2.04 (1.57)
Relationship quality with a parent[a] (range: 1–5), mean (*SD*)	4.59 (0.71)	4.67 (0.65)
Neighborhood social cohesion (range: 0–5), mean (*SD*)	3.89 (1.27)	3.85 (1.29)
Religious service attendance, %		
Never or seldom	24.69	26.61
Less than once a week	37.06	35.21
At least once a week	38.25	38.18
Has romantic partner, %	34.06	30.84
Has a learning disability, %	12.93	15.43
PPVT (range: 13–146), mean (*SD*)	102.55 (14.54)	100.31 (14.42)
School connectedness (range: 1–5), mean (*SD*)	3.73 (0.76)	3.70 (0.75)
GPA (range: 1–4), mean (*SD*)	2.87 (0.78)	2.74 (0.77)
Delinquency (range: 0–15), mean (*SD*)	2.64 (2.68)	2.99 (2.84)
Health status and health behavior		
Somatic symptoms (range: 0–4), mean (*SD*)	1.77 (0.41)	1.78 (0.42)
Pubertal development (range: −10.23-9.59), mean (*SD*)	0.21 (2.11)	0.00 (2.18)
Physical health condition diagnosis[a], %	23.58	23.08
Overweight/obesity[a], %	19.32	22.83
Functional limitations[a], %	0.67	0.42
Self-rated health[a] (range: 1–5), mean (*SD*)	3.92 (0.89)	3.82 (0.91)
Suicidal ideation[a], %	13.86	13.41
Sleep disturbance[a], %	24.65	24.22
Physical inactivity[a], %	4.89	4.36
Cigarette smoking[a], %	17.65	15.68
Binge drinking[a], %	5.95	5.95
Marijuana use[a], %	14.50	15.30
Illicit drug use[a], %	11.27	11.79
History of STIs[a], %	2.07	2.26
Preventative health care use[a], %	66.69	65.49

Table is based on non-imputed data. Means and proportions are weighted by the Wave IV Add Health sample weight. p-values come from $\chi 2$ or analysis of variance tests. Cumulative percentages for categorical variables may not add up to 100% due to rounding

[a]Pre-baseline covariate for Wave IV outcome

Discussion

This study used a nationally representative sample of U.S. adolescents to examine the relationships between total screen time—measured as the combined time spent on three screen-based activities—and a wide array of health and well-being outcomes observed 12 to 13 years later in adulthood. A central question motivating this research is whether increases in screen-based leisure during adolescence—well before the advent of social media—can constitute a developmental disruption strong enough to produce enduring consequences more than a decade later.

Increased screen time was not associated with most of the assessed outcomes

Across the 38 outcomes examined, only a small number showed nominal associations with adolescent screen time, and none remained statistically significant after Bonferroni correction. Moreover, the observed effect sizes were modest. Several explanations may account for this overall pattern.

First, from a developmental cascade perspective, one-year increases in screen time during the period of adolescence covered in this study may constitute relatively weak perturbations that, on average, do not propagate across domains or persist over long developmental intervals. In a pre-internet media ecology that was generally less interactive, less personalized, and less continuously accessible than today's algorithm-driven platforms, increases in screen time may have been insufficient to reorganize developmental

Table 2 Screen time and subsequent health and Well-Being in adulthood (National longitudinal study of adolescent to adult health [Add health]: N=11,054)

Outcome	Screen time over the past week		
	Reference[a]	Total hours of screen time	≥14 h of screen time
		RR/OR/β [95% CI][b, c,d]	RR/OR/β [95% CI][b, c,d]
Physical health			
Number of physical health conditions	0.00	−0.01 [−0.03, 0.02]	0.01 [−0.04, 0.06]
Cancer	1.00	1.01 [0.83, 1.22]	1.13 [0.72, 1.78]
High cholesterol	1.00	1.02 [0.93, 1.12]	0.99 [0.80, 1.21]
Hypertension	1.00	0.97 [0.91, 1.04]	0.99 [0.84, 1.15]
Diabetes	1.00	0.92 [0.77, 1.12]	0.88 [0.59, 1.32]
Asthma	1.00	0.98 [0.92, 1.05]	1.06 [0.94, 1.19]
Migraines	1.00	1.02 [0.96, 1.08]	1.01 [0.89, 1.14]
Allostatic load[e]	0.00	0.04 [0.00, 0.07]*	0.03 [−0.02, 0.08]
Overweight/obesity	1.00	1.01 [0.99, 1.03]	1.02 [0.98, 1.06]
Functional limitations	1.00	0.91 [0.81, 1.02]	0.96 [0.76, 1.22]
Cognitive health[e]	0.00	−0.01 [−0.03, 0.02]	0.02 [−0.03, 0.07]
Self-rated health	0.00	−0.01 [−0.04, 0.02]	−0.01 [−0.06, 0.03]
Health behavior			
Sleep disturbance	1.00	1.00 [0.97, 1.03]	1.04 [0.98, 1.10]
Physical inactivity	1.00	0.99 [0.93, 1.05]	0.99 [0.87, 1.14]
Cigarette smoking	1.00	1.01 [0.97, 1.05]	1.04 [0.98, 1.12]
Binge drinking	1.00	1.05 [0.98, 1.12]	1.07 [0.94, 1.23]
Marijuana use	1.00	1.03 [0.97, 1.09]	1.11 [0.99, 1.23]
Prescription drug misuse[e]	1.00	1.03 [0.98, 1.09]	1.06 [0.94, 1.20]
Illicit drug use	1.00	1.06 [1.02, 1.10]**	1.06 [0.98, 1.15]
History of STIs	1.00	0.95 [0.89, 1.02]	1.02 [0.88, 1.18]
Preventative health care use	1.00	0.97 [0.95, 1.00]*	0.95 [0.92, 0.99]*
Mental health			
Depressive symptoms	0.00	0.01 [−0.02, 0.04]	0.04 [−0.01, 0.09]
Depression diagnosis	1.00	0.96 [0.90, 1.03]	0.90 [0.81, 1.00]*
Anxiety diagnosis	1.00	0.97 [0.90, 1.04]	1.02 [0.91, 1.15]
PTSD diagnosis	1.00	1.03 [0.83, 1.29]	0.95 [0.67, 1.36]
ADD/ADHD diagnosis	1.00	1.07 [0.93, 1.23]	0.98 [0.71, 1.34]
Suicidal ideation	1.00	1.01 [0.92, 1.12]	0.92 [0.72, 1.17]
Perceived stress[e]	0.00	0.02 [−0.01, 0.05]	0.02 [−0.03, 0.07]
Psychological well-being			
Happiness	0.00	−0.02 [−0.05, 0.01]	−0.04 [−0.09, 0.02]
Job satisfaction[e]	0.00	−0.01 [−0.04, 0.02]	0.00 [−0.05, 0.05]
Optimism[e]	0.00	−0.02 [−0.05, 0.00]	−0.02 [−0.08, 0.04]
Sense of control[e]	0.00	−0.05 [−0.08, −0.02]**	−0.05 [−0.11, 0.00]
Social factors			
Loneliness[e]	0.00	0.02 [−0.01, 0.05]	0.01 [−0.05, 0.06]
Romantic relationship quality[e]	0.00	−0.02 [−0.05, 0.01]	−0.04 [−0.09, 0.01]
Parenting satisfaction[e, f]	0.00	−0.01 [−0.05, 0.03]	0.03 [−0.04, 0.11]
Relationship quality with parent	0.00	−0.01 [−0.04, 0.01]	−0.02 [−0.07, 0.03]
Civic and prosocial behavior			

Table 2 (continued)

Outcome	Screen time over the past week		
	Reference[a]	Total hours of screen time	≥14 h of screen time
Voting[e]	1.00	0.97 [0.93, 1.01]	0.99 [0.93, 1.05]
Volunteering[e]	1.00	0.96 [0.92, 1.00]	0.96 [0.89, 1.03]

RR risk ratio, *OR* odds ratio, *CI* confidence interval

*$p < 0.05$ before Bonferroni correction; **$p < 0.01$ before Bonferroni correction; ***$p < 0.05$ after Bonferroni correction (the p-value cutoff for Bonferroni correction was 0.05/38 = 0.001 for each outcome)

[a]If the reference value is 1, the effect estimate is OR or RR; if the reference value is 0, the effect estimate is β

[b]The analytic sample was restricted to those who participated in the survey at the exposure wave (Wave II) and had valid sampling weights at the outcome wave (Wave IV). Multiple imputation was performed to impute missing data on the covariates and outcomes. All models are adjusted for Wave I covariates, pre-baseline levels of total screen time and pre-baseline levels of the outcome variable (where available). Specifically, all models controlled for sociodemographic and family factors (age, sex, race/ethnicity, nativity status, geographic region, family structure, number of siblings, household income, household welfare receipt, insurance status, smoker in household, mother age, mother race/ethnicity, parent nativity, parental education, mother employment status, mother religious service attendance, mother health status, mother happiness, parent has a disability, parent has obesity, parent has alcoholism, childhood maltreatment by parents), psychosocial and academic factors (mental health condition diagnosis, depressive symptoms, happiness, self-esteem, life expectancy, relationship quality with a parent, parental control, neighborhood social cohesion, religious service attendance, romantic relationship status, has a learning disability, PPVT, school connectedness, GPA, delinquency), health status and health behavior (somatic symptoms, pubertal development, physical health condition diagnosis, overweight/obesity, functional limitations, self-rated health, suicidal ideation, sleep disturbance, physical inactivity, cigarette smoking, binge drinking, marijuana use, illicit drug use, history of STIs, preventative health care use), and total screen time assessed at Wave I

[c]An outcome-wide analytic approach was used, and a separate model was run for each outcome. A different type of model was run depending on the nature of the outcome: (1) for each binary outcome with a prevalence of ≥10%, a generalized linear model (with a log link and Poisson distribution) was used to estimate a RR; (2) for each binary outcome with a prevalence of < 10%, a logistic regression model was used to estimate an OR; and (3) for each continuous outcome, a linear regression model was used to estimate a β

[d]All continuous outcomes were standardized (mean = 0, standard deviation = 1), and β was the standardized effect size

[e]Outcome for which the same measures wasn’’t available at Wave I

[f]Analysis for this outcome was restricted to participants who reported having at least one child (n = 5,316)

trajectories in durable ways. At the same time, when effects do occur, they may plausibly depend more on content than on duration alone—for example, exposure to risky behaviors portrayed in media (Christodoulou et al., 2020), as we will discuss below. Because Add Health measures time spent on screens, but not content or quality, we could not test content-specific hypotheses directly.

Second, screen time was assessed via self-report, which may introduce measurement error and attenuate associations. Prior work suggests that effect sizes can be smaller when media exposure is self-reported than when it is measured directly (Jones-Jang et al., 2020; Parry et al., 2021). Although our exposure measure was assessed contemporaneously in adolescence (which may reduce long-term recall concerns), adolescents can misjudge time passage during leisure, which could still introduce error (Smith et al., 2017). Some behavioral outcomes (e.g., illicit drug use) may also be affected by social desirability bias, potentially biasing estimates toward the null.

Third, screen-based leisure is heterogeneous in its motivations and functions, and this heterogeneity may yield effects that cancel out at the population level. Adolescents may engage in similar “screen time” durations for very different reasons (e.g., entertainment, coping, learning) to satisfy different needs or motivations (Katz et al., 1973). Therefore, it might be that the antecedents of the activity practiced, and not the activity itself, that are related to health and well-being (Twenge et al., 2020). The combination of the engaged activity and its underlying motivation can affect the degree of gratification obtained (Brinberg et al., 2023). Unfortunately, Add Health does not include detailed measures of motives, social context, or content, which limits our ability to disaggregate these possible pathways.

Fourth, the long interval between exposure and outcome assessment may have diluted any early effects of adolescent screen time. After a long period of follow-up, young adults in our study may have undergone a series of life transitions that could have affected the study outcomes more than any increase in their screen time from a decade earlier. To address these issues, studies with continued assessment of the exposure (i.e., through repeated measures) can help to understand the impacts of persistent screen-based leisure time. Nagata and colleagues (2023) used Add Health to examine averaged screen time from 1994 (Wave I) to 2018 (Wave V) with cardiovascular health in adulthood. Compared to the present study, Nagata et al.‘s (2023) work had a longer exposure period and a shorter follow-up time. They found a small association between this life-averaged assessment of screen time and cardiovascular risk. Consistent with this possibility, our study found a very small association

Table 3 Robustness to unmeasured confounding (E-Values) for the association between screen time and subsequent health and Well-Being in adulthood (National longitudinal study of adolescent to adult health [Add health]: $N=11{,}054$)

Outcome	Screen time over the past week	
	Total hours of screen time	≥ 14 h of screen time
	E-values[a] [EE[b], LCI[c]]	E-values[a] [EE[b], LCI[c]]
Physical health		
Number of physical health conditions	[1.08, 1.00]	[1.11, 1.00]
Cancer	[1.08, 1.00]	[1.51, 1.00]
High cholesterol	[1.17, 1.00]	[1.14, 1.00]
Hypertension	[1.20, 1.00]	[1.14, 1.00]
Diabetes	[1.38, 1.00]	[1.52, 1.00]
Asthma	[1.16, 1.00]	[1.30, 1.00]
Migraines	[1.14, 1.00]	[1.08, 1.00]
Allostatic load[d]	[1.22, 1.06]	[1.20, 1.00]
Overweight/obesity	[1.10, 1.00]	[1.15, 1.00]
Functional limitations	[1.42, 1.00]	[1.23, 1.00]
Cognitive health[d]	[1.08, 1.00]	[1.14, 1.00]
Self-rated health	[1.12, 1.00]	[1.12, 1.00]
Health behavior		
Sleep disturbance	[1.03, 1.00]	[1.24, 1.00]
Physical inactivity	[1.12, 1.00]	[1.09, 1.00]
Cigarette smoking	[1.11, 1.00]	[1.26, 1.00]
Binge drinking	[1.26, 1.00]	[1.35, 1.00]
Marijuana use	[1.20, 1.00]	[1.45, 1.00]
Prescription drug misuse	[1.22, 1.00]	[1.31, 1.00]
Illicit drug use[d]	[1.31, 1.16]	[1.31, 1.00]
History of STIs	[1.28, 1.00]	[1.15, 1.00]
Preventative health care use	[1.19, 1.06]	[1.27, 1.08]
Mental health		
Depressive symptoms	[1.10, 1.00]	[1.23, 1.00]
Depression diagnosis	[1.24, 1.00]	[1.47, 1.05]
Anxiety diagnosis	[1.22, 1.00]	[1.17, 1.00]
PTSD diagnosis	[1.22, 1.00]	[1.28, 1.00]
ADD/ADHD diagnosis	[1.35, 1.00]	[1.18, 1.00]
Suicidal ideation	[1.14, 1.00]	[1.40, 1.00]
Perceived stress[d]	[1.15, 1.00]	[1.15, 1.00]
Psychological well-being		
Happiness	[1.15, 1.00]	[1.22, 1.00]
Job satisfaction[d]	[1.12, 1.00]	[1.05, 1.00]
Optimism[d]	[1.18, 1.00]	[1.16, 1.00]
Sense of control[d]	[1.26, 1.14]	[1.27, 1.00]
Social factors		
Loneliness[d]	[1.16, 1.00]	[1.09, 1.00]
Romantic relationship quality[d]	[1.17, 1.00]	[1.23, 1.00]
Parenting satisfaction[d,,e]	[1.11, 1.00]	[1.21, 1.00]
Relationship quality with parent	[1.11, 1.00]	[1.23, 1.00]
Civic and prosocial behavior		
Voting[d]	[1.22, 1.00]	[1.13, 1.00]
Volunteering[d]	[1.25, 1.00]	[1.25, 1.00]

[a]The formula for calculating *E*-values can be found in VanderWeele and Ding (2017)

[b]EE, effect estimate. *E*-values for effect estimates are the minimum strength of association on the risk ratio scale that an unmeasured confounder would need to have with both the exposure and the outcome to fully explain away the observed association between the exposure and outcome, conditional on the measured covariates

[c]LCI, lower confidence interval. *E*-values for the limit of the 95% CI closest to the null denote the minimum strength of association on the risk ratio scale that an unmeasured confounder would need to have with both the exposure and the outcome to shift the CI to include the null value, conditional on the measured covariates

[d] Outcome for which the same measures wasn''t available at Wave I

[e]Analysis for this outcome was restricted to participants who reported having at least one child ($n=5{,}316$)

between one-year increases in adolescent screen time and allostatic load—a marker of cardiovascular health—twelve years later. The weaker, less robust associations observed in our analysis could reflect a longer time lag between exposure and outcome. It is possible that small long-term effects only emerge when screen use is sustained over time. Given the differences in these findings across the two studies, we hypothesize that the small effects of screen time on cardiovascular health are stable across different life stages. Still, further research with extended exposure measurement and strong confounding control is needed to confirm this hypothesis.

Possible mechanisms of the associations found according to the type of screen-based activity

To explore potential mechanisms behind the small effects observed for total screen time, we examined whether these small associations were also present when analyzing the three screen-based activities—watching TV, watching videos, and playing video games—separately. The patterns of associations found were broadly similar, but there was some variation. For example, in our sensitivity analysis, watching videos and playing video games, but not watching TV, were both associated with an increased risk of illicit drug use. Conversely, increases in time spent watching TV and playing video games, but not watching videos, were both associated with a reduced sense of control. The nuances of these activities may explain the modest associations found.

One possible explanation is that watching videos and playing video games may have exposed adolescents to more mature or risk-related content. Such content can desensitize viewers and reduce their ability to enjoy lower levels of stimulation, as shown in recent studies (Christodoulou et al., 2020). It may also shape attitudes in ways that favor substance use (Boers et al., 2020). By contrast, broadcast television in the 1990 s was subject to federal regulation standards and often included content designed to protect minors, specifically under the Children's Television Act of 1990. Unlike video games or rented movies, broadcast television was mandated to provide educational programming and adhered to strict indecency and educational standards during waking hours. In line with this interpretation, some studies have even found that watching TV may offer a protective effect compared to other leisure activities (Tibbits et al., 2009).

A second possibility concerns the structure of engagement in the three screen-based activities. The ease of engaging in long, unplanned sessions may differ by activity. In the 1990 s, it was more common to spend extended time watching broadcast TV or playing video games than watching rented or personal video collections. Repeated long TV or gaming sessions may have led to feelings of shame, particularly among adolescents with an external locus of control. This could undermine their belief in their ability to regulate behavior (Granow et al., 2018; Lloyd et al., 2019).

These interpretations remain speculative, as Add Health does not measure content, social co-use, or motivations; future studies with richer exposure characterization are needed to test these mechanisms directly.

Differences between the main analysis and the sensitivity analyses

In our sensitivity analyses, we found some evidence of associations between total screen time and several outcomes that were not observed in our main models. These additional associations were consistent with the previous literature, which used less rigorous approaches to confounding control. These include links between screen use and memory skills (Kovess-Masfety et al., 2016), tobacco and marijuana use (Kelleghan et al., 2020), diagnosis of attention disorders (Morita et al., 2022), stress (Keles et al., 2020), depressive symptoms (Li et al., 2022), diagnosis of depression (Twenge et al., 2018), optimism (Oberle et al., 2020), romantic relationship quality (Reizer & Hetsroni, 2014), voting (Ksiazek et al., 2019), and volunteering (Filsinger & Freitag, 2019).

This pattern may reflect the limitations of conventional methods in accounting for confounding and selection biases. Media use is shaped by personal and contextual factors that are not always controlled in simpler models (Hartanto et al., 2021). Moreover, associations between screen use and several outcomes are likely bidirectional (Morita et al., 2022), thus failing to adjust for prior values of exposures and outcomes can lead to inflated estimates due to reverse causality.

In contrast, our main analyses adjusted for earlier values of both the exposure and the outcomes. As a result, our estimates represent the effect of a one-year increase in screen time—that is, *incident* rather than *prevalent* exposure. The predominantly null findings in our rigorous main models suggest that, for most adolescents in the pre-Internet era, a one-year increase in screen activity is likely a transient fluctuation rather than a disruption potent enough to reorganize developmental trajectories and produce lasting effects across multiple domains (Chaku & Davis-Kean, 2024). Consequently, the associations emerging in the sensitivity analyses likely reflect distinct developmental cascades already established among high-frequency users—driven by prevalent, accumulated exposure—which unadjusted models fail to distinguish from incident change. With this in mind, we can suspect that focusing exclusively on reducing screen time without considering its quality and context may not have a substantial long-term impact on well-being.

Comparison with recent studies about screen-based activities

While the long-term societal context has changed considerably since the 1990 s, some parallels with more recent findings remain informative. A recent outcome-wide study by de la Rosa et al. (2024), which used three waves of data and focused on adults rather than adolescents, found that increases in screen time over a two-year period were associated with increased body mass index and decreased self-control—outcomes that are related to allostatic load and sense of control, respectively. These associations mirror two of the few non-null findings in our study, despite substantial differences in study population, timeframe, and digital context. Both studies also found largely null associations across most other outcomes.

Additionally, more recent research has begun to disentangle the effects of various types of screen activities for certain outcomes related to self-control and illicit drug use. For example, social media use has been linked more consistently to ADHD symptom trajectories than playing video games or watching TV, potentially through impulsivity and response inhibition pathways (Wallace et al., 2023). A similar pattern was observed by Doggett et al. (2019), who found that internet use and messaging were robustly associated with cannabis use among Canadian adolescents. Notably, watching TV and playing video games were only associated with cannabis use among girls.

Together, these studies suggest that while traditional forms of screen use may still carry some risk, the more interactive and socially driven characteristics of modern digital environments appear to have stronger and more consistent links to developmental outcomes among adolescents.

Policy implications and future research

Although direct policy recommendations should be made with caution, these cross-cohort similarities suggest that some mechanisms—particularly those involving physiological regulation and self-regulatory capacities—may be consistently affected by sustained increases in screen time, even with data from before widespread internet use. Even small effects on indicators such as cardiovascular risk or self-control can accumulate over time and produce meaningful impacts on health care systems and the broader economy (Platt et al., 2017). However, given the differences in digital environments between the 1990s and today, contemporary interventions should move beyond duration-only limits to address both modality-specific features of modern screen activities and the broader social ecology of use—such as peer dynamics, parenting practices, and individual self-regulatory traits that jointly shape screen engagement (Chen et al., 2025).

Importantly, our findings from the pre-Internet era may serve as a historical control for understanding the developmental impact—or lack thereof—of traditional, less interactive screen use. When considered alongside more recent studies that report stronger effects for socially interactive and algorithm-driven digital activities (e.g., Wallace et al., 2023), our results help contextualize which types of screen use may carry greater long-term risk. This historical reference point suggests that if modern studies observe larger associations, these may be plausibly attributed to distinctive features of the post-internet environment—such as persistent connectivity, real-time feedback, and personalized content delivery. Accordingly, future policies should move beyond generic screen time limits and instead focus on the specific characteristics of digital engagement that are most likely to disrupt developmental trajectories. Research that distinguishes between types of screen activities, spans multiple exposure periods, and accounts for evolving technological contexts will be essential for developing nuanced, developmentally informed guidelines.

Strengths and limitations

This study has several limitations that warrant consideration. First, these findings must be interpreted within their historical context: our data were collected before widespread internet access. Since 1996, the media environment has changed dramatically, especially with the rise of social media and algorithmic content delivery. Therefore, our findings may not be generalized to contemporary forms of screen engagement. However, as mentioned above, this historical context is also a strength, as it allows us to isolate the effects of traditional screen-based activities without the influence of internet interactivity.

Second, screen time was self-reported, which may introduce measurement error that could cause attenuation bias, skewing estimates toward the null. However, our overall findings were consistent across continuous and dichotomized coding of the exposure, suggesting that attenuation bias alone may not fully explain the observed null findings. Future studies could benefit from more robust designs, such as intensive longitudinal methods using objective data from digital devices to avoid self-report error.

Third, our models do not capture potential nonlinear associations, such as a 'Goldilocks effect' in which moderate screen time may be less harmful than very low or very high levels. We dichotomized screen time following Strasburger and Hogan (2013), defining high use as 14 or more hours per week. However, recent research on smartphone use suggests nonlinear effects. For instance, Kelly et al. (2019) found that going from zero to two hours of daily use raised depression incidence among girls from 11% to 16%, while increasing to five hours raised it to 37%. If similar nonlinear effects had been observed from increasing screen-time in the 1990s, our linear models and dichotomization approach could have obscured them.

Fourth, we lacked data on important characteristics of screen use, including users' motivations, content viewed, social context, device type, and parental controls. These unmeasured variables could confound our results. To assess the robustness of our findings against potential confounding, we calculated *E*-values for all associations (VanderWeele & Ding, 2017). This metric determines the minimum strength of association that an unmeasured confounder must have with both the exposure and the outcome to account for the observed results. In several cases, even relatively modest unmeasured confounding could have been sufficient to explain the detected associations. However, it is important to highlight that our analysis controlled for a comprehensive set of potential confounders, meaning that any unidentified confounding variables would need to exhibit associations independent of those already accounted for—or proxy ones—to influence the observed relationships between screen time and the outcomes. Among plausible unmeasured factors, motivations and contextual drivers of screen use—what content is consumed, with whom, and with how much agency—should be prioritized in future research (Brinberg et al., 2023; Chen et al., 2025).

Finally, while we employed multiple imputation by chained equations to address missing data, this method assumes that data are missing at random; if data were missing not at random, bias could persist. However, given that our sensitivity analysis using complete-case data yielded effect sizes largely similar in magnitude to those from the imputed models, it appears unlikely that missing-data patterns substantially distorted our main conclusions. Among the strengths of this study are its large sample size, long follow-up period, and use of an innovative outcome-wide analytic approach. This analytical framework facilitated comparability across all the associations examined and reduced the potential for bias arising from reverse causation and researcher subjectivity. Moreover, presenting both significant and non-significant findings in our outcome-wide analysis helps minimize publication bias and offers meaningful contributions to future meta-analyses. By reporting all results, regardless of statistical significance, this study promotes a more thorough understanding of the topic, enhances research transparency, and broadens the evidence base for further synthesis.

Conclusion

By employing a rigorous methodological approach, this study found that increases in screen time during the pre-Internet era were generally not associated with long-term health and well-being in early adulthood. The most consistent evidence pointed to a slight reduction in sense of control and a modest increase in illicit drug use, though both associations were small in magnitude. These mostly null results underscore the need for research to approach screen-based leisure with greater specificity. Rather than treating screen time as a uniform exposure, future work should aim to disentangle the effects of different types of content, motivations for use, and the social context in which screen-based activities occur. Further research is needed to evaluate whether these findings are replicated in different populations and under contemporary digital conditions. Studies using recent datasets will be particularly useful in clarifying the evolving relationship between screen-based activities and long-term health and well-being.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s12144-026-09093-7.

Author contributions TVW designed the analytical framework. RW got access to the database, performed all analyses, and wrote the description of the methods and tables in the text and supplementary materials. PdlR performed the literature search and wrote the first draft of the introduction, results and discussion. All authors critically reviewed the text and contributed intellectually to its content in successive revisions.

Funding Open Access funding provided thanks to the CRUE-CSIC agreement with Springer Nature. PdlR is supported by Universidad Internacional de la Rioja. ES is supported by the Japan Society for the Promotion of Science (JSPS KAKENHI Grant Numbers JP19KK0418 and JP23K09740). TVW wishes to acknowledge John Templeton Foundation (Grant 61665) as it supported general well-being research within the team. The funders had no role in preparing the manuscript or the decision to publish it.

Data Availability Parts of the datasets generated and/or analyzed during the current study are publicly available in the Adolescent to Adult Health repository (https://www.cpc.unc.edu/projects/addhealth/documentation/publicdata). However, this study utilized the extensive restricted-use data available by contractual agreement. Per the Add Health website (https://data.cpc.unc.edu/projects/2/view), "Restricted -Use Data will be distributed only to certified researchers who commit themselves to maintaining limited access. To be eligible to enter into a contract, researchers must complete the Contract Application, which includes: a security plan, an IRB approval letter, and a $1000 payment by check (NEW contract only). This website also has links for how to apply for the restricted-use dataset. No third-party data was used." Code used to run analyses for this study are available upon reasonable request.

Declarations

Statement regarding ethical approval Add Health has been approved by several ethical committees, including the University of North Carolina IRB. Research was conducted in accordance with the Declaration of Helsinki and its later amendments.

Statement regarding informed consent Written informed consent was obtained for all Add Health participants in accordance with the University of North Carolina School of Public Health Institutional Review Board guidelines that are based on the Code of Federal Regulations on the Protection of Human Subjects 45CFR46.

Statement regarding the welfare of animals Not applicable.

Statement regarding data source This research uses data from Add Health, funded by grant P01 HD31921 (Harris) from the Eunice Kennedy Shriver National Institute of Child Health and Human Development (NICHD), with cooperative funding from 23 other federal agencies and foundations. Add Health is currently directed by Robert A. Hummer and funded by the National Institute on Aging cooperative agreements U01 AG071448 (Hummer) and U01AG071450 (Aiello and Hummer) at the University of North Carolina at Chapel Hill. Add Health was designed by J. Richard Udry, Peter S. Bearman, and Kathleen Mullan Harris at the University of North Carolina at Chapel Hill.

Statement regarding conflict of interests On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

Adelantado-Renau, M., Moliner-Urdiales, D., Cavero-Redondo, I., Beltran-Valls, M. R., Martínez-Vizcaíno, V., & Álvarez-Bueno, C. (2019). Association between screen media use and academic performance among children and adolescents: A systematic review and meta-analysis. *JAMA Pediatrics, 173*(11), 1058. https://doi.org/10.1001/JAMAPEDIATRICS.2019.3176

Azur, M. J., Stuart, E. A., Frangakis, C., & Leaf, P. J. (2011). Multiple imputation by chained equations: What is it and how does it work? *International Journal of Methods in Psychiatric Research, 20*(1), 40–49. https://doi.org/10.1002/mpr.329

Biddle, S. J. H., García Bengoechea, E., Pedisic, Z., Bennie, J., Vergeer, I., & Wiesner, G. (2017). Screen time, other sedentary behaviours, and obesity risk in adults: A review of reviews. *Current Obesity Reports, 6*(2), 134–147. https://doi.org/10.1007/s13679-017-0256-9

Boers, E., Afzali, M. H., & Conrod, P. (2020). A longitudinal study on the relationship between screen time and adolescent alcohol use: The mediating role of social norms. *Preventive Medicine, 132*, Article 105992. https://doi.org/10.1016/j.ypmed.2020.105992

Brinberg, M., Ram, N., Wang, J., Sundar, S. S., Cummings, J. J., Yeykelis, L., & Reeves, B. (2023). Screenertia: Understanding stickiness of media through temporal changes in screen use. *Communication Research, 50*(5), 535–560. https://doi.org/10.1177/00936502211062778

Carson, V., Hunter, S., Kuzik, N., Gray, C. E., Poitras, V. J., Chaput, J.-P., Saunders, T. J., Katzmarzyk, P. T., Okely, A. D., Connor Gorber, S., Kho, M. E., Sampson, M., Lee, H., & Tremblay, M. S. (2016). Systematic review of sedentary behaviour and health indicators in school-aged children and youth: An update. *Applied Physiology, Nutrition, and Metabolism, 41*(6, Suppl. 3), S240–S265. https://doi.org/10.1139/apnm-2015-0630

Chaku, N., & Davis-Kean, P. E. (2024). Positioning adolescence in the developmental timeline. *Journal of Research on Adolescence*, *34*, 1191–1200. https://doi.org/10.1111/jora.12928

Chen, S., Chen, C., Xu, H., Wang, L., Xie, W., Tao, W., et al. (2025). The interdependent effects of parental, peer, and self factors on children's screen time: A cross-lagged network panel study. *Current Psychology, 44*, 6315–6325. https://doi.org/10.1007/s12144-025-07509-4

Christodoulou, G., Majmundar, A., Chou, C., & Pentz, M. A. (2020). Anhedonia, screen time, and substance use in early adolescents: A longitudinal mediation analysis. *Journal of Adolescence*, *78*(1), 24–32. https://doi.org/10.1016/j.adolescence.2019.11.007

Dajches, L., Terán, L., Yan, K., & Aubrey, J. S. (2021). Not another teen show: Exploring the impact of sexual scripts in sexually oriented teenage television on adolescent girls' romantic relationship and sexual expectations. *Journal of Broadcasting & Electronic Media*, *65*(4), 575–594. https://doi.org/10.1080/08838151.2021.1981903

de la Rosa, P. A., Cowden, R. G., Bulbulia, J. A., Sibley, C. G., & VanderWeele, T. J. (2024). Effects of Screen-Based leisure time on 24 subsequent health and Well-being outcomes: A longitudinal Outcome-Wide analysis. *International Journal of Behavioral Medicine*. https://doi.org/10.1007/s12529-024-10307-0

Doggett, A., Qian, W., Godin, K., De Groh, M., & Leatherdale, S. T. (2019). Examining the association between exposure to various screen time sedentary behaviours and cannabis use among youth in the COMPASS study. *SSM - Population Health, 9*, Article 100487. https://doi.org/10.1016/j.ssmph.2019.100487

Filsinger, M., & Freitag, M. (2019). Internet use and volunteering: Relationships and differences across age and applications. *Voluntas : International Journal of Voluntary and Nonprofit Organizations, 30*(1), 87–97. https://doi.org/10.1007/s11266-018-0045-4

Granow, V. C., Reinecke, L., & Ziegele, M. (2018). Binge-watching and psychological well-being: Media use between lack of control and perceived autonomy. *Communication Research Reports, 35*(5), 392–401. https://doi.org/10.1080/08824096.2018.1525347

Hartanto, A., Quek, F. Y. X., Tng, G. Y. Q., & Yong, J. C. (2021). Does social media use increase depressive symptoms? A reverse causation perspective. *Frontiers in Psychiatry, 12*, Article 641934. https://doi.org/10.3389/fpsyt.2021.641934

Jones-Jang, S. M., Heo, Y.-J., McKeever, R., Kim, J.-H., Moscowitz, L., & Moscowitz, D. (2020). Good news! Communication findings may be underestimated: Comparing effect sizes with self-reported and logged smartphone use data. *Journal of Computer-Mediated Communication, 25*(5), 346–363. https://doi.org/10.1093/jcmc/zmaa009

Katz, E., Blumler, J. G., & Gurevitch, M. (1973). Uses and Gratifications Research. *Public Opinion Quarterly, 37*(4), 509. https://doi.org/10.1086/268109

Keles, B., McCrae, N., & Grealish, A. (2020). A systematic review: The influence of social media on depression, anxiety and psychological distress in adolescents. *International Journal of Adolescence and Youth*, *25*(1), 79–93. https://doi.org/10.1080/02673843.2019.1590851

Kelleghan, A. R., Leventhal, A. M., Cruz, T. B., Bello, M. S., Liu, F., Unger, J. B., et al. (2020). Digital media use and subsequent cannabis and tobacco product use initiation among adolescents. *Drug and Alcohol Dependence, 212*, Article 108017. https://doi.org/10.1016/j.drugalcdep.2020.108017

Kelly, Y., Zilanawala, A., Booker, C., & Sacker, A. (2019). Social media use and adolescent mental health: Findings from the UK millennium cohort study. *EClinicalMedicine*, *6*, 59–68. https://doi.org/10.1016/j.eclinm.2018.12.005

Kovess-Masfety, V., Keyes, K., Hamilton, A., Hanson, G., Bitfoi, A., Golitz, D., et al. (2016). Is time spent playing video games associated with mental health, cognitive and social skills in young children? *Social Psychiatry and Psychiatric Epidemiology, 51*(3), 349–357. https://doi.org/10.1007/s00127-016-1179-6

Ksiazek, T. B., Kim, S. J., & Malthouse, E. C. (2019). Television news repertoires, exposure diversity, and voting behavior in the 2016 U.S. election. *Journalism & Mass Communication Quarterly, 96*(4), 1120–1144. https://doi.org/10.1177/1077699018815892

Lemenager, T., Neissner, M., Sabo, T., Mann, K., & Kiefer, F. (2020). Who am i" and "How should i be": A systematic review on self-concept and avatar identification in gaming disorder. *Current Addiction Reports, 7*(2), 166–193. https://doi.org/10.1007/S40429-020-00307-X/TABLES/3

Li, L., Zhang, Q., Zhu, L., Zeng, G., Huang, H., Zhuge, J., et al. (2022). Screen time and depression risk: A meta-analysis of cohort studies. *Frontiers in Psychiatry*, *13*, 1058572. https://doi.org/10.3389/FPSYT.2022.1058572/BIBTEX

Lloyd, J., Frost, S., Kuliesius, I., & Jones, C. (2019). Locus of control and involvement in videogaming. *New Media & Society*, *21*(7), 1613–1635. https://doi.org/10.1177/1461444819828308

Marciano, L., Camerini, A. L., & Morese, R. (2021). The developing brain in the digital era: A scoping review of structural and functional correlates of screen time in adolescence. *Frontiers in Psychology, 12*, Article 671817. https://doi.org/10.3389/fpsyg.2021.671817

Mérelle, S. Y. M., Kleiboer, A. M., Schotanus, M., Cluitmans, T. L. M., Waardenburg, C. M., Kramer, D., et al. (2017). Which health-related problems are associated with problematic video-gaming or social media use in adolescents? A large-scale cross-sectional study. *Clinical Neuropsychiatry*, *14*(1), 11–19.

Morita, M., Ando, S., Kiyono, T., Morishima, R., Yagi, T., Kanata, S., et al. (2022). Bidirectional relationship of problematic Internet use with hyperactivity/inattention and depressive symptoms in adolescents: A population-based cohort study. *European Child & Adolescent Psychiatry, 31*(10), 1601–1609. https://doi.org/10.1007/s00787-021-01808-4

Nagata, J. M., Lee, C. M., Lin, F., Ganson, K. T., Pettee Gabriel, K., Testa, A., et al. (2023). Screen time from adolescence to adulthood and cardiometabolic disease: A prospective cohort study. *Journal of General Internal Medicine, 38*(8), 1821–1827. https://doi.org/10.1007/s11606-022-07984-6

Oberle, E., Ji, X. R., Kerai, S., Guhn, M., Schonert-Reichl, K. A., & Gadermann, A. M. (2020). Screen time and extracurricular activities as risk and protective factors for mental health in adolescence: A population-level study. *Preventive Medicine, 141*, Article 106291. https://doi.org/10.1016/j.ypmed.2020.106291

Odgers, C. L., & Jensen, M. R. (2020). Annual research review: Adolescent mental health in the digital age: Facts, fears, and future directions. *Journal of Child Psychology and Psychiatry, 61*(3), 336–348. https://doi.org/10.1111/jcpp.13190

Owens, E. W., Behun, R. J., Manning, J. C., & Reid, R. C. (2012). The impact of Internet pornography on adolescents: A review of the research. *Sexual Addiction & Compulsivity, 19*(1–2), 99–122. https://doi.org/10.1080/10720162.2012.660431

Parry, D. A., Davidson, B. I., Sewall, C. J. R., Fisher, J. T., Mieczkowski, H., & Quintana, D. S. (2021). A systematic review and meta-analysis of discrepancies between logged and self-reported digital media use. *Nature Human Behaviour, 5*(11), 1535–1547. https://doi.org/10.1038/s41562-021-01117-5

Platt, J. M., Keyes, K. M., & Galea, S. (2017). Efficiency or equity? Simulating the impact of high-risk and population intervention strategies for the prevention of disease. *SSM - Population Health, 3*, 1–8. https://doi.org/10.1016/j.ssmph.2016.11.002

Reizer, A., & Hetsroni, A. (2014). Media exposure and romantic relationship quality: A slippery slope? *Psychological Reports*, *114*(1), 231–249. https://doi.org/10.2466/21.07.PR0.114k11w6

Smith, L. J., Gradisar, M., King, D. L., & Short, M. (2017). Intrinsic and extrinsic predictors of video-gaming behaviour and adolescent bedtimes: The relationship between flow states, self-perceived risk-taking, device accessibility, parental regulation of media and bedtime. *Sleep Medicine, 30*, 64–70. https://doi.org/10.1016/j.sleep.2016.01.009

Strasburger, V. C., Hogan, M. J., Mulligan, D. A., Ameenuddin, N., Christakis, D. A., Cross, C., et al. (2013). Children, adolescents, and the media. *Pediatrics, 132*(5), 958–961. https://doi.org/10.1542/peds.2013-2656

Tibbits, M. K., Caldwell, L. L., Smith, E. A., & Wegner, L. (2009). The relation between profiles of leisure activity participation and substance use among South African youth. *World Leisure Journal, 51*(3), 150–159. https://doi.org/10.1080/04419057.2009.9728267

Twenge, J. M., Blake, A. B., Haidt, J., & Campbell, W. K. (2020). Commentary: Screens, teens, and psychological well-being: Evidence from three time-use-diary studies. *Frontiers in Psychology, 11*, Article 181. https://doi.org/10.3389/fpsyg.2020.00181

Twenge, J. M., Joiner, T. E., Rogers, M. L., & Martin, G. N. (2018). Increases in depressive symptoms, suicide-related outcomes, and suicide rates among U.S. adolescents after 2010 and links to increased new media screen time. *Clinical Psychological Science, 6*(1), 3–17. https://doi.org/10.1177/2167702617723376

VanderWeele, T. J., & Ding, P. (2017). Sensitivity analysis in observational research: Introducing the E-value. *Annals of Internal Medicine, 167*(4), 268–274. https://doi.org/10.7326/M16-2607

VanderWeele, T. J. (2019). Principles of confounder selection. *European Journal of Epidemiology, 34*(3), 211–219. https://doi.org/10.1007/s10654-019-00494-6

VanderWeele, T. J., Mathur, M. B., & Chen, Y. (2020). Outcome-wide longitudinal designs for causal inference: A new template for empirical studies. *Statistical Science, 35*(3), 437–466. https://doi.org/10.1214/19-STS728

Wallace, J., Boers, E., Ouellet, J., Lebel, C., MacMaster, F. P., & Dewey, D. (2023). Screen time, impulsivity, neuropsychological functions and their relationship to growth in adolescent attention-deficit/hyperactivity disorder symptoms. *Scientific Reports, 13*, Article 18108. https://doi.org/10.1038/s41598-023-44105-7

Zhu, X., Griffiths, H., Xiao, Z., Ribeaud, D., Eisner, M., Yang, Y., & Murray, A. L. (2023). Trajectories of screen time across adolescence and their associations with adulthood mental health and behavioral outcomes. *Journal of Youth and Adolescence*, *52*(7), 1433–1447. https://doi.org/10.1007/s10964-023-01782-x