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Young Adolescents' Digital Technology Use and Mental Health Symptoms: Little Evidence of Longitudinal or Daily Linkages

Michaeline Jensen, Ph.D.[1], **Madeleine George, Ph.D.**[2], **Michael Russell, Ph.D.**[3], **Candice Odgers, Ph.D.**[4,5]

[1]University of North Carolina at Greensboro

[2]Purdue University

[3]Penn State University

[4]University of California, Irvine

[5]Duke University

Abstract

This study examines whether adolescents' digital technology use is associated with mental health symptoms (N=388) during early to mid-adolescence. Adolescents completed an initial Time 1 (T1) assessment in 2015, followed by a 14-day ecological momentary assessment (EMA) via mobile phone in 2016–2017 which yielded 13,017 total observations over 5270 study days. Adolescents' T1 technology use did not predict later mental health symptoms. Adolescents' reported mental health was also not worse on days when they reported spending more versus less time on technology. Little was found to support daily quadratic associations (whereby adolescent mental health was worse on days with little or excessive use). Adolescents at higher risk for mental health problems also exhibited no signs of increased risk for mental health problems on higher technology use days. Findings from this EMA study do not support the narrative that young adolescents' digital technology usage is associated with elevated mental health symptoms.

Keywords

technology; mental health; adolescence; ecological momentary assessment; digital technology usage; early adolescence

Introduction

For better or for worse, digital technologies are integrated into the daily lives of modern adolescents. Nearly all adolescents have at least one mobile device to call their own (95%), with 89% owning their own smartphones (Victoria Rideout & Robb, 2018). Teens spend an average of 6.67 hours per day on screen media for non-school purposes, with pre-teens spending an average of 4.6 hours per day (Vicky Rideout, 2016). This constant connectivity

Correspondence: Michaeline Jensen, Ph.D., Department of Psychology, The University of North Carolina at Greensboro, 296 Eberhart Bldg, PO Box 26170, Greensboro, NC 27412-5001., mrjensen@uncg.edu.

has been accompanied by growing concern among parents, the public, and even industry stakeholders that technology (particularly smartphone use) is harming adolescents' mental health, and more specifically, is responsible for recent increases in depression, loneliness, and suicidal ideation (Rosenstein & Sheehan, 2018; Twenge, 2017). Despite this widespread public attention to the negative implications of technology use, the research base around technology and mental health is far from conclusive (Orben & Przybylski, 2019), with very little data to suggest *causal* processes (Bell, Bishop, & Przybylski, 2015; Odgers, 2018).

Despite widespread fears, we also see evidence that engagement with the digital world can have "real-world" benefits to youth, including enhancement of important skills like communication, social connection, and facility with technology (Ito et al., 2008). Given the ubiquity of technology adoption, alongside rising rates of mental health problems (Mojtabai, Olfson, & Han, 2016) among young people, it is imperative that conclusions and recommendations around adolescent technology use and mental health be solidly based in evidence from rigorous research (Guernsey, 2014).

Technology and Mental Health: Evidence to Date

There are two primary theories for how/why technology use and mental health might be related, representing both causal and selection effects. The displacement hypothesis asserts that time youth spend on technology occurs at the expense of time that could be spent doing other "real life" social or cognitively enriching activities (and the mental health benefits of those activities which are displaced are lost; Kraut et al., 1998). Alternatively, the social compensation hypothesis is that youth with mental health difficulties may leverage technology as a tool to make up for real or perceived deficits in social skills, and thus that associations between time spent on technology and mental health may result from *selection* into certain types technology use (Campbell, Cumming, & Hughes, 2006; Shapira et al., 2003; Valkenburg & Peter, 2007).

A number of recent reviews and meta-analyses summarize the associations between technology use and adolescent wellbeing and mental health. Across these reviews, cross-sectional designs using retrospective reporting and small effect sizes consistently stand out (Baker & Algorta, 2016; Seabrook, Kern, & Rickard, 2016). In their systematic review of 43 studies of adolescents and young adults, Best and colleagues (2014) conclude that the majority of studies in their review reported *either mixed or no effects* of online social technologies on adolescent mental wellbeing. Specific identified benefits included increases in self-esteem, perceived social support, and social capital; safe identity experimentation; and increased ability to self-disclose, and specific identified harms included increased social isolation, depression, and cyber-bullying. In a recent meta-analysis of social networking site use across all ages, Huang (2017) concluded that the mean correlation across all studies (most of which were cross-sectional) between time spent on social networking sites and psychological wellbeing was negative and low ($r=-.07$, CI-.09 to $-.04$), such that more social networking site use was weakly associated with worse psychological wellbeing. These results are consistent with a recent secondary analysis which analyzed three large-scale datasets (totaling over 350, 0000 youth) via specification curve analysis to demonstrate that digital technology use is associated with only slightly worse adolescent wellbeing, with technology use accounting for less than 1% (.4%) of the variation in wellbeing across these still cross sectional studies (Orben & Przybylski, 2019).

Recent reviews also highlight that the *nature* of online interactions is likely more important than the quantity or frequency of technology use (Baker & Algorta, 2016; Marino, Gini, Vieno, & Spada, 2018). Online social networking site use tends to be related to *less* internalizing, to the extent that it includes positive interactions, enhances social support, and facilitates social connectedness, and is associated with more internalizing in instances when it is excessive, reduces time spent in in-person interactions, and in which interactions are negative or involve social comparisons (Clark, Algoe, & Green, 2018; Seabrook et al., 2016). One fairly consistent finding is that those youth who report psychological distress around their *online* activities —that their technology use includes distressing or problematic elements conceptualized as “problematic technology use”, signs of “addiction” or not being able to forego technology use, and using technology to escape and avoid otherwise coping with the real world — are also more likely to report psychological distress in their *offline* lives (Andreassen et al., 2016; Augner & Hacker, 2012; Marino et al., 2018; Morrison, Morrison, & Gore, 2017). Notably, the dominance of cross-sectional designs makes it impossible to know if perceived problematic use of technology use leads to other forms of psychopathology, or if those youth with existing problems offline are more likely to bring those mental health difficulties into the online sphere.

The few experiments that have been conducted on this topic are informative, though by no means conclusive. In two experiments with college students, instant messaging has been associated with reductions in distress (Dolev-Cohen & Barak, 2013), and replenishment of self-esteem and perceived relational value after social exclusion (Gross, 2009). However, in another experiment, in which Danish adults were assigned to take a break from Facebook, those assigned to take a Facebook break reported greater life satisfaction and more positive emotions compared to those in the control condition who continued their Facebook use as usual (Tromholt, 2016). Results also suggested stronger effects among those whose use was already potentially problematic (as evidenced by heavy use, passive use, and envy of others on Facebook). However, the validity of these findings has been questioned due to the fact that the participants were not blind to their condition and the generalizability of these findings to adolescents is likely limited due to the nature of the sample (unpaid adult volunteers recruited via Facebook ads, 86% women).

The existing literature highlights the importance of measuring both the quality and the quantity of the different types of activities youth engage in online rather than just relying on a gross sum of time spent on screens, which may include potentially beneficial social interactions with close friends alongside likely less beneficial passive viewing of content. The key to understanding the role of technology in mental health likely lies in understanding *how* it is used, and teens use technology in a myriad of ways. Indeed, teens divide their digital media use across a variety of activities, including passive consumption (watching online videos or TV, reading, or listening to music; 2.1 hours per day) and interactive consumption (playing games, browsing websites; 1.32 hours per day), communication (using social media and video-chatting; 1.4 hours per day), creation (making art or music, writing; .15 hours per day), and other use (.38 hours per day; Rideout, 2016).

Daily Associations between Technology and Mental Health

Daily assessment methods like ecological momentary assessment (EMA; Shiffman et al., 2008) facilitate "in the moment" reporting on lived experiences, like time spent utilizing technology and daily mental health. EMA methods may reduce the recall bias of retrospective self-report (which emerging evidence suggests is quite poor for estimates of time spent using technology; Ellis et al., 2018) and facilitate accurate assessments of intermittent time allocation and mental health symptoms over the course of the day; they also allow investigators to examine within-person linkages between these experiences over time. The present study utilized EMA to examine daily linkages between different types of technology use and mental health symptoms. Through multilevel modeling of EMA data, we can parse the *who* (are people who use more technology more likely to experience mental health symptoms, compared to other people?) from the *when* (are individuals more or less likely to experience mental health symptoms on days when they use more/less technology, compared to themselves?). *Who* questions are largely seen in the literature's prevalent cross-sectional designs, but few studies have tackled *when* study questions using EMA designs. Furthermore, this design's partitioning of within and between person associations allows us to test the ergodicity of technology-mental health associations (whether aggregate *inter*-individual processes operate similarly at the *intra*-individual level) and avoid falling prey to the ecological fallacy and incorrectly generalizing findings from between-person studies to individual adolescent experiences (Fisher, Medaglia, & Jeronimus, 2018; Molenaar, 2004).

The few studies that have utilized EMA in this domain have yielded mixed results. In a study of college students using experience sampling, no significant associations emerged between daily social networking site use and depression (Jelenchick, Eickhoff, & Moreno, 2013). In an EMA of adults, momentary supportive online interactions were associated with momentary positive affect, but were not related to momentary negative affect (Oh, Ozkaya, & Larose, 2014). In contrast, another experience sampling study (Kross et al., 2013) showed that quantity of Facebook use was associated with worse affect at the next timepoint (a lagged effect), but not the inverse (affect did not relate to next time point Facebook use). This study concluded that this effect was not attributable to loneliness, nor was it moderated by other risk factors. Prior research from our team has also shown daily associations between several indicators of technology use and increased externalizing symptoms (though effect sizes were small) in a sample of adolescents at risk for mental health problems: daily time spent online, time spent on social media, and time spent on a mobile phone texting were associated with more same-day ADHD and conduct disorder symptoms, and time spent on the internet and texts sent were also associated with more conduct disorder symptoms (George, Russell, Piontak, & Odgers, 2018). However, time spent online, time spent texting, and amount of texts sent were associated with *less* same day anxiety, and increased numbers of text messages sent were also associated with *less* same day depression.

The Present Study

The present study utilizes a baseline assessment of mental health problems and digital technology use alongside intensively gathered longitudinal EMA data collected on adolescents' mobile phones to test how (or if) technology is related to worse mental health, by answering the following *primary study questions* (which were specified a-priori within the study team, prior to accessing the study data):

Question 1a: Doe adolescents' self-reported access to and use of technology predict later mental health symptoms?

Question 1b Does adolescents' self-reported access to and use of technology predict later mental health symptoms, over and above T1 mental health?

Question 2a: Do adolescents experience more mental health problems on days when they use more technology (daily linkages, using each person as their own control)?

Question 2b: Do adolescents with higher average daily technology use have higher levels of mental health problems on average (cross-sectional associations at the person level)?

Emerging research suggests that digital technology-mental health associations may be less straightforward than the linear associations addressed in questions 1 and 2. One new area of inquiry examines the "digital goldilocks hypothesis", or the idea that associations between technology use and mental well-being may be best characterized by a quadratic function, such that only at extremely high or low rates of use does digital technology use demonstrate negative associations with mental health, while the majority of adolescents who report moderate usage of digital technology fare comparatively better on measures of wellbeing. Przybylski and Weinstein (2017) recently tested this hypothesis using a preregistered plan from a large representative sample of English adolescents, and concluded that most children's use of technology was not related to poorer mental health, but at extremely high levels of use these associations did emerge (e.g. more than 1 hour 40 minutes of weekday or 3 hours 35 minutes of weekend video game play, more than 3 hours 41 minutes of weekday or 4 hours 50 minutes of weekend video watching). Notably, even at these high levels the effect sizes were small, accounting for less than 1% of the observed variability in mental wellbeing and associations were based on cross-sectional reports, limiting tests of directionality. Our study tests the digital goldilocks hypothesis *at the daily level* using EMA data.

There is also some concern that youth with existing mental health risks may be susceptible to a technology amplification of symptoms (the "poor get poorer" hypothesis"; Kraut et al., 2002; Scott et al., 2017; Selfhout et al., 2009). That is, youth who already struggle socially or emotionally may experience increased social isolation due to time spent online, or exacerbated difficulty with focus, attention, and self-regulation due to the constant multitasking afforded by smartphones and other technologies. Although, contrary to these expectations, a recent nationally representative survey of 1,141 adolescents illustrated that those adolescents who reported the lowest levels of social and emotional wellbeing were also more likely to report that social media had a positive versus negative effect on them (Victoria Rideout & Robb, 2018). They were more likely to report that using social media made them feel less depressed, better about themselves, and less lonely, as compared to their peers with higher levels of reported social and emotional wellbeing. Our sample is diverse on a number of dimensions that might predispose adolescents to mental health problems (i.e. past mental health risk, economic disadvantage) and/or increase vulnerability to different types of technology use effects (i.e. age, gender), and thus well positioned to examine subgroup differences in daily associations.

We tested these potentially complex nonlinear and interactive relations between technology use and mental health by asking the following *exploratory study questions* (which were not specified a-priori before accessing the study data):

Question 3a: Do adolescents experience more mental health problems on days when their technology use falls at the extremes of their own distribution of usage (e.g., much more or much less than their own average technology use; daily digital goldilocks effects)?

Question 3b: Do adolescents with digital technology usage at the very low and high ends of the technology use distribution, compared to other adolescents, report experiencing more mental health problems on average (cross-sectional person-level digital goldilocks effects)?

Question 4a: Are adolescents with pre-existing mental health vulnerabilities more likely to experience a negative coupling between daily technology usage and daily mental health symptoms as compared to their peers (moderation of daily linkages)?

Question 4b: Do adolescents with pre-existing mental health vulnerabilities exhibit stronger associations between digital technology usage and mental health symptoms as compared to their peers (moderation of person-level associations)?

Method

Sample and Procedure

The study design is depicted in Figure 1. The sample was drawn from the population of children enrolled in grades 3–6 in North Carolina Public Schools during the 2011–2012 school year based on administrative data from the North Carolina Department of Public Instruction (NCDPI). Participants completed an initial T1 Adolescent Survey (N = 2,104) between April and August of 2015, at which time participants were enrolled in grades 5–8 and ranged in age from 9 to 15 (M_{age} = 12.36, SD = 1.12). The sample was representative of the state population of public-school children with respect to economic disadvantage, gender, and ethnicity. Participants and their parents were contacted and consented by phone. Early and mid-adolescents were surveyed by phone and reported on demographics, mental health, and problem behaviors. The majority of parents provided consent to link survey data to administrative data from the NCDPI (n = 2048, 97.3%) and gave permission to contact their child for future studies (n = 1867, 88.7%).

A subsample of 395 early to mid-adolescents were recruited to participate in a Home Visit and a 14-day EMA between April 2016 and February 2017. Of these, 388 adolescents completed at least one EMA survey for the present study and comprise our analysis sample. The vast majority of adolescents (94%) fell between the ages of 12–15 (full range = 10–17 years of age) at the time of the EMA. Adolescents were selected based on their: 1) proximity to two geographically distinct cations (central, urban NC, and western, rural NC) from which staff could make in-person home visits, and 2) representation to the statewide public-school population in terms of economic disadvantage, gender, race, and ethnicity, though the

395 adolescents who agreed to participate in the EMA were more likely to be White (60.6% versus 51.3%) and less likely to be economically disadvantaged (measured as current receipt of free/reduced lunch; 40.8% versus 55.4%) compared to the overall state public school population. All procedures, protocols, and measures were approved by the Duke University Institutional Review Board for the study (approval #D0396). A Home Visit was conducted by two interviewers who installed MetricWire (MetricWire Inc., 2016), a phone-based survey application, to deliver the EMA on the participant's own mobile phone or a study-administered phone (49.9% of adolescents elected to use their own phones). Participants received three daily surveys for the next 14 days, one each in the morning, afternoon, and evening. Survey questions assessed participants' daily experiences, technology use, behaviors, and mood. Eighty percent of survey prompts were answered, resulting in 13,017 total observations over 5270 study days for the measures analyzed here.

Measures

Covariates.—At the initial T1 Adolescent Survey adolescents reported their birthdate, *gender* (49.74% female), race, and Hispanic ethnicity. *Race/Ethnicity* was re-coded into four categories reflecting White (not-Hispanic; 59.79% of sample), Black (not-Hispanic; 19.07% of sample), Hispanic (of any race; 12.89% of sample), and other race/ethnicity (including Asian, American-Indian, Native Hawaiian/Pacific Islander, multiracial, and those who did not report on race/ethnicity; 6.44% of sample). *Age* was calculated based on self-reported birthdate and the date of the first EMA survey (M_{ageEMA} = 13.37, *SD* = 1.14). Family *economic disadvantage* was determined based on eligibility for free and/or reduced lunch using school administrative records. Schools use verified household income to determine eligibility; cutoffs vary with household size and are on the order of 175% the federal poverty level. Those families who were persistently eligible for free or reduced lunch across all years for which administrative data is available (2009–2016) are classified as persistently economically disadvantaged (31.07% of the sample).

In the EMA, students reported daily in the evening on whether they attended school that day or not (0=attended school and 1= no school). This daily *school attendance* covariate is included in multilevel models to account for potential weekend effects and third variable confounding (i.e. adolescents may report fewer internalizing and externalizing problems and more technology use in their unstructured time on days when they do not attend school). A person-mean of school attendance was also computed across the study period and reflects the percentage of days school was not attended (higher= more days out of school) and is included as a level 2 covariate to account for summer and school break seasonality (i.e. in summer a student would report 100% days off school).

T1 Mental Health.—Adolescents reported on their psychological distress, conduct, and temperament during the initial T1 Adolescent Survey. *Psychological distress* was assessed with six items from the well-validated Kessler (K6) Psychological Distress (Furukawa, Kessler, Slade, & Andrews, 2003; Green, Gruber, Sampson, Zaslavsky, & Kessler, 2010). Responses ranged from 0 (none of the time) to 4 (all of the time) and were averaged to yield a total score (M=4.17, SD=.61; α=.85). *Conduct problems* were assessed using the 25 item Problem Behavior Frequency Scale (Miller-Johnson, Sullivan, & Simon, 2004). For each item, responses capture the frequency of a behavior over the last 30 days, ranging from 0 (never) to 5 (20 or more times) and were averaged to create a total score (*M* = 0.13, *SD* = 0.21; α=.88). Adolescents responded to 16 questions from the Early Adolescent Temperament Questionnaire (L. K. Ellis & Rothbart, 2001), a widely used instrument to measure *effortful control*, deficits in which are associated with risk for ADHD (Eisenberg et al., 2009; Martel & Nigg, 2006). Response options ranged from 1 (not at all like me) to 5 (very much like me) and were averaged to yield a total score (M=3.73, SD=.60; α=.77). Adolescents scoring in the highest quartile for baseline psychological distress and conduct problems, and the lowest quartile on T1 effortful control were classified as being at *T1 risk* for internalizing (worry and depression), conduct problems, and inattention/hyperactivity, respectively.

T1 Technology Access and Use.—At the T1 adolescent survey adolescents answered questions adapted from the PEW Internet & American Life national surveys (Lenhart, Ling, Campbell, & Purcell, 2010) reporting on their *mobile phone ownership* (0=no, 1=yes), *social media access* (0=no access, 1= uses social media) and *social media use frequency (“*How often do you use social networking sites like Facebook or Instagram?” (0) I do not have social media, (1) less often then every few weeks, (2) every few weeks, (3) 1–2 days per week, (4) 3–5 days per week, (5) about once per day, (6) several times a day).

Daily Technology Use.—Adolescents reported each evening on the number of *text messages sent* (“how many texts or online messages did you send today?”). Daily reports that exceeded 10,000 text messages (11 daily observations, or .002% of daily observations) were coded as missing. Adolescents also reported each evening on the number of hours spent online or on their phone using technology for the following purposes: *school work, communication* (online or on phone talking to others or sending messages), *entertainment* (browsing social media, watching videos, playing games), and *creating content* (posting on social media, creating videos, etc). Reports on these items which exceeded 24 hours daily were coded as missing (<.018% of daily observations). These items, which tap time spent on technology for various purposes were chosen because they allowed for an assessment of time allocation that could be compared across participants’ preferred platforms, and in line with literature which suggests that passive use of technology (e.g. entertainment) may be more detrimental to wellbeing than time spent in active use (i.e. communicating or creating content; Deters and Mehl, 2013; Verduyn et al., 2015). Time spent online or on their phone using technology for school work, communication, entertainment, and creating content were summed to yield a measure of *total screen time* that day.

Daily Externalizing Symptoms.—*Inattention and hyperactivity* were assessed with four EMA-adapted questions from studies of attention-deficit hyperactivity in children (Tangney, Baumeister, & Boone, 2004; Whalen, Odgers, Reed, & Henker, 2011), assessing the presence of attention difficulties (e.g. “I’m having a hard time concentrating or focusing”, morning, afternoon, and evening; “I’m having a hard time finishing things”; afternoon and evening), hyperactivity (“So far today, I’ve felt restless or like I was always ‘on the go”, afternoon and evening), and impulsivity (“I’ve been doing things without thinking first”; morning, afternoon, and evening). Items were dichotomized at the daily level to reflect the presence or absence of each symptom that day, and a daily symptom count computed. Person-means were computed by averaging the daily measures across the study period and reflect the average number of symptoms across all days. The average participant endorsed .82 symptoms of inattention/hyperactivity on an average day (Mean=.82, SD=.88; α =.83). Across all study days for all participants, at least one symptom of inattention/hyperactivity was endorsed on 44% of days, with 17% of the sample never endorsing any symptoms of inattention/hyperactivity.

Conduct problems were assessed with seven (yes/no) questions in the afternoon and evening about whether adolescents engaged in aggressive and deviant behavior (i.e., “So far today, I took or stole something that didn’t belong to me”). Due to the low base rates of the fairly serious conduct problems queried, responses were dichotomized at the daily level to yield indicator of the presence (1) or absence (0) any conduct problems that day. Person-means were computed by averaging the daily measures across the study period and reflect the proportion of days on which adolescents endorsed a conduct problem (*M*= .08, *SD*=.17, α =.72). Across all study days for all participants, a conduct problem was endorsed on only 8% of days, with 66% of the sample never endorsing any conduct problems.

Daily Internalizing Symptoms.—Adolescents responded to questions from the Tire in the morning, afternoon, and evening each day. Administered items which most closely overlap with diagnostic criteria for internalizing problems were chosen for the present study. *Depressive* symptoms were measured by asking adolescents to use a slider scale to indicate whether they felt “sad”, “tired”, and “lonely,” on a scale ranging from 1 (not at all) to 100 (very); these three symptoms were averaged across the day to yield a daily depressive symptom score, and a person-mean depression score was computed by averaging daily depressive symptoms across all study days (*M*=21.34, *SD*= 12.48; α =.69). A key symptom of anxiety (*worry)* was assessed using the same slider scale to respond to a question asking adolescents to indicate whether they were “worried about something” (averaged across the day to yield a daily worry score), and a person-mean worry score was computed by averaging daily worry symptoms across all study days (Mean=18.32, SD= 17.13).

Data Analyses

For clarity, specific analytic procedures for each study question are presented alongside each study question’s results below. All analyses were conducted in Mplus 7.2 (Muthén & Muthén, 2017) with FIML estimation to handle missing data at the person level (level 2) and MLR estimation to account for non-normality. Listwise deletion was employed at the daily level (level 1), and thus the number of level 1 observations varied slightly from one model to the next (due to participant non-response or skipping items) and the n’s for each analysis are reported in Table 2. Given the large number of comparisons necessary to test 6 indicators of technology use predicting 4 mental health dimensions, plus exploratory quadratic effects and T1 risk interactions, the Benjamini Hochberg procedure for adjusted significance tests was utilized to manage the False Discovery Rate (FDR; Benjamini and Hochberg, 1995). The FDR method of error control is less conservative than other alternatives like the Bonferroni method (McDonald, 2015) and was computed by ordering the *p* values for each study question from smallest to largest (smallest has a rank of i=1, the second smallest has i=2, etc.), with each p value compared to its Benjamini-Hochberg critical value using the following formula: (i/m)Q (i = rank, m = total number of tests, Q = the allowable false discovery rate of .05). Traditional *p* values are reported in all tables, with those that meet FDR-corrected significance levels marked with an asterisk. To encourage the open sharing and reproducibility of our research all Mplus output files (including syntax and variance/covariance matrices which allows for replication) are available at the adaptlab.org website.

Results

Descriptive statistics (means, standard deviations, skew, kurtosis, and percentage of the sample comprising each categorical variable) and correlations between study variables can be found in Supplemental Table S1. Adolescents sent an average of 47 texts per day; 10.73% of adolescents reported never sending any texts over the study period. Adolescents reported an average of 4.18 hours of daily screen time (3.41% of the sample never reported using technology). That screen time was divided among technology for school work (mean= .79 hours per day; 20.2% never reported using technology for school), communication (mean=1.34 hours per day; 13.7% of adolescents never reported using technology to communicate), entertainment (mean=1.83 hours per day; 5.8% of adolescents never reported using technology for entertainment) and creating content (mean= .38 hours per day; 45.7% of adolescents never reported using technology to create content).

Age was associated with more total daily screen time, including time spent daily using technology for school work and communication but not time spent on technology for entertainment or creating content. There were no differences between males and females on any technology use measure. African-American adolescents reported spending significantly more time per day on total screen time (6.16 hours) than white adolescents, who reported the least total screen time (3.51 hours); adolescents of Hispanic and other race/ethnicity reported levels of use between these two extremes. This race/ethnicity difference persisted for time spent using technology for school work, communication, entertainment, and creating content. Adolescents from economically disadvantaged households reported more daily screen time (5.24 hours) than adolescents from non-disadvantaged households (3.68 hours); this difference was also evident in time spent on technology for school work, communication, and creating content, but not for entertainment. Number of text messages sent did not differ by any demographic categorization. These demographic differences did not appear to be due to differing rates of personal phone ownership (the nature of differences persisted when non-phone owners were excluded from analyses).

Primary Study Questions

Question 1

Analyses.: We sought to replicate prior findings demonstrating cross-sectional relations between technology use and worse mental health in a longitudinal sample. T2 mental health outcomes were measured using the person-level averages of daily conduct problems, inattention/hyperactivity, depression, and worry across the entire 2-week EMA period. We tested Q1a (Does adolescents' self-reported access to and use of technology relate to later mental health symptoms?) by regressing T2 mental health outcomes on T1 mobile phone ownership, social media access, social media use frequency, and demographic covariates. In order to answer Q1b (Does adolescents' self-reported access to and use of technology predict later mental health symptoms, *over and above T1 mental health*?), T1 levels of mental health symptoms (psychological distress for worry and depression, T1 conduct problems for conduct problems, and T1 effortful control for inattention/hyperactivity) were included as additional covariates.

Results.: Results for Q1a are shown in the upper panel of Table 1; adolescents' phone ownership, social media access, and frequency of social media use were unrelated to later depression, worry, and inattention/hyperactivity symptoms. Adolescents' social media access and use frequency were both related to higher levels of later conduct problems, though these associations did not meet FDR-corrected significance levels accounting for multiple comparisons. Adolescents' phone ownership was unrelated to later conduct problems. Results for Q1b are shown in the lower panel of Table 2; adolescents' phone ownership, social media access, and frequency of social media use were unrelated to all domains of later mental health symptoms. Those associations between social media access and use frequency which emerged with conduct problems in Q1a were reduced to statistical non-significance once T1 conduct problems were controlled for.

Question 2

Analyses.: EMA is unique in that the daily associations allow for the adolescent to serve as his or her own control across time, testing whether changes in adolescents' technology use are associated with *within-individual* risk for same-day mental health symptoms, holding all stable characteristics (e.g., sex, race/ethnicity, or socioeconomic status) constant over time. The nature of the EMA assessment (days nested within people) allows for the parsing of within-person associations at the daily level (Q2a: Do adolescents experience more mental health problems on days when they use more technology, relative to their own usage?) and between-person associations (Q2b: Do adolescents who use more technology have higher levels of mental health problems on average, compared to other adolescents?). We examined question 2 in a two-level model:

$$\text{Level 1:} \quad \text{Mental Health}_{ij} = \beta_{0j} + \beta_1\left(\text{dTU}_{ij}\right) + \beta_2\left(\text{dSchoolDay}_{ij}\right) + \varepsilon_{ij}$$

$$\text{Level 2:} \quad \beta_0 = \gamma_{00} + \gamma_{01}\left(\text{mTU}_j\right) + \gamma_{02}\left(\text{mSchoolDay}_j\right) + \gamma_{03}\left(\text{Age}_j\right) + \gamma_{04}\left(\text{Gender}_j\right) + \gamma_{05}\left(\text{Disadvantage}_j\right) + \gamma_{06}\left(\text{Black}_j\right) + \gamma_{07}\left(\text{Hispanic}_j\right) + \gamma_{08}\left(\text{Other}_j\right) + \upsilon_{0j}$$

Level 1 modeled daily mental health symptoms for day *i* and person *j* as a function of a person-specific intercept term (β_{0j}), daily Technology Use ($\beta_{2;}$ dTU_{ij}), whether the adolescent went to school that day ($\beta_{2;}$ 0=attended school and 1= no school), and a residual term (ε_{ij}). Level 2 modeled the person-specific intercept as a function of person-average Technology Use ($\gamma_{01;}$ mTU_j), average non-school days (γ_{02} ; the percentage of study days not in school, to account for summer and school break seasonality), person-level covariates (γ_{03}–γ_{08}), and a random person-specific error term (υ_{0j}). The binary nature of daily conduct problem symptoms was modeled using multilevel logistic regression and the count nature of daily inattention/hyperactivity symptoms was modeled using a Poisson distribution; neither of these models included a level 1 residual term.

We parsed daily and person level variation in technology use by leaving the daily technology use variables in raw (uncentered) form, while accounting for the difference in average technology use (across days). This approach (in contrast to a person-mean centering approach) allows for the interpretation of daily technology use variables (level 1 predictors) in their natural metrics (number of texts and hours) such that the zero point represents a day with no technology use, while still accounting for the fact that some adolescents use more or less technology than other adolescents overall. Thus, the models yield pure level 1 estimates of daily linkages between adolescents' technology use and mental health (over and above person-level relations) and pure level 2 estimates of person-level relations between adolescents' technology use and mental health (over and above daily linkages and covariates), allowing level 1 and level 2 relations to differ in magnitude and direction (contextual effects; Hoffman and Stawski, 2009).

Results.: Results for Q2a are shown in Table 2: No daily linkages (β_1) between digital technology usage and mental health symptoms emerged. Days when adolescents reported relatively higher levels of texts sent, technology for school work, technology for communication, technology for entertainment, technology for creating content, and total screen time were not more likely to be days when the adolescents reported conduct problems, more symptoms of inattention/hyperactivity, or higher levels of worry or depression.

The person-level relations (γ_{01}) addressed in Q2b were slightly more robust than daily linkages (Table 2), though only two relations persisted when corrected for false discovery rates. Adolescents who spent more time using technology for school work reported *more* inattention/hyperactivity symptoms on average; a 1-hour increase in average daily technology use for school work was associated with a 20% increase in the average counts of inattention/hyperactivity symptoms (IRR=1.20). Adolescents who reported sending more text messages on average reported *fewer* depressive symptoms (each additional 10 texts sent was associated with a .066-point decrease in average depressive symptoms; standardized $\beta = -.089$).

We conducted a sensitivity analysis to determine if our decision to use listwise deletion to handle missing data at the daily level influenced study results. Q2 models were estimated using FIML for daily observations with partial missingness. Inattention/hyperactivity models were not identified and thus results are not available. For the remaining 3 outcomes, results were consistent with those using listwise deletion for 15/18 of the coefficients of interest, with 3 new associations meeting FDR-corrected significance cutoffs: average daily technology for school work was associated with higher average levels of conduct problems (*b*=.28, *SE*=.09, *OR*=1.32, *p*=<.01) and depression (*b*=1.66, *SE*=.51 *β*=.16, *p*=<.01) and daily time spent on technology for entertainment was associated with lower levels of same-day worry (*b*=−.43, *SE*=.14 β=−.07, *p*=<.01).

Exploratory Study Questions

Question 3

Analyses.: We tested the digital "goldilocks hypothesis" (Przybylski & Weinstein, 2017) which posits that relations between technology use and mental health are quadratic, with increased risk at both very high and very low levels of technology use. We examined within-person associations (Q3a: Do adolescents experience more mental health problems on days when their technology use falls at the extremes of their own distribution of usage, that is, much more or much less than their own average technology use?) and between-person associations (Q3b: Do adolescents with digital technology usage at the very low and high ends of the technology use distribution, compared to other adolescents, report experiencing more mental health problems on average?). We tested Question 3 by adding two terms to the equation above in Q2: daily technology use squared (β_3;dTU^2_{ij}), and person-average Technology Use squared ($\gamma_{09;}$ mTU^2_j). Person-average technology use was grand mean centered to facilitate interpretation of lower order terms. Exploring potential non-linear associations involved testing 48 potential quadratic effects, all of which are reported in the interest of full disclosure and to avoid selective reporting.

$$\text{Level 1:} \quad \text{Mental Health}_{ij} = \beta_{0j} + \beta_1\left(\text{dTU}_{ij}\right) + \beta_2\left(\text{dSchoolDay}_{ij}\right) + \boldsymbol{\beta_3}\left(\mathbf{dTU^2_{ij}}\right) + \varepsilon_{ij}$$

$$\text{Level 2:} \quad \beta_0 = \gamma_{00} + \gamma_{01}\left(\text{mTU}_j\right) + \gamma_{02}(\text{mSchoolDay}_{j)} + \gamma_{03}\left(\text{Age}_j\right) + \gamma_{04}\left(\text{Gender}_j\right) + \gamma_{05}\left(\text{Disadvantage}_j\right) + \gamma_{06}\left(\text{Black}_j\right) + \gamma_{07}(\text{Hispanic}_{j)} + \gamma_{08}(\text{Other}_{j)} + \boldsymbol{\gamma_{09}}\left(\mathbf{mTU^2_j}\right) + \upsilon_{0j}$$

Results.: Of the 24 possible daily quadratic effects tested in Q3a which examined associations between 6 daily indicators of technology use and 4 daily mental health dimensions, only five were significant at *p*<.05, and three of these met the FDR-corrected significance level (see Supplemental Table S1 for full results). Adolescents' daily technology use for creating content had a significant quadratic relation with daily depression ($b_{quadratic}$=.08, SE= .02, p<.01). The left panel of Figure 2 depicts this quadratic relation graphically by plotting the expected level of adolescents' daily depressive symptoms (y axis) across the entire range of all 3548 daily observations of daily technology use for creating content (x axis) and reveals a shallow "u" shape. For the vast majority of observations—99% of daily observations fall within the grey shaded region— the association between technology use for creating content and daily depressive symptoms was weakly negative (days with relatively *more* technology use for creating content tended to be days with relatively *fewer* depressive symptoms). For instance, at 2 hours of technology use for creating content per day, an additional hour of use is associated with about a 1-point decrease in depressive symptoms (b=−.957, SE= .338, p=.003). Only in the very far reaches of the distribution of daily technology use for creating content—less than the highest 1% of observations shown in the white region of the graph— did the association between daily technology use for creating content and depressive symptoms become positive, such that days with relatively more technology use tended to be days with relatively more depressive symptoms.

Adolescents' daily technology use for creating content also had a significant quadratic relation with daily conduct problem symptoms ($b_{quadratic}$=−.11, SE=.03, p<.01), which took the form of a downward curving line (see the left panel of Figure S1). For nearly all daily observations there was no association between daily hours on technology creating content (shown by the nearly flat line in the shaded grey regions depicting 99% of observations), and only in the very farthest reaches of the distribution was technology use for creating content associated with lower expected odds of daily conduct problem symptoms. Adolescents' daily technology use for school work had a small but significant quadratic relation with daily symptoms of inattention/hyperactivity ($b_{quadratic}$=−.01, SE<.01, p<.01), which took the form of an inverted "U" (see Figure S3). For most daily observations, more time spent on technology for school work was associated with more reported same-day symptoms of inattention/hyperactivity, but in the very farthest reaches of the daily distribution (>1% of the daily observations), more time spent on technology for school work was associated with fewer symptoms of inattention/hyperactivity. Notably, these three observed quadratic relations should be interpreted with extreme caution and may not be trustworthy, given that these curvilinear associations are driven by observations in the tail of the distributions and are based on a tiny minority of daily observations,.

Of the 24 possible person-level quadratic effects tested in Q3b, only four were significant at p<.05 (see Supplemental Table S1 for full results), with three reaching the FDR-corrected significance cutoff. Specifically, average technology for creating content had similar quadratic associations with average depressive symptoms ($b_{quadratic}$=−2.00, SE= .47, p<.01), average symptoms of inattention/hyperactivity($b_{quadratic}$=−.80, SE= .17, p<.01), and average conduct problems ($b_{quadratic}$=−.39, SE= .13, p<.01). For instance, as seen in the right panel of Figure 1, the association between average daily hours of technology use creating content and average daily depressive symptoms takes an *inverted* u-shape. For the majority of the sample, as technology use for creating content increased, so too did depressive symptoms (individuals who reported more technology use on average also reported higher average depressive symptoms). For those individuals at the top end of the technology use spectrum, however (~5% of the sample in the light grey and white regions of the graph, falling above about 1.6 average hours per day), the association became negative (individuals who used more technology for creating content reported lower depressive symptoms). The quadratic associations between average daily hours spent creating content and average daily conduct problems and average daily symptoms of inattention/hyperactivity took this same form (see Figures S1 and S2), with the majority of adolescents seeing positive associations (those adolescents who spent more time on technology creating content tended to report more symptoms of conduct problems and inattention/hyperactivity), though for a subset of adolescents at the upper end of the technology use range, more time spent on technology creating content over the study period was associated with fewer average externalizing problems. Again, we urge caution in interpreting these quadratic relations, as it they are based on a small subset of individuals in the sample. Notably, there was little consistency between the daily and person-level quadratic associations observed. For instance, the daily and person-level associations between depicted in Figure 2 (between the time adolescents spend on technology creating content and depressive symptoms) differ in sign, whereas those in Figure S1 (between the time adolescents spend on technology creating content and conduct problems) share the same sign but very different magnitudes. This lack of consistency between the daily and person levels highlights the importance of testing the ecological fallacy, and not over-generalizing person-level associations to the within person processes.

Question 4

Analyses.: Lastly, we explored whether adolescents with existing mental health vulnerabilities exhibit stronger associations between their technology usage and mental health symptoms at the daily (Question 4a: Are adolescents with pre-existing mental health vulnerabilities more likely to experience a negative coupling between daily technology usage and daily mental health symptoms as compared to their peers?) and between person-level (Question 4b: Do adolescents with pre-existing mental health vulnerabilities exhibit stronger associations between digital technology usage and mental health symptoms as compared to their peers?). Interaction terms were computed between all six 6 indicators of technology use (texts sent, technology for school work, technology for communication, technology for entertainment, technology for creating content, and total screen time) and select indicators of mental health risk: age (younger adolescents may be more susceptible to technology effects), economic disadvantage, gender (females at risk for internalizing and males at risk for externalizing), and T1 levels of mental health symptoms (psychological distress for worry and depression, T1 conduct problems for conduct problems, and T1 effortful control for inattention/hyperactivity). This method allowed for separate tests of whether adolescents traditionally deemed to be at higher risk negative effects of digital technology (e.g., females, those from low-SES households) exhibit stronger daily linkages (a cross-level interaction tested within-person, β_3), and whether adolescents at high risk experience stronger relations between average technology use and mental health symptoms (a between-person interaction, γ_{10}).

$$\text{Level 1:} \quad \text{Mental Health}_{ij} = \beta_{0j} + \beta_1(\text{dTU}_{ij}) + \beta_2(\text{dSchoolDay}_{ij}) + \boldsymbol{\beta_3}(\mathbf{dTU_{ij}\ xRisk_j}) + \varepsilon_{ij}$$

$$\text{Level 2:} \quad \beta_0 = \gamma_{00} + \gamma_{01}(\text{mTU}_j) + \gamma_{02}(\text{mSchoolDay}_j) + \gamma_{03}(\text{Age}_j) + \gamma_{04}(\text{Gender}_j) + \gamma_{05}(\text{Disadvantage}_j) + \gamma_{06}(\text{Black}_j) + \gamma_{07}(\text{Hispanic}_j) + \gamma_{08}(\text{Other}_j) + \boldsymbol{\gamma_{09}}(\mathbf{Risk_j}) + \boldsymbol{\gamma_{10}}(\mathbf{mTU_j\ x\ Risk_j}) + \upsilon_{0j}$$

We report all 192 potential daily and person-level interactions tested in the interest of full disclosure and to avoid selective reporting.

Results.: Of the 96 potential *daily* linear interactions tested in Q4a (high risk moderation of Question 2a), examining effects of 6 daily technology use variables on 4 outcomes as moderated by 4 indicators of risk (age, economic disadvantage, gender, and T1 risk), only 10 met a significance cutoff of $p \leq .05$, and *all* were reduced to non-significance when FDR-corrected to account for multiple comparisons (see Supplemental Tables S3–S6 for full results).

Of the 96 potential *person-level* linear interactions tested in Q4b (high risk moderation of Question 2b; supplemental Tables S3–S6), 13 met a significance cutoff of $p \leq .05$. Of those, only 2 met the FDR-corrected cutoff for significance accounting for multiple comparisons. Age moderated the person-level association between technology use for entertainment and conduct problems: At younger ages, more technology use for entertainment was associated with a higher average likelihood of endorsing a conduct problem (e.g. age 12 b=.35, SE=.09, OR=1.42, p<.01), whereas at older ages, technology use for entertainment was associated with *less* likelihood of conduct problem endorsement (e.g. age 15 b= −.31, SE=.16, OR= .73, p=.05). The person-level association between technology use for entertainment and conduct problems was also moderated by T1 mental health risk (those in the upper quartile for T1 conduct problems were classified as being at highest risk). Although those adolescents in the T1 risk group were more likely to endorse conduct problems on average, they did not see a significant association between their average time spent on technology for entertainment and their average conduct problems (b=−.08, SE=.19, OR=.92 p=.68). In contrast, among those adolescents not classified as being at T1 risk, more technology use for entertainment was associated with a higher average likelihood of endorsing a conduct problem (b=.21, SE= .10, OR=1.23, p=.04).

Discussion

Scientist, parents, and the public are clamoring to know if adolescents' mental health is somehow harmed by their frequent technology use. Much of the literature on this question to date has been cross-sectional in nature (prohibiting causal inference), and what few experimental, longitudinal, and pre-registered studies exist have largely yielded mixed results with small effect sizes. The present study utilized "in-the-moment" EMA surveys on adolescents' phones to measure the daily co-occurrence of technology use and mental health symptoms. Across four specific study questions, the resounding conclusion was that there is little evidence of longitudinal or daily associations between technology and mental health symptoms; technology use did not predict later mental health symptoms, and only 3 of the 144 potential daily associations tested were significant.

Adolescents' baseline technology use did not predict later mental health symptoms, over and above baseline mental health risk. This is consistent with a number of other longitudinal studies which have failed to replicate cross-sectional associations between digital technology use and mental health (Nesi, Miller, & Prinstein, 2017; Nesi & Prinstein, 2015; Ohannessian, 2009; Selfhout et al., 2009). It may be that today, when frequent technology use is the norm among most adolescents, these previously reported cross-sectional associations have dissipated over time.

Adolescents exhibited no significant daily linkages between any of the 6 indicators of technology use and the 4 domains of mental health symptomatology. Even in sensitivity analyses with increased power at the daily level, only one significant daily effect emerged, and it was contrary to the hypothesized direction: adolescents' daily time spent on technology for entertainment was associated with *less* same-day worry. This lack of same-day co-occurrence of mental health symptoms with any type of technology use is in line with other EMA studies which failed to find associations between online interactions and social networking site use with negative affect and depression (Jelenchick et al., 2013; Oh et al., 2014), but in contrast to one study which showed associations between quantity of Facebook use and worsened affect among adults (Kross et al., 2013), and some of our own team's work among high-risk adolescents (with existing behavioral and attentional problems) which evidenced small same-day associations between technology use and symptoms of externalizing problems (attention deficit hyperactivity disorder and conduct disorder; George et al., 2018).

Only two significant associations emerged at the person-level using the EMA data, and neither was prototypical of hypothesized technology- poorer mental health associations. First, adolescents who reported sending more text messages on average reported *lower* average depression symptoms. Second, adolescents who spent more time on technology for school work on average reported more frequent symptoms of inattention/hyperactivity. We observed similar associations between technology use for school and higher average conduct problems and depression (which met traditional cutoffs of $p<.05$ for statistical significance but not FDR-corrected cutoffs accounting for multiple comparisons, but which did meet FDR-corrected significance levels in sensitivity analyses with more statistical power). We would hope that time spent on technology for school work would impart the most benefits for adolescents, though should not be surprised that those adolescents with the most difficulty sustaining attention and exerting self-control (and perhaps those who struggle with depression or conduct problems) would spend more time toiling on computerized homework assignments. Similarly, the finding that frequent texters are the least depressed is consistent with the extant literatures on social connections both online and face to face (Seabrook et al., 2016; Seeman, 1996) as well as our past finding that daily text messaging was associated with less daily depression symptoms, as adolescents reported lower levels of depression on days when they were most connected to others online via text messaging (George et al., 2018).

Recent research has suggested that the lack of clarity in the literature may be due at least in part to the presence of *non-linear* associations between technology and mental health, such that ill effects are not seen for most use, but that extreme users may see small decrements in mental health (Przybylski & Weinstein, 2017). There was very little support for this goldilocks hypothesis in the present study. We explored 24 possible daily and 24 possible person-level quadratic effects, with 3 daily associations and 3 person-level associations evidencing non-linear associations. The most consistent finding was that the average time spent by adolescents using technology for creating content was curvilinearly associated with average depressive symptoms, conduct problems, and symptoms of inattention/hyperactivity such that, for the majority of the sample, more time spent on technology creating content was associated with higher levels of depressive symptoms and externalizing symptoms, but for the heaviest users of technology for creating content, more time spent on technology for this purpose was associated with fewer depressive and externalizing symptoms. Interestingly, this pattern is in the opposite direction of that usually put forth about the goldilocks hypothesis (that the highest users will be at the greatest risk). Here, instead, we see that those adolescents who spend the most time on technology creating their own content may instead be enjoying better mental health. We did not see consistent evidence of a goldilocks effect for daily technology use: the three quadratic associations which emerged were of varying signs and magnitudes and seemed to be driven by daily observations in the very farthest reaches (<1%) of the distribution. Nonetheless, these results, in which associations between and within adolescents differ not only in their magnitude, but also in their signs, serve as a reminder of an old and cardinal rule of interpreting aggregate (between-person) associations and attempting to generalize them to the individual – the ecological fallacy (Molenaar, 2004). Indeed, the lack of group-to-individual generalizability of psychological sciences in general, and in technology-mental health effects in particular, means that we should not expect the associations generated from large-scale cross-sectional surveys of adolescents' digital technology use and mental health to generalize to associations within an adolescent over time (Fisher et al., 2018; Molenaar & Campbell, 2009).

Lastly, we found little evidence that adolescents' technology-mental health associations were moderated by pre-existing vulnerability for technology-related problems or psychopathology, as measured by age, gender, economic disadvantage, and T1 mental health risks. This is somewhat surprising given expectations that offline risk may exacerbate or increase online problems but may also reflect the fact that the measures used in this study captured different types of screen time rather than more nuanced measures of content and type of digital technology usage.

Conclusions

In our longitudinal study of adolescents followed intensively over time on their mobile devices we found little evidence to support a linkage, correlational or causal, between adolescents' digital technology usage and mental health symptoms. These findings stand in stark contrast with the popular narrative that smartphones are destroying young peoples' lives and leading to increased mental health problems. Our study's conclusions are strengthened by recent data collection, utilization of in-the-moment EMA assessment of multiple domains of technology use and mental health, our sample (diverse on multiple indicators of risk) drawn from a population representative sampling frame of those enrolled in public schools, the inclusion of daily and person-level control variables to account for potential confounding, and our transparency around the presentation of null findings, which revealed few significant associations across 100s of planned and exploratory models.

Despite these strengths, the study has a number of limitations which should be noted. First, although the assessment of daily linkages provides a higher resolution than what is typically captured in this field and allows for an estimation of the co-occurrence of technology use and mental health symptoms, the daily reporting does not provide a means of identifying which of the two comes first within a day. Given the lack of same day associations in general, the inability of establishing ordering of effects was less relevant. Second, we sampled mostly young to mid adolescents (full range 10–17 with 94% of the T2 EMA sample falling between the ages of 12–15), which may mask unique processes in early adolescence (for example) and does not allow us to speak to associations among older adolescents. This focus on early to mid-adolescence is important, given that much of parent concern and policy-relevant focus on smartphone use focuses on early adolescence (e.g. the Wait until 8th initiative; Thayer, 2017). While there was little evidence of moderation by age in this sample, future research is required to test for associations across the entire adolescent range (now defined as between age 10 and 24; see Sawyer et al., 2018). Third, although we did use internal procedures for pre-specifying our primary study questions and hypotheses, we did not *formally* preregister the present study. We recognize that there are many design decisions that can shape final study results (Orben & Przybylski, 2019) and that pre-registration serves to protect against potential bias and selective reporting. In order to mitigate this limitation, we have transparently presented all the results of the dozens of models estimated and have made available study materials to facilitate replication. Finally, although technology usage and mental health symptoms were captured daily and through a method that is known to reduce bias in reporting, both measures came from a single informant via self-report on relatively few items (which was necessary to reduce participant burden in completing multiple surveys each day). Our sample of young adolescents reported spending relatively less time on technology (4.18 hours of average daily total screen time) than other recent estimates, including Rideout (2016) who reported that teens (ages 13–18) retrospectively reported spending 6.67 hours and "tweens" (ages 8–12) reported spending 4.6 hours per day on screen media for non-school purposes. It is difficult to know if this difference is attributable to a difference in data collection method (daily reporting or a single survey), the younger age of our sample, or real differences in levels of technology usage between our North Carolina population representative sample and the nationally representative adolescents surveyed in this study. Although our measures of daily technology use facilitate understanding the purpose of time spent on technology (and are thus not influenced by shifting fads in platforms), this method of measurement disallows an analysis of associations with specific types of technology use (i.e. gaming or social media use); future research is required to assess associations with more fine-grained assessments of social media use specifically and should incorporate more objective measures of digital technology usage (i.e., device logs or sensor-based measures) and of mental health (i.e., informant rated, or analyses of online digital archives such as twitter and text-messaging content).

Considerable time and energy have been dedicated recently to understanding the role that digital technologies may play in adolescents' mental health. These results, and those of many other studies cited here, suggest that we need to move beyond a focus on adolescents' *quantity* or *frequency* of technology use and towards a more comprehensive approach to establishing best practices for educating, parenting and supporting young people growing up in the digital age. Young people are unlikely to stop using digital technologies, and in many ways these results suggest that, with respect to mental health outcomes, perhaps they don't need to. Limited research monies and resources could instead be directed toward better understanding how modern technologies may impact other dimensions of wellbeing (i.e. sleep), or toward how they can be leveraged to better assess young peoples' experiences (i.e. EMA, objective assessment of social interactions) or support adolescents' health and behavior (i.e. e-health or gamified interventions).

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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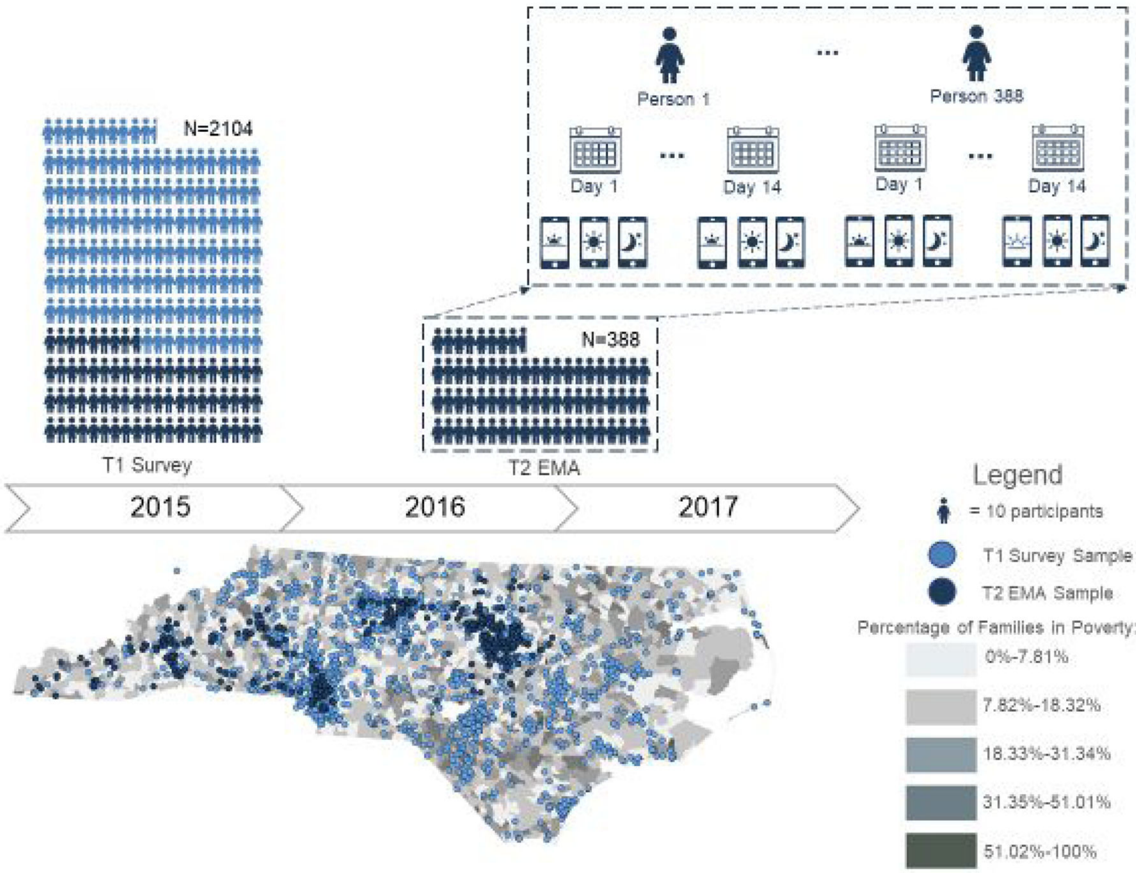

Figure 1.
Study Design

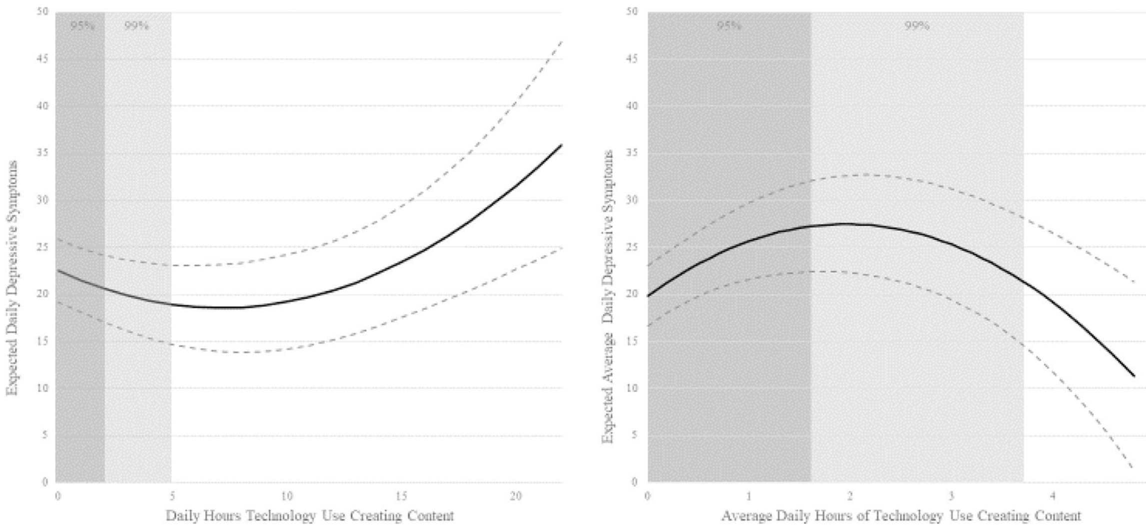

Figure 2.

Quadratic Associations- Time spent on Technology Creating Content and Daily Depressive Symptoms. Left panel depicts within-person daily quadratic association of daily technology use creating content (X axis) and expected depressive symptoms (Y axis). Right panel depicts between-person average quadratic associations between technology use creating content (X axis) and expected depressive symptoms (Y axis). *Dashed lines* represent the 95% confidence interval. The full ranges of reported hours of technology use creating content are depicted, *grey shading* reflects the 95th and 99th percentiles for technology use creating content.

Table 1

Longitudinal Associations between Adolescents' T1 Technology Use and Later Mental Health (Question 1)

	Conduct					Inattention/Hyperactivity					Depression					Worry				
	b	***SE***	***CI***	**β**	***p***	***b***	**SE**	**CI**	**β**	***p***	***b***	**SE**	**CI**	**β**	***p***	***b***	**SE**	**CI**	**β**	***p***
Unadjusted for T1 Risk																				
Phone Ownership	−01	.02	−.04, .03	−.01	.81	−.03	.10	−.22, .17	−.02	.79	.67	1.37	−2.00, 3.35	.03	.62	1.44	1.89	−2.27, 5.15	.04	.45
SM Access	**.04**	**.02**	**.01, .07**	**.11**	**.03**	−.01	.10	−.21, .20	>−.01	.95	1.07	1.40	−1.67, 3.80	.04	.45	−.24	.80	−4.06, 3.59	−.01	.07
SM Use Frequency	**.01**	**.00**	**.00, .01**	**.10**	**.04**	>−.01	.02	−.04, .04	−.00	.93	.35	.28	−.20, .91	.07	.22	.16	.39	-.61, .92	.02	.68
Adjusted for T1 Risk																				
Phone Ownership	−01	.02	−.03, .03	-.02	.72	−.03	.10	−.22, .16	−.02	.73	.67	1.35	−1.98, 3.32	.03	.62	1.43	1.88	−2.27, 5.12	.04	.45
SM Access	.03	.02	−.01, .06	.07	.16	−.03	.10	−.23, .17	−.02	.76	.87	1.40	−1.88, 3.61	.03	.54	−.51	1.95	−4.33, 3.32	−.01	.79
SM Use Frequency	<.01	<.01	>−.01, .01	.06	.26	−.01	.02	−.05, .03	−.03	.65	.33	.28	−.23, .88	.06	.25	.13	.39	−.64, .89	.02	.75

Note. N=388. SM= Social Media. Associations between each type of technology use and each type of mental health symptom are tested in single level regressions, alongside covariates of age, gender, economic disadvantage, and dummy coded race/ethnicity. Models adjusted for T1 risk each include an additional covariate tapping T1 mental health risk (psychological distress for worry and depression, T1 conduct problems for conduct problems, and T1 effortful control for inattention/hyperactivity). Raw regression coefficients (*b*), standard errors (SE), 95% confidence intervals (CI), and standardized regression coefficients (β) are reported. Significant relations ($p \leq .05$) bolded. No coefficients met FDR-corrected significance levels.

Table 2

Multilevel Models testing Daily Associations between Adolescents' Technology Use and Mental Health Symptoms (Question 2)

	Conduct					Inattention/Hyperactivity					Depression					Worry				
	b	***SE***	***CI***	***OR***	***p***	***b***	**SE**	**CI**	**IRR**	***p***	***b***	**SE**	**CI**	**β**	***p***	***b***	**SE**	**CI**	**β**	***p***
Texts Sent (in 10s) *3572 days, N=370*																				
Daily β_1	<.01	<.01	−.01, .00	1.00	.94	>−.01	<.01	>−.01, <.01	1.00	.17	.02	.02	−.01, .05	.04	.26	<.01	.02	−.03, .03	>−.01	.98
Person-m slope γ_{01}	.00	.36	−.02, .02	1.00	.67	−.01	.01	−.01, .01	1.00	.71	**−.07***	**.02**	**−.10, −.04**	**−.09**	**<.01**	−.02	.04	−.09, .05	−.02	.56
Tech School Work *3537 days, N=370*																				
Daily β_1	.07	.05	−.02, .14	1.07	.15	.02	.01	−.00, .03	1.02	.06	.10	.15	−20, .35	.02	.51	.37	.26	−.14, .88	.04	.15
Person-m slope γ_{01}	**.21**	**.12**	**<.01, .48**	1.27	**.05**	**.19 ***	**.05**	**.09, .28**	**1.20**	**<.01**	**1.62**	**.64**	**.37, 2.88**	**.16**	**.01**	**1.66**	**.83**	**.04, 3.28**	**.12**	**.05**
Tech Communication *3530 days, N=366*																				
Daily β_1	.05	.04	−.03, .13	1.05	.24	>−.01	.01	−.02, .01	1.00	.79	−.23	.16	−.54, .08	−.05	.15	−.12	.15	−.42, .17	−.02	.42
Person-m slope γ_{01}	.18	.12	−.04, .41	1.20	.11	.08	.05	−.03, .18	1.08	.15	.46	.53	−.57, 1.49	.06	.38	.29	.63	−.94, 1.52	.03	.64
Tech Entertainment *3541 days, N=367*																				
Daily β_1	.01	.03	−.05, .07	1.01	.70	−.01	.01	−.03, .01	.99	.16	−.08	.10	−.26, .11	−.02	.43	−.11	.13	−.37, .15	−.02	.40
Person-m slope γ_{01}	.14	.09	−.04, .32	1.15	.12	.09	.05	−.01, .19	1.10	.07	.21	.36	−.50, .92	.03	.56	.47	.54	−.58, 1.53	.05	.38
Tech Creating Content *3548 days, N=368*																				
Daily β_1	.09	.07	−.04, .22	1.09	.17	.01	.02	−.03, .04	1.01	.63	−.28	.34	−.95, .38	−.03	.41	.06	.31	−.56, .67	<.01	.86
Person-m slope γ_{01}	**.60**	**.24**	**.14, 1.08**	1.83	**.01**	**.30**	**.13**	**.05, .55**	1.35	**.02**	1.43	1.28	−1.10, 3.9	.08	.27	1.24	1.18	−1.06, 3.55	.05	.29
Total Screen Time *3611 days, N=370*																				
Daily β_1	.03	.02	>−.01, .06	1.03	.08	>−.01	<.01	−.01, .01	1.00	.56	−.08	.07	−.21, .06	−.04	.26	−.02	.08	−.17, .18	−.01	.76
Person-m slope γ_{01}	**.09**	**.04**	**.01, .17**	1.09	**.03**	**.06**	**.02**	**.02, .10**	1.06	**.01**	.30	.22	−.14, .73	.13	.18	.32	.27	−.21, .86	.07	.23

Note. Associations between each type of technology use and each mental health domain are tested in separate multilevel models alongside covariates of daily school attendance and person-level mean school attendance, age, gender, economic disadvantage, and dummy coded race/ethnicity. Conduct problems is a binary variable at the daily level and modeled using logistic regression. Inattention/hyperactivity symptoms is a count at the daily level and modeled using a Poisson distribution. Raw regression coefficients (*b*), standard errors (SE), and the 95% confidence intervals (CI) are reported.

Effect size estimates are reported as Odds Ratios (OR; binary conduct problems), Incident Risk Ratios (IRR; count inattention/hyperactivity symptoms), and standardized regression coefficients (β; continuous depression and worry symptoms). Significant relations ($p \leq .05$) bolded. Coefficients which met FDR-corrected significance level marked with an asterisk.