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Examining Early Adolescent Positive and Negative Social Technology Behaviors and Well-being During the COVID-19 Pandemic

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Abstract

Public concerns of how frequently adolescents used screens during the pandemic shutdowns fueled the need to research whether these behaviors were conducive or detrimental to their wellbeing. The aims of this longitudinal survey study of 586 middle school students in the Northeast U.S. were to examine (a) changes in positive and negative social technology behaviors prior to the coronavirus disease (COVID-19) pandemic (fall 2019) compared to during the pandemic (fall 2020) including any differences by subgroups and (b) whether changes in social technology behaviors were associated with wellbeing outcomes and any moderating factors. We found that during this time period, there were significant increases in frequency of checking social media, social technology use before bedtime, and problematic internet use. Students also experienced significant increases in social anxiety, loneliness, and depressive symptoms, but also increased strategies of coping when stressed. By following our preregistered analytical plan, each research aim was addressed within a multilevel modeling framework with time nested within students. We found extremely small effects of social technology behaviors associated with wellbeing, such as online support seeking being related to strategies when coping with stress. Though we found statistically significant effects, none of the findings met our effect size criteria (i.e., effect of ≥.05). Overall, we did not find any strong support that the changes in wellbeing that adolescents experienced during the COVID-19 social distancing was meaningfully related to their social technology use, which is counter to the popular assumption that adolescent wellbeing is intricately tied to their social technology use.

Keywords

social media; adolescence; wellbeing; problematic internet use; online support

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As the coronavirus disease (COVID) outbreak became a full-fledged pandemic, governments across the world have implemented policies to mitigate the outbreak, which includes school closures, social distancing, and quarantining. Meanwhile, U.S. parent-led organization, ParentsTogether, released survey results with over 3,000 concerned parents regarding their children's screen time during the COVID-19 pandemic. The survey shows that the average time spent online for children has doubled after school closures and parents are concerned by what their children have encountered online during social isolation, ranging from bullying to sexual predation (Parents Together Foundation, 2020). While limited, current studies focusing on adolescent mental health during COVID-19 have pointed to a rise in the prevalence of child and adolescent mental illness. Just as 1 in 5 adults in the U.S. experience mental illness, 1 in 6 of children aged 6–17 are afflicted with mental health disorders each year (National Alliance on Mental Health, 2021), underlining the importance of intervening as these vulnerable adolescents enter adulthood. Even prior to the pandemic, digital devices were ubiquitous in our young people's lives with 95% of all U.S. adolescents having at least one mobile device of their own (Rideout & Robb, 2018). Online viewing of screen media was shown to increase from an average of 4:44 hr per day in tweens aged 8–12 to an average of 7:22 hr per day in teens aged 13–18 (Rideout & Robb, 2019). The early adolescent period (ages 11–14) is one of the most relevant developmental periods to examine the impact of social media on wellbeing given that the majority of children get their first smartphone by age 11 (Rideout & Robb, 2019) and many tweens are signing up for social media sites meant for ages 13+. Despite this, early adolescence has been largely neglected in prior research about social technology use, which often focuses on college-aged or older adolescent populations.

Pandemic as a Potential for Both Negative and Positive Consequences

The constant connectivity of adolescents using social technologies has fueled parent, educator, and practitioner concerns about how this ever-present digital landscape negatively contributes to adolescent wellbeing. A perspective that is emerging to counter these omnipresent fears is the possibility of digital technologies being a *positive* tool for adolescent development, fostering social connections and enhancing mental health. Prior studies have shown that young people often turn to social media to seek social support to feel better about themselves (Rideout & Fox, 2018) and for advice related to their mental distress (Pretorius et al., 2019). Early research conducted during the COVID-19 pandemic has indicated that social media has helped individuals, particularly adolescents, feel more socially supported (Cauberghe et al., 2021; Saud et al., 2020). Supportive peers provide protective benefits for adolescent mental health and online communication may be a critical way that peer-to-peer communication can occur among young people (Odgers & Jensen, 2020).

Conversely, increased online communication for adolescents could give way to unsympathetic online behaviors and online harassment. Cyberbullying occurs most often between a perpetrator and a victim and is defined as a repeated and intentional infliction of harm through electronic media, such as social technologies and social media (Wachs et al., 2019). A possible explanation behind cyberbullying and sending hate messages is the concept of toxic online disinhibition. The internet lacks face-to-face contact, which allows many to feel as if they are part of an anonymous and invisible mass and thus, loosening social restrictions and in turn, less self-monitoring (Wachs & Wright, 2018). Toxic online disinhibition is also considered an indicator of decreased ability to empathize and recognize social cues (Wachs et al., 2019). As COVID-19 related lockdowns across the globe caused substantial increases in online activity for children, this could lead to potentially increased rates of cyberbullying victimization in an adolescent virtual world where there is a lack of adult presence (Armitage, 2021). Psychology research has found that both perpetrator and victim roles in cyberbullying are positively correlated with depression and anxiety (Wright et al., 2018).

Past research has demonstrated that increased use of mobile phones and other screens used to view social media are associated with poor sleep behavior in adolescents (Vernon et al., 2018). How and when adolescents interact with their screens before bedtime has been found to have negative consequences on sleep time and duration (Charmaraman et al., 2021). The lowering of sleep quality could also be exacerbated by the fact that social isolation during the COVID-19 pandemic has led to increased screen time. In fact, in a cross-sectional survey for parents conducted across various countries, researchers found that screen time increased significantly for children of all ages, ranging from 3 to 17 years old, since the pandemic starting in their respective countries and more time on social media was significantly associated with decreased sleep duration on weekends (Kaditis et al., 2021).

Parent-assisted behavioral change and setting household internet rules is considered an effective method to reduce children's screen time (Samaha & Hawi, 2017), but the COVID-19 pandemic has caused parenting to be significantly more difficult (Spinelli et al., 2020). A study based in Turkey looking at parenting practices in relation to children's screen times during the early months of the outbreak showed that although the vast majority of parents set up screen time rules, children's screen times had increased as it was difficult to keep children busy at home, particularly for larger low-income families ((Eimaya & Irmak, 2021)). Whereas children tend to follow parental restrictions, adolescents often rebel against authority if parents attempt to overly restrict their media use (Padilla-Walker et al., 2018). Emerging research has suggested that the presence of household screen rules ameliorates the negative social technology behavior consequences of early initiation into social media under age 13 (Charmaraman et al., in press). Indeed, initiation into social media was likely expedited due to social distancing practices of the pandemic, especially given that TikTok was the most downloaded app in the U.S. in the early months of the COVID-19 pandemic. Given the public and parent concern over how or when to limit screen use given the new reliance on screens to continue remote learning, we explore whether household screen rules during the pandemic affected any pandemic-related changes in social technology use and associations with adolescent wellbeing.

In this "new normal" world of parents juggling jobs, caregiving, and homeschooling, studies that investigate how social distancing is influencing digital technology use and early adolescent wellbeing are all the more timely and critical. Given the many positive and negative associations with technology and mental health, the role of online and offline social interactions in promoting or hindering wellbeing is particularly salient during the heightened use of social technology of the COVID-19 pandemic. In the proposed study, we will examine changes in social technology behaviors pre and postsocial distancing, any subgroup differences, and whether observed changes in social technology behavior are linked with changes in wellbeing outcomes.

Theoretical Framework

Social technology behaviors are not individual acts in isolation but rather choices made within larger social contexts (Bronfenbrenner, 1979). While social media use, due to the digital age, has steadily risen over the years, the COVID-19 pandemic has further enabled both parents and their children to have increased technology use (Drouin et al., 2020), in fact, as of 2018, 70% of adolescents in the U.S. use social media frequently (Biernesser et al., 2020). We argue that the ecology of online social networking is a developmental context in which adaptive and maladaptive experiences can help or hinder social competence and mental wellbeing (Charmaraman et al., 2020), particularly in the societal context of social distancing. According to the *stimulation hypothesis* (Valkenburg & Peter, 2007), being able to connect online decreases potential negative consequences, such as social anxiety and increases positive consequences, such as opportunities to feel confidence in social abilities. Previous studies looking at use of social media and adolescent mental health have found that actively engaging on social media can help mental health, such as feeling social support, social reward, and reduced feelings of loneliness (Biernesser et al., 2020). This perspective is dependent on the social milieu, such that during the COVID-19 pandemic, being online to connect with others is often the sole form of communication available, which may not provide the added benefit of decreased social anxiety and increased confidence.

An alternative theoretical perspective is the *displacement hypothesis* (i.e., Kraut et al., 2002) wherein social media displaces meaningful live interactions for more superficial or negative communications, which may lead to social isolation and reduced social support. For instance, socially withdrawn individuals who have problematic internet behaviors tend to be depressed (e.g., Yang & Tung, 2007). In a COVID social distancing context, social media may not necessarily be considered a more “superficial” form of teen communication, but rather the normal interactive socializing experiences outside of everyday schooling and home interactions. More time spent on social media in adolescence has been linked to negative outcomes such as increased parent–child conflict, interference with family activities, and increased isolation among family members (e.g., Dworkin et al., 2018). These patterns may have been disrupted during social distancing when the majority of adolescents were sequestered at home, spending most of their waking time with family members. Early adolescents typically transition from being family-centered to more peer-focused, which is often based on *social comparison* processes (Suls et al., 2002). Social comparisons involve the need to gain accurate self-evaluations (Festinger, 1954; Suls et al., 2002), and is considered a major source of influence on teen health attitudes, intentions, and behaviors (Keefe, 1994). Social technologies have increased the frequency of social comparisons. For instance, adolescents who are connected to each other online may learn through observation or gain vicarious experiences from online posts, which can reduce (or intensify) negative feelings of isolation or provide positive role modeling to increase socially supportive interactions.

With the cancelation of most in-person extracurricular activities, adolescents may have turned to social media to explore their personal interests, hobbies, and identity development, which is a positive development and vital for their formative years. With the increased use of online technologies during the social distancing period of the pandemic, we hypothesize that for some adolescents (e.g., socially anxious), the extended online context might help them thrive (e.g., stimulation hypothesis). However, for other adolescents, they will feel a sense of grief over changes to in-person daily life due to the COVID-19 outbreak and the resulting mandatory physical distancing.

Research Aims

Aim 1

We will explore the changes in positive and negative social technology behaviors during the COVID-19 pandemic and explore potential differences in changes in social technology behaviors by subgroups including age, gender, race, mother's education, and household composition.

> Since these are exploratory aims, we do not have any directional hypotheses. We predict that adolescents from two parent households vs. single parent households and only children vs. sibling households may demonstrate different patterns of social technology use during the social distancing period. Age and gender have been associated with differences in the frequency of social technology use as well as differences in motivations for using social technology (Rideout & Robb, 2019).

Aim 2

Are changes in social technology behaviors during the social distancing period of COVID-19 associated with wellbeing outcomes? Do we observe differences in the relationship between social technology behaviors and wellbeing outcomes in relation to digital access, household screen rules, or COVID-19 related grief, controlling for the subgroups for which we identified statistically meaningful differences in social technology behaviors in Aim 1?

> We hypothesize that increases in negative social technology behaviors will be associated with higher scores on depression, social anxiety (online and offline), and loneliness and less frequent use of coping strategies when stressed, and will be moderated by digital access, household screen rules, and COVID-19 related grief.

Method

Procedure

We received Institutional Review Board approval from Brandeis University to conduct our study. In the Fall of 2019 (Time 1, n = 1,007), we collected data from students in grades 6th–9th in two school districts in Northeastern United States, which varied in regard to socioeconomic characteristics and urbanicity. In Time 2 (n = 968), we collected data during a COVID-19 social distancing period (October–December 2020), while schools in our study were in a hybrid mode of partial in-school and at-home online learning. Data were collected during designated in-person days to encourage participation and retention of our longitudinal sample.

Sample Description of Cohorts

Students in the overall sample (i.e., the 1,415 students who participated in either Time 1, Time 2, or both time points) were 51% female, 48% male, and 1% nonbinary gender or missing, and represented diverse racially/ethnically backgrounds, with over half identifying as racial/ethnic minorities (46% White, 15% Hispanic, 9% Black, 6% Asian, 7% biracial, 5% Native American, 1% Middle Eastern, and 10% other/unknown race/ethnicity). The average age of the Time 1 sample was 12.25 (SD = 1.46) and the Time 2 sample was 13.02 (SD = 1.43). Fifty-nine percent of mothers at Time 1 and Time 2 had a college degree or higher. At Time 1, 80% of students reported living in a two parent household, while 73% of students at Time 2 reported living in a two parent household. At Time 1 and Time 2, 20% reported living in a single child home.

The current analysis focused on data from the 586 students who participated in both Time 1 (pre-COVID-19) and Time 2 (during COVID-19 social distancing). Students in the longitudinal sample were 53% female, 47% male, and <1% nonbinary gender or missing, and represented racially/ethnically diverse backgrounds, with almost half identifying as a racial/ethnic minorities (58% White, 15% Hispanic, 9% Black, 6% Asian, 6% biracial, 3% Native American, 3% Middle Eastern, and <1% other/unknown race/ethnicity). The average age of the longitudinal sample was 12.53 (SD = 1.18) at Time 1 and 13.67 (SD = 1.26) at Time 2. Sixty-seven percent of all mothers had a college degree or higher. At Time 1, 76% of students reported living in a two parent household, while 73% of students at Time 2 reported living in a two parent household. Sixteen percent of students reported living in a single child home.

Attrition analyses compared the demographic representations of those who completed both Time 1 and Time 2 surveys (two time point sample) versus students who only completed the survey at Time 1 (single time point sample). Chi-square analyses were used to compare the samples by gender, race/ethnicity, two parent household and having multiple children in the home at baseline. Independent samples t-tests were used to compare age and average mother's education at baseline. Results suggested statistically meaningful differences between the two samples suggesting that students who completed surveys at both Time 1 and Time 2 were more likely to be female. More females completed both survey time points than males, single time point: Male = 54%, Female = 46%, two time point: Male = 47%, Female = 53%; $\chi^2(1, N = 1{,}033) = 4.05$, $p = .04$, more White students were retained than non-White students, single time point: Non-White = 62%, White = 38%, two time point: Non-White = 47%, White = 53%; $\chi^2(1, N = 1{,}033) = 22.71$, $p < .001$), fewer Black students were retained than non-Black students, single time point: Non-Black = 88%, Black = 12%, two time point: Non-Black = 92%, Black = 8%; $\chi^2(1, N = 1{,}033) = 4.74$, $p = .03$, and fewer Latinx students were retained than non-Latinx students, single time point: Non-Latinx = 82%, Latinx = 18%, two time point: Non-Latinx = 91%, Latinx = 9%; $\chi^2(1, N = 1{,}033) = 16.17$, $p < .001$. More students from two parent households (single time point: Non-Two Parent = 32%, Two Parent = 68%, two time point: Non-Two Parent = 24%, Two

Parent = 76%; $\chi^2(1, N = 1{,}033) = 7.93$, $p = .01$, and households with multiple children, single time point: Single child home = 25%, Multiple children home = 75%, two time point: Single child home = 16%, Multiple children home = 84%; $\chi^2(1, N = 1{,}033) = 12.44$, $p < .001$, were retained. Students in the two time point sample had a higher average mother's education, single time point: $M = 3.67$, $SD = 1.20$, two time point: $M = 3.86$, $SD = 1.05$, $t(706.62) = -2.55$, $p = .01$, and were younger, single time point: $M = 12.89$, $SD = 1.21$, two time point: $M = 12.53$, $SD = 1.18$, $t(1{,}031) = 4.87$, $p < .001$, at baseline.

Measures

Covariates—Covariates were considered for inclusion if prior research documented links between the covariate and (a) social technology behaviors or (b) psychosocial outcomes. Among the covariates available for inclusion in the current data, six variables met these criteria: Gender, race/ethnicity, age, mother's education (as a proxy for socioeconomic status), two parent household, and presence of siblings in the household. Prior research demonstrates small to moderate gender differences in frequency of social media use and moderate to large gender differences in levels of depression and anxiety (Coyne et al., 2020). Emerging studies demonstrate that racial/ethnic minority groups tend to initiate social media at younger ages, compared to their white peers, to reduce feelings of social isolation (Zhai et al., 2020). Adolescents also tend to increase their frequency of social media use as they age (Coyne et al., 2020). Mother's educational attainment has been strongly associated with childrens' short-term and long-term health and wellbeing (e.g., Prickett & Augustine, 2016) and is inversely related to child media viewing (Hesketh et al., 2007). Adolescents living in single parent households are more likely to engage in problematic texting behaviors problematic texting behaviors (Coyne et al., 2018). As an indicator that household composition and the presence of siblings can influence daily life stress, a recent study of adolescents in Korea, sibling rivalry was significantly associated with problematic internet and smartphone use (Seo et al., 2021).

Students self-reported their gender as either male, female or other. Students reported their race/ethnicity by selecting from the following options: White, Black, Asian, Native American, Middle Eastern, Latin American, Hispanic or Other. If a student selected multiple race/ethnicities, they were categorized as "Biracial." Due to small sample sizes, and to reduce the risk of misinterpreting findings from underrepresented demographic groups, students who identified as only Middle Eastern, Native American, Biracial, or unknown were recoded as "Other" race/ethnicity. Student age was measured by calculating the difference between the student's date of birth and the date the survey was completed. Mother's education was reported as a categorical variable ranging from "less than high school" to "graduate or professional level." The variables representing two parent household status and the presence of siblings in the home were derived from a household roster in which students reported the people who lived in their home with them.

Moderators

Digital Access: Digital Access was measured using a list of five dichotomous (yes/no) items related to limited internet access, poor Wi-Fi, limited or no access to a computer or quiet space to complete work, needing help from family to complete assignments or having unlimited data on their current phone. A total scale score was generated by adding the number of “yes” responses.

Household Screen Rules: Household Screen Rules were measured with a single item asking students about the maximum amount of time they are allowed to go online or use their phone. The 8-point response scale ranged from 1 = *30 min or less* to 8 = *no limits*.

COVID-19 Related Grief Scale: COVID-19 Related Grief Scale (Conrad et al., 2021; Cronbach’s α = .81) was asked only at Time 2 and included six items measured on a 5-point Likert scale from 1 = *Strongly Disagree* to 5 = *Strongly Agree*. The items asked students to rate the extent to which COVID-19 has impacted their daily life by having them miss out on significant life events, worry about losing touch with friends due to social distancing, losing things they need like school-provided lunch or teach help, feeling stunned or shocked about what is happening, feeling empty, and feeling frustrated after losing routines or activities.

Frequency of Online Behaviors

Frequency of Checking Social Media: Frequency of Checking Social Media was measured using a self-reported, single item that asked students how often they check their social media on a typical school day. The item’s 6-point scale ranged from 1 = *Never* to 6 = *More than every hour*. See Table 1 for descriptives of each outcome.

Social Technology Use Before Bedtime: Social Technology Use Before Bedtime (Cronbach’s α = .75) included four items asking students how often they typically watched YouTube videos, texted friends, checked social media, played online games, within 1 hr of going to sleep. The 4-point response scale ranged from 1 = *Never* to 4 = *Most nights*. In the originally planned approach, if the youth reported engaging in any of these self-reported behaviors “Most nights” they were given a score of “1,” otherwise, they were given a score of “0.” However, models using this dichotomous version of the variable did not converge. As an alternative approach, the average of these four items was used in place of the dichotomous score. This alternative approach alleviated convergence issues.

Negative Online Behaviors

Secretive Online Behaviors: Secretive Online Behaviors included two dichotomous items asking students whether they had anyone in their online network or had joined a social media site that their parents would disapprove of. Output from this model suggested that the model would not converge due to singularity, a convergence issue that occurs when some elements of the variance–covariance matrix are zero (Barr et al., 2013). Singularity further suggests that the model may have poor power, and is at high risk for false convergence. As such, further testing of this outcome was not pursued.

Problematic Internet Use: Problematic Internet Use (Cronbach’s α = .82) was measured using five items from the Problematic Internet Use scale (PRIUSS;). Items included, “How often do you lose motivation to do other things that need to get done because of the internet?,” “Feel nervous or anxious when you’re NOT online?,” “Become moody or depressed when you’re not online?,” “Lose sleep because you can’t quit what you’re doing online?," "Feel that using the internet negatively affects your school performance?." These items were associated with a 5-point response scale ranging from 1 = *Never* to 5 = *Very Often*.

Online Harassment: Online Harassment (Cronbach's α = .78) was measured by asking participants about how often someone else made rude or mean comments online, someone else spread rumors online, or the participant was hurt by someone excluding them online. These three items were reported on a 4-point scale ranging from 1 = *Never* to 4 = *Often*.

Unsympathetic Online Behaviors: Unsympathetic Online Behaviors (Cronbach's α = .69) included four items asking students if they were careful about what they say online so they don't come across in a bad way, whether they like putting embarrassing photos of friends online, whether they had been mean or rude to friends online or whether they had left someone out online. These four items were answered on a 4-point scale ranging from 1 = *Not at all like me* to 4 = *Very much like me*.

Positive Online Behaviors

Positive Social Media Use: Positive Social Media Use (Cronbach's α = .78) was adapted from the Digital Citizenship Scale (Jones & Mitchell, 2016) and the Facebook Relationship Maintenance Behavior Scale (Ellison et al., 2014). The eight items on this scale assessed using social media for educational purposes, providing social support to friends, joining groups that make them feel less lonely, organizing civic engagement activities or raising awareness of issues the participant cares about. Participants responded to each item using a 5-point Likert scale ranging *Never* (1) to *Always* (5).

Online Social Support Seeking: Online Social Support Seeking (Cronbach's α = .84) was measured by adapting three items from the Perceived Support subscale of the Facebook Measure of Social Support (McCloskey et al., 2015). Participants were asked to respond to statements regarding their social media sites: "When I am stressed out, I turn to my friends for help on this site," "The support I get on this site makes me feel better," "This site makes me feel close to people." Students responded using a 5-point scale ranging from 1 = *Strongly Disagree* to 5 = *Strongly Agree*.

Wellbeing

Strategies to Cope When Stressed: Strategies to Cope When Stressed (Cronbach's α = .73) included nine items asking what makes students feel better when they are stressed out. Items included being alone, spending time with family, close friends, or pets, posting on social media, watching TV, playing online games, exercising or sports, or spending time outdoors. Students used a 4-point scale ranging from 1 = *Mostly disagree* or 4 = *Mostly agree* to respond to each item. A review of Cronbach's alphas suggested that the internal reliability of the scale would be improved if we dropped three (being alone, posting on social media, playing online games) of the nine items. The final, six-item scale had a Cronbach's α of .73.

Online Social Anxiety Scale: Online Social Anxiety Scale (Cronbach's α = .92) included three items adapted for use in an online context from the Fear of Negative Evaluation Scale [a subscale within the Social Anxiety Scales for Adolescents (SAS-A; Nelemans et al., 2019)]. These items included, "I worry about what others think of me on social media," "I worry about what others say about me on social media," "I'm afraid that others won't like me on social media." This scale used a 4-point response format ranging from *Mostly Disagree* (1) to *Mostly Agree* (4).

Social Anxiety: Social Anxiety (Cronbach's α = .80) was measured using three items that assessed adolescents' comfort meeting new people, asking others for help, and doing new things in front of people. These items were derived from the Social Avoidance and Distress Scale [a subscale of the Social Anxiety Scales for Adolescents (SAS-A; Nelemans et al., 2019)]. Students used a 4-point response format ranging from *Mostly Disagree* (1) to *Mostly Agree* (4) to respond to each item.

Loneliness: Loneliness (Cronbach's α = .81) was measured using three items from the Loneliness Scale (Hughes et al., 2004) that asked students how often they feel that they lack companionship, feel left out or feel isolated from others. Students used a 3-point scale ranging from 1 *Hardly ever* to 3 *Often* to respond to each item.

Depressive Symptoms: Depressive Symptoms (Cronbach's α = .80) were measured using the 10-item The Center for Epidemiologic Studies Depression Scale Revised (CESDR-10), which has been validated on diverse adolescent samples (Haroz et al., 2014). Participants reported the number of days in the past week they felt the presence of 10 depressive symptoms, such as "I was bothered by things that usually don't bother me" and "I had trouble keeping my mind on what I was doing." Response choices included "Not at all or less than 1 day," "1–2 days," "3–4 days," or "5–7 days."

Analytic Approach

Prior to pursuing the proposed analyses, we preregistered our analytical plan with the Open Science Framework. We completed data cleaning procedures including a review of frequency distributions and descriptive statistics for all variables. Through this process we: (a) recoded incorrectly coded values (e.g., recoding values of "999" to missing), (b) removed duplicate observations, suggesting a participant completed the survey more than once, (c) combined responses into a single "other" group when we observed exceedingly small representation (i.e., less than 2% of the sample) of demographic groups to avoid misrepresentation due to a lack of power, (d) tested for nonnormality among dependent variables, and (e) conducted appropriate tests of reliability for all scales and removed items that brought a scale's reliability below .60 (only scales with a reliability of at least .60 were included in the analyses).

In all models, statistically significant relationships are reported with appropriate effect sizes, the magnitude of which is determined both by traditional conventions for interpreting effect sizes (e.g., Cohen, 1988) and comparisons with effect sizes reported in recent review studies of the role of social technology in adolescent development (Odgers & Jensen, 2020). This meta-analysis demonstrated there is a history in the literature identifying effect sizes between .06 and .11. Alternately, Ferguson & Heene, (2021) argue that statistically meaningful findings with associated effect sizes below .20 should be interpreted with great caution (or perhaps not interpreted at all). The current research capitalizes on the fact that data collection opportunely but unintentionally overlapped with the nationwide lockdowns associated with the COVID-19 pandemic. Data collected at Time 1 was not specifically intended to assess adolescent social technology use during a pandemic. Given this, and the fact that this research represents previously unexplored questions regarding links between social distancing and adolescent social media use, we interpret effect sizes between .05 and .20 to represent an initial signal suggesting that the current research findings warrant further research and effect sizes greater than .20 to suggest initial support for our research hypotheses.

All analyses were conducted in the statistical software package, R 3.6. Each research Aim was addressed within a multilevel modeling (MLM) framework (with time nested within students), to account for nonindependence of observations that occurs in longitudinal data collection. Analyses focused primarily on examining the change in slope (i.e., the coefficient of the variable representing time) of student outcomes that was observed between Time 1 and Time 2. Power analyses were conducted in G*Power 3.1.9.4 and suggested that, with a matched sample of 586 youth, we had the power of .80 to detect effects as small as .07 between waves. We established an α of .05 as the cutoff for identifying statistically meaningful results.

For each outcome, we attempted to test whether there is a statistically meaningful random effect associated with time. However, these models did not converge (most likely due to a result of model overfitting). Without a random effect of time, there is an increased risk of underestimating standard errors, a limitation that is noted in the discussion. Issues with model convergence were addressed by reducing (or, if necessary, increasing) the convergence controls (default convergence controls are set at 1e–6). We did not reduce convergence controls below 1e–3.

Results

Aim 1: Change in Social Technology Behaviors During COVID-19 Pandemic

To address Aim 1, we first considered whether there was significant change in each social technology behavior by comparing a null model to a model with a main effect of time. For two outcomes, Online Harassment, $\chi^2(df = 1) = 1.71$, $p = .19$; $B = 3.28$, $p = .19$, and Unsympathetic Online Behaviors, $\chi^2(df = 1) = 3.65$, $p = .06$; $B = 5.86$, $p = .05$, adding a main effect of time did not improve model fit, suggesting the outcomes did not change over time. As such, Online Harassment and Unsympathetic Online Behaviors were removed from further analysis. The remaining social technology behaviors, which all demonstrated increases overtime, included: Frequency of Checking Social Media, $\chi^2(df = 1) = 67.95$, $p < .001$; $B_{time} = 5.48$, $p < .001$, $\eta^2 = .08$, Social Technology Use Before Bedtime, $\chi^2(df = 1) = 36.04$, $p < .001$; $B_{time} = 2.08$, $p < .001$, $\eta^2 = .05$, Problematic Internet Use, $\chi^2(df = 1) = 67.78$, $p < .001$; $B_{time} = 2.50$, $p < .001$, $\eta^2 = .05$, Positive Social Media Use, $\chi^2(df = 1) =$

7.73, $p = .005$; $B_{time} = 7.62$, $p = .005$, $\eta^2 = .009$, and Online Social Support Seeking, $\chi^2(df = 1) = 17.63$, $p < .001$; $B_{time} = 1.45$, $p < .001$, $\eta^2 = .02$.

Aim 1: Examining Subgroup Differences in Changes in Social Technology Behaviors During Social Distancing

In the next set of models, we added main effects of the six covariates of interest (age, gender, race, mother's education, two parent household, single child status). All covariates significantly predicted at least one social technology outcome except for the variable representing whether there were multiple children in the home. As such, this variable was removed as a covariate from subsequent models.

Next, to explore whether there were subgroup differences in changes in social technology behavior overtime, we added interaction terms, represented as the product of time and each covariate. There was a significant effect of Time × Age ($B = -.19$, $p = .001$, $\eta^2 = .01$) in predicting the Frequency of Checking Social Media and Social Technology Use Before Bedtime ($B = -.10$, $p < .001$, $\eta^2 = .01$).

To further probe these interactions, we conducted tests of simple slopes, considering age at two values: 1 *SD* and 1.5 *SD*s below the mean and 1 and 1.5 *SD*s above the mean. Results demonstrated that the slope of Frequency of Checking Social Media was not significantly different from zero for younger adolescents or older adolescents when age was set at 1 *SD* or 1.5 *SD*s above and below the mean. In all, these findings suggest that although the growth in Frequency of Checking Social Media is different for younger and older adolescents, neither group individually is demonstrating statistically significant growth in the Frequency of Checking Social Media.

The same pattern for the interaction between Time × Age emerged in regard to Social Technology Use Before Bedtime. In addition, there was a significant effect of Time × Black [vs. White] ($B = -.39$, $p = .009$, $\eta^2 = .001$) in predicting Online Social Support Seeking, suggesting that, when compared with White youth, Black youth demonstrated larger increases in Online Social Support Seeking between Time 1 and Time 2. To further probe this interaction, we conducted tests of simple slopes, which suggested that the slope of Online Social Support Seeking was not significantly different from zero for Black or White youth, suggesting that although the difference between Black and White students in the growth in Online Social Support seeking is statistically meaningful, neither Black nor White students actually demonstrated statistically meaningful increases in Online Social Support Seeking. Refer to Table 2.

Aim 2: Examining the Relationship Between Change in COVID-19 Social Technology Behaviors and Wellbeing Outcomes

To address Aim 2, we first considered whether there was significant change in each measure of wellbeing by comparing a null model to a model with a main effect of time. One outcome, Online Social Anxiety, $\chi^2(df = 1)=.72$, $p = .40$; $B_{time} = 2.84$, $p = .40$, did not show change over time and was removed from further analysis. The remaining four measures of wellbeing, which all demonstrated increases over time, included: Strategies to Cope When Stressed, $\chi^2(df = 1) = 29.62$, $p < .001$; $B_{time} = 1.52$, $p < .001$, $\eta^2 = .03$, Social Anxiety,

$\chi^2(df = 1) = 46.31$, $p < .001$; $B_{time} = 2.26$, $p < .001$, $\eta^2 = .05$, Loneliness, $\chi^2(df = 1) = 51.53$, $p < .001$; $B_{time} = 1.57$, $p < .001$, $\eta^2 = .06$, and Depressive Symptoms, $\chi^2(df = 1) = 103.16$, $p < .001$; $B_{time} = 2.23$, $p < .001$, $\eta^2 = .11$).

To evaluate whether changes in social technology behaviors were associated with changes in wellbeing, we examined interaction terms between time and each social technology behavior. It is important to note that although these models consider the relationship between two longitudinal processes, the results do not reflect causality. That is, we cannot make conclusions regarding which came first—a change in social technology behaviors or a change in wellbeing. Changes in Problematic Internet Use ($B = -.14$, $p = .003$, $\eta^2 = .008$), Online Social Support Seeking ($B = .15$, $p = .001$, $\eta^2 = .003$), and Positive Social Media Use ($B = -.13$, $p = .01$, $\eta^2 = .004$) predicted changes in Strategies to Cope When Stressed. To further probe these interactions, we examined simple slopes at 1*SD* and 1.5 *SDs* above and below the mean of each moderator. Tests of simple slopes for Problematic Internet Use and Positive Social Media Use were not significant at 1 *SD* or 1.5 *SD*s above and below the mean. Our tests of simple slopes in relation to Online Social Support suggested that youth who demonstrated the most growth in Online Social Support Seeking (Online Social Support Seeking was 1 *SD* above the mean or higher) also demonstrated the most growth in Strategies to Cope When Stressed ($B = .72$, $p < .01$, $\eta^2 = .01$; see Figure 1). That is, youth who were seeking more Online Social Support during COVID-19 also demonstrated growth in the use of Strategies to Cope When Stressed during COVID-19.

Changes in Problematic Internet Use ($B = 1.01$, $p < .01$, $\eta^2 = .002$) and Positive Social Media Use ($B = 1.13$, $p < .01$, $\eta^2 = .002$) predicted changes in Depressive Symptoms. Youth who demonstrated growth in Problematic Internet Use or Positive Social Media Use demonstrated more growth in Depressive Symptoms than youth whose Problematic Internet Use and Positive Social Media use remained stable overtime. However, tests of simple slopes at 1*SD* and 1.5 *SD*s above and below the mean of each moderator were not significant, suggesting that growth in Depressive Symptoms was not actually significantly different from zero. Refer to Table 3.

Aim 2: Potential Moderators

To examine whether Digital Access, Household Screen Rules, or COVID-19 Related Grief moderated the relationship between changes in social technology behaviors and changes in wellbeing, we focused on the two wellbeing outcomes (Strategies to Cope When Stressed and Depressive Symptoms) that demonstrated change in relation to changes in social technology behaviors. Three-way interaction terms were created by multiplying time by the social technology behaviors associated with changes in wellbeing (Problematic Internet Use, Online Social Support Seeking, Positive Social Media Use) and the three moderators. None of the three-way interactions tested were statistically significant, suggesting that Digital Access, Household Screen Rules, and COVID-19 Related Grief do not moderate relationships between changes in social technology and changes in wellbeing.

Summary of Results

Prior to testing all models, we established that effect sizes of .05 or higher would be interpreted as representing practically meaningful findings. Under these criteria, results from the current analyses suggest that there were statistically meaningful changes in both social technology behaviors and adolescent wellbeing between the period prior to the COVID-19 pandemic (Fall 2019) and during the COVID-19 pandemic (Fall 2020). During this time period, adolescents in our study demonstrated increases in the Frequency of Checking Social Media, Social Technology Use before Bedtime, and Problematic Internet use. Students also demonstrated increases in the use of Strategies to Cope when Stressed, Social Anxiety, Loneliness, and Depression.

We tested a series of moderation models both in regard to changes in social technology behaviors and wellbeing. None of our findings that were statistically meaningful (i.e., had an α of <.05), met our effect size criteria (i.e., effect of ≥.05), suggesting that we were not able to detect subgroup differences in changes in social technology nor whether changes in social technology use were related to changes in wellbeing. Our final models, which examined whether Digital Access, Household Screen Rules, or COVID-19 Related Grief moderated the relationship between changes in social technology and changes in wellbeing, also did not yield any statistically meaningful results. Given that our power analyses suggested we had sufficient power to detect effect sizes of .07, it is possible that some of the relationships we tested may have had statistically meaningful effects that we were unable to detect (i.e., effects of less than .07).

Discussion

The first aim of this study was to explore changes in social technology behaviors during the COVID-19 pandemic and any potential demographic subgroup differences. There were multiple positive (e.g., online support seeking) and negative (e.g., problematic internet use) changes in adolescent social technology behaviors during the COVID-19 pandemic social distancing. Interestingly, although there were significant increases in frequency of checking social media and social technology use before bedtime, there were no increases in negative online interactions with others (e.g., online harassment). These preliminary findings with our convenience sample in the Northeast during unusual and unprecedented times may provide some relief to parents and educators that the increased time spent on social technology did not necessarily expose youth to harmful social interactions more than in prepandemic time periods. Fears that overreliance on internet-based communications would result in toxic disinhibition (Wachs & Wright, 2018) can be somewhat put aside until further research is more conclusive regarding the prevalence of online harassment during social distancing. In alignment with previous pre-COVID-19 research on subgroup differences in adolescent social technology use, demographic factors such as age, gender, race, mother's education, and single versus two parent households were found to be significantly related to at least one social technology behavior during the COVID-19 pandemic of 2020. We found no practically meaningful significant subgroup differences in relation to changes in social technology behavior prior to and during, which may be due to the fact that the changes in behaviors during the social distancing of the pandemic were not substantial enough to detect subgroup differences.

The second aim of the study was to examine how wellbeing was associated with changes in social technology behaviors during the COVID-19 pandemic. Most negative wellbeing indicators increased during the pandemic (e.g., Social Anxiety, Loneliness, Depression), however, we also found significant increases in methods to cope with stress—some of which may have been more escapist methods (e.g., watching TV) and others more about connecting with family and friends. The only negative wellbeing indicator that did not change was Online Social Anxiety, which is interesting given our Aim 1 findings that there were no changes in online harassment compared to prepandemic times, which could be a potential trigger for online social anxiety.

We found some extremely small effects of social technology behaviors associated with wellbeing, such as Online Support Seeking being related to Strategies when Coping with Stress. Although these findings were not practically meaningful, these trends provide some support for the *stimulation hypothesis*—the theory that increased time on social technologies may improve opportunities to gain social skills, such as finding online support for any psychosocial difficulties. The increased instances of Positive Social Media behaviors that increased connection and sense of belonging with others online during the pandemic provide an alternative view of the value-added online activities of adolescents during this social distancing period. While we tested the idea that Digital Access, Household Screen Rules and COVID Grief may attenuate the relationships between wellbeing and social technology behaviors, the models suggested that there was no moderation. This could be due to the timing of the data collection whereas in spring of 2020, digital access issues may have been exacerbated compared to fall of 2020. Additionally, household screen rules may not be as critical in predicting adolescent social technology use since parents often transition to active discussions and focusing on autonomy in adolescence rather than relying on rules and curfews (Ho et al., 2020). The fact that we did not find meaningful moderators may indicate that there was not enough variability in these indicators to detect moderation in our sample, especially given that there were no meaningful differences found in wellbeing associated with *change* in social technology behaviors during the pandemic.

Overall, we did not find any strong support that the changes in wellbeing that adolescents experienced during the COVID-19 pandemic social distancing was meaningfully related to their social technology use, which is counter to the popular assumption that adolescent wellbeing is intricately tied to their social technology use. A future direction would be to test associations with wellbeing cross-sectionally pre- and post-COVID pandemic to understand the relationship at different time points rather than focusing on the change over time. In the current paper, a goal was to understand their collective resources for coping while stressed, rather than examine the individual contributions, which we have added as an important direction for future research. Another avenue for future research would be to use different instruments to measure person-specific susceptibilities (Valkenburg et al., 2021), such as utilizing moderators that may draw on dispositional attributes such as self-esteem contingency or social anxiety as well as social context moderators, such as peer norms.

Limitations

Given that time was measured using only two time points, the models did not converge when a random effect of time was added. Omitting the random effect of time increases the risk of Type 1 error due to possibly underestimated standard errors. To reduce our risk of Type 1 error, we elected to test moderation effects only in the presence of significant main effects, since there is a significant increase in power required to detect moderating effects in the absence of a main effect (Rogers, 2002). It is possible that some of the moderation effects that we did not explore may be statistically meaningful. As is the case with self-report survey research, these findings are subject to recall biases. Since the Time 2 data collection was conducted in late fall of 2020, when many schools were already engaged in hybrid learning, the peak effects of the COVID-19 pandemic may not have been fully captured by the time data collection commenced. For instance, the COVID-19 Grief measure may have been more critical in March through July of 2020, when families and schools were on lockdown and many personal engagements were canceled.

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Data availability statement:

As this is an actively recruiting, ongoing longitudinal dataset, we are currently making the data and study materials available upon request and completion of data sharing agreements. Our preregistered analytic plan for the present study is available at https://osf.io/2jrxp.

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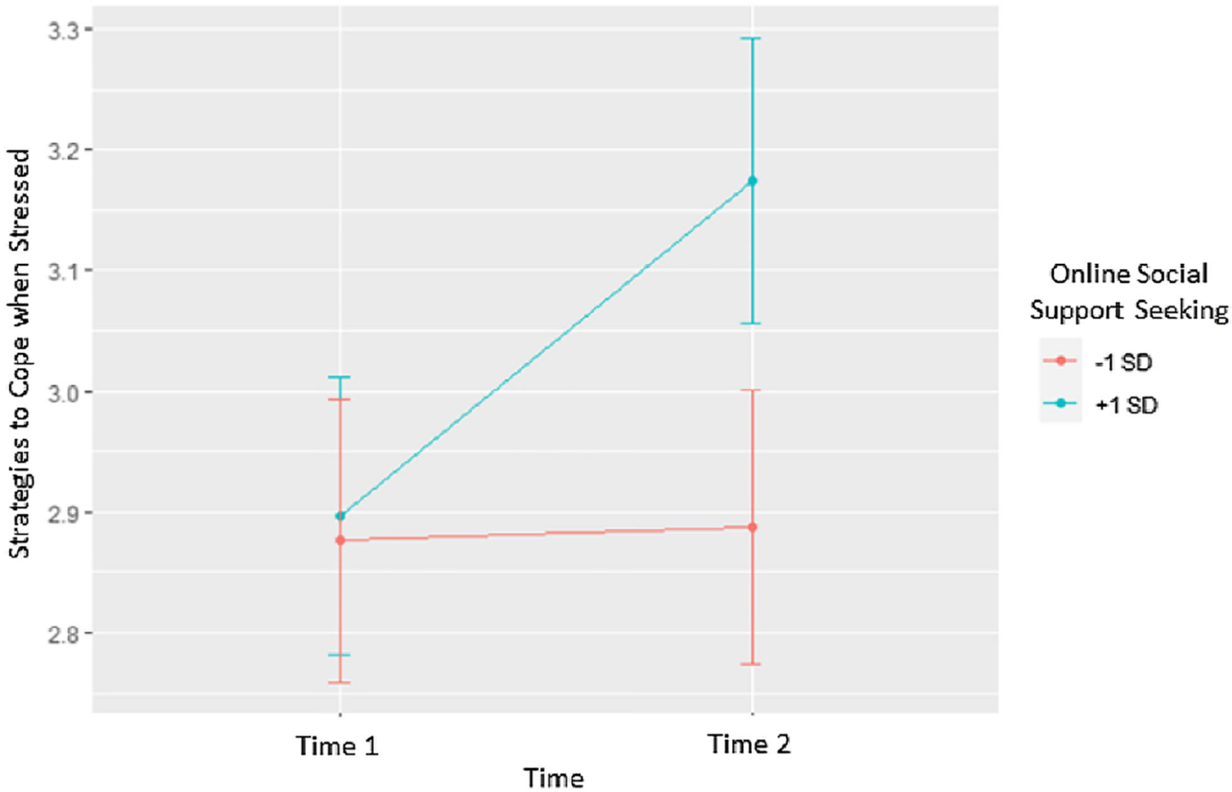

Figure 1.
Longitudinal Relationship Between Online Social Support Seeking and Strategies to Cope When Stressed

Table 1

Descriptives of Outcomes

Outcomes	Time 1					Time 2				
	N	Min	Max	*M*	*SD*	*N*	Min	Max	*M*	*SD*
Frequency of online behaviors										
Frequency of checking social media	998	1	6	3.75	1.91	945	1	6	4.23	1.72
Sleep behaviors	909	1	4	2.38	0.91	841	1	4	2.55	0.89
Negative online behaviors										
Secretive behaviors: Parent disapproval of network friend	821	0	1	0.21	0.41	815	0	1	0.22	0.41
Secretive behaviors: Parent disapproval of social media site	960	0	1	0.12	0.32	925	0	1	0.15	0.36
Problematic internet behaviors	916	1	5	1.67	0.68	841	1	5	1.90	0.83
Online harassment	877	1	4	1.50	0.65	831	1	4	1.52	0.66
Unsympathetic online behaviors	863	1	5	1.49	0.70	822	1	5	1.51	0.75
Positive online behaviors										
Positive media use	961	1	5	2.60	0.77	896	1	5	2.67	0.79
Online social support	911	1	5	2.28	0.90	798	1	5	2.45	0.88
Wellbeing										
Coping while stress	867	1	4	2.92	0.63	806	1	4	3.08	0.64
Online social anxiety	892	1	4	1.86	0.79	860	1	4	1.88	0.97
Social anxiety	900	1	4	2.38	0.80	862	1	4	2.60	0.91
Loneliness	928	1	3	1.45	0.52	862	1	3	1.60	0.60
Depression	930	0	30	6.84	4.95	857	0	30	8.95	6.28

Table 2

Subgroup Differences in Changes in Social Technology Behaviors Between Time 1 and Time 2

	Frequency of checking social media			**Sleep behaviors**			**Problematic internet behaviors**			**Positive media use**			**Online social support**		
Predictors	**Estimates**	**CI**	***p***	**Estimates**	**CI**	***p***	**Estimates**	**CI**	***p***	**Estimates**	**CI**	***p***	**Estimates**	**CI**	***p***
(Intercept)	−4.21	[−6.96 to −1.45]	**.003**	−0.91	[−2.33 to 0.52]	.212	0.08	[−1.15 to 1.31]	.900	2.17	[1.01 to 3.32]	**<.001**	0.62	[−0.82 to 2.05]	.399
Time	2.63	[1.00 to 4.25]	**.002**	1.28	[0.44 to 2.12]	**.003**	0.42	[−0.31 to 1.14]	.263	0.18	[−0.50 to 0.85]	.611	0.65	[−0.21 to 1.51]	.137
Age	0.63	[0.44 to 0.82]	**<.001**	0.29	[0.20 to 0.39]	**<.001**	0.10	[0.01 to 0.18]	**.026**	0.01	[−0.06 to 0.09]	.721	0.09	[−0.01 to 0.19]	.069
Gender	0.68	[0.23 to 1.14]	**.003**	0.03	[−0.21 to 0.26]	.816	0.14	[−0.07 to 0.34]	.188	0.38	[0.19 to 0.57]	**<.001**	0.30	[0.06 to 0.53]	**.014**
Mother's education	−0.21	[−0.43 to 0.02]	.078	−0.10	[−0.22 to 0.02]	.102	0.06	[−0.05 to 0.16]	.282	0.03	[−0.06 to 0.13]	.482	0.02	[−0.10 to 0.13]	.802
Two parent household	−0.36	[−0.95 to 0.22]	.219	−0.34	[−0.64 to −0.03]	**.029**	−0.16	[−0.42 to 0.10]	.218	−0.04	[−0.28 to 0.21]	.761	0.01	[−0.29 to 0.31]	.963
Black	−0.26	[−1.12 to 0.61]	.562	0.26	[−0.23 to 0.75]	.307	0.18	[−0.23 to 0.60]	.392	0.21	[−0.16 to 0.59]	.270	0.33	[−0.14 to 0.79]	.172
Asian	−0.93	[−1.93 to 0.06]	.065	−0.36	[−0.85 to 0.13]	.154	0.19	[−0.24 to 0.61]	.391	−0.02	[−0.43 to 0.39]	.942	−0.16	[−0.69 to 0.37]	.553
Latinx	−0.08	[−0.87 to 0.71]	.837	0.12	[−0.28 to 0.52]	.548	0.12	[−0.23 to 0.47]	.500	−0.09	[−0.42 to 0.23]	.569	0.00	[−0.40 to 0.41]	.995
Other race	0.03	[−0.61 to 0.67]	.931	−0.18	[−0.51 to 0.15]	.279	−0.06	[−0.35 to 0.22]	.660	−0.04	[−0.31 to 0.23]	.764	0.34	[0.01 to 0.68]	**.047**
Multiple children	0.53	[−0.09 to 1.15]	.091	0.03	[−0.29 to 0.35]	.843	0.01	[−0.27 to 0.29]	.935	−0.06	[−0.32 to 0.19]	.625	0.19	[−0.14 to 0.51]	.265
Time × Age	−0.19	[−0.30 to −0.08]	**.001**	−0.10	[−0.16 to −0.05]	**<.001**	−0.01	[−0.06 to 0.04]	.758	0.00	[−0.05 to 0.04]	.942	−0.02	[−0.08 to 0.04]	.468
Time × Gender	−0.10	[−0.38 to 0.18]	.474	−0.02	[−0.17 to 0.12]	.763	0.06	[−0.07 to 0.18[	.385	0.03	[−0.09 to 0.14]	.651	0.04	[−0.11 to 0.18]	.613
Time × Mother's education	0.06	[−0.08 to 0.21]	.372	0.03	[−0.04 to 0.11]	.371	−0.05	[−0.11 to 0.01]	.125	−0.04	[−0.10 to 0.02]	.179	−0.03	[−0.11 to 0.04]	.406
Time × Two parent household	0.22	[−0.14 to 0.59]	.236	0.12	[−0.07 to 0.31]	.218	0.06	[−0.10 to 0.23]	.443	−0.04	[−0.19 to 0.12]	.641	−0.07	[−0.26 to 0.12]	.457
Time × Black	0.21	[−0.33 to 0.76]	.442	−0.11	[−0.41 to 0.19]	.469	−0.07	[−0.33 to 0.19]	.608	−0.10	[−0.33 to 0.13]	.392	−0.39	[−0.69 to −0.10]	**.009**

Predictors	Frequency of checking social media			Sleep behaviors			Problematic internet behaviors			Positive media use			Online social support		
	Estimates	**CI**	***p***	**Estimates**	**CI**	***p***	**Estimates**	**CI**	***p***	**Estimates**	**CI**	***p***	**Estimates**	**CI**	***p***
Time × Asian	0.03	[−0.59 to 0.66]	.916	0.05	[−0.25 to 0.36]	.729	−0.13	[−0.40 to 0.14]	.347	0.00	[−0.25 to 0.26]	.991	0.11	[−0.23 to 0.46]	.521
Time × Latinx	0.07	[−0.41 to 0.55]	.769	−0.20	[−0.44 to 0.05]	.113	−0.07	[−0.28 to 0.14]	.510	0.05	[−0.14 to 0.25]	.589	−0.01	[−0.26 to 0.24]	.928
Time × Other race	−0.16	[−0.57 to 0.25]	.446	0.12	[−0.09 to 0.33]	.265	0.05	[−0.14 to 0.23]	.622	0.05	[−0.12 to 0.22]	.541	−0.17	[−0.39 to 0.05]	.131
Time × Multiple children	−0.34	[−0.74 to 0.05]	.087	−0.03	[−0.24 to 0.17]	.743	−0.01	[−0.19 to 0.17]	.916	0.04	[−0.13 to 0.20]	.661	−0.11	[−0.32 to 0.09]	.281
Random effects															
σ^2	1.66			0.37			0.3			0.25			0.39		
τ_{00}	1.31_{trackid}			0.39_{trackid}			0.24_{trackid}			0.31_{trackid}			0.38_{trackid}		
ICC	0.44			0.51			0.45			0.56			0.5		
N	$1{,}189_{\text{trackid}}$			$1{,}097_{\text{trackid}}$			$1{,}105_{\text{trackid}}$			$1{,}152_{\text{trackid}}$			$1{,}069_{\text{trackid}}$		
Observations	1,656			1,511			1,519			1,599			1,480		
Marginal R^2/ conditional R^2	0.130/0.513			0.080/0.547			0.074/0.491			0.080/0.592			0.062/0.528		

Table 3

Changes in Social Technology Behaviors and Wellbeing Between Time 1 and Time 2

	Loneliness			Coping while stress			Depression			Social anxiety		
Predictors	**Estimates**	**CI**	***p***	**Estimates**	**CI**	***p***	**Estimates**	**CI**	***p***	**Estimates**	**CI**	***p***
(Intercept)	0.94	[0.50 to 1.37]	**<.001**	2.33	[1.77 to 2.90]	**<.001**	0.29	[−0.13 to 0.71]	.175	1.95	[1.25 to 2.65]	**<.001**
Time	−0.06	[−0.28 to 0.16]	.607	0.23	[−0.06 to 0.52]	.124	−0.22	[−0.43 to −0.01]	**.036**	0.07	[−0.28 to 0.42]	.686
Problematic internet	0.25	[0.13 to 0.37]	**<.001**	0.21	[0.05 to 0.37]	**.009**	0.16	[0.04 to 0.27]	**.007**	0.26	[0.06 to 0.45]	**.009**
Online support	0.09	[−0.02 to 0.20]	.093	−0.13	[−0.28 to 0.01]	.061	0.05	[−0.05 to 0.15]	.368	0.15	[−0.02 to 0.32]	.085
Positive media	−0.06	[−0.17 to 0.06]	.311	0.31	[0.16 to 0.46]	**<.001**	−0.11	[−0.22 to 0.00]	.053	−0.06	[−0.24 to 0.12]	.512
Check social media	−0.01	[−0.06 to 0.05]	.827	−0.03	[−0.10 to 0.04]	.386	−0.01	[−0.05 to 0.04]	.811	−0.03	[−0.11 to 0.06]	.537
Sleep behaviors	0.00	[−0.10 to 0.10]	.961	−0.08	[−0.22 to 0.05]	.207	0.11	[0.01 to 0.20]	**.024**	−0.08	[−0.24 to 0.08]	.344
Time × Prob	0.02	[−0.06 to 0.09]	.661	−0.14	[−0.24 to −0.05]	**.003**	0.10	[0.03 to 0.17]	**.004**	0.02	[−0.10 to 0.13]	.787
Time × Online	−0.02	[−0.09 to 0.04]	.498	0.15	[0.06 to 0.24]	**.001**	0.00	[−0.06 to 0.06]	.975	−0.04	[−0.15 to 0.07]	.480
Time × Positive	0.07	[−0.01 to 0.14]	.084	−0.13	[−0.23 to −0.03]	**.012**	0.11	[0.04 to 0.18]	**.002**	0.04	[−0.07 to 0.16]	.463
Time × Check	−0.01	[−0.04 to 0.02]	.559	0.01	[−0.03 to 0.06]	.606	−0.01	[−0.04 to 0.03]	.744	−0.01	[−0.07 to 0.04]	.615
Time × Sleep	0.01	[−0.05 to 0.08]	.678	0.04	[−0.04 to 0.13]	.286	−0.04	[−0.10 to 0.02]	.202	0.04	[−0.06 to 0.14]	.410
Age	0.00	[−0.02 to 0.02]	.799	−0.03	[−0.05 to 0.00]	.054	0.00	[−0.02 to 0.02]	.898	0.00	[−0.03 to 0.04]	.824
Gender	0.09	[0.03 to 0.16]	**.002**	−0.04	[−0.12 to 0.03]	.266	0.13	[0.08 to 0.19]	**<.001**	0.25	[0.15 to 0.35]	**<.001**
Mother's education	−0.04	[−0.06 to −0.01]	**.006**	0.06	[0.02 to 0.09]	**.001**	−0.04	[−0.06 to −0.01]	**.004**	−0.07	[−0.11 to −0.03]	**.001**
Two parent household	−0.01	[−0.08 to 0.06]	.805	0.09	[0.00 to 0.18]	**.046**	−0.05	[−0.12 to 0.01]	.104	0.00	[−0.11 to 0.11]	.986
Black	0.21	[0.10 to 0.33]	**<.001**	−0.10	[−0.25 to 0.05]	.176	0.15	[0.04 to 0.26]	**.009**	0.11	[−0.08 to 0.30]	.254
Asian	0.13	[0.01 to 0.25]	**.035**	−0.08	[−0.24 to 0.07]	.283	0.09	[−0.03 to 0.21]	.126	−0.01	[−0.20 to 0.19]	.956
Latinx	0.06	[−0.02 to 0.15]	.158	−0.05	[−0.16 to 0.06]	.398	0.06	[−0.02 to 0.15]	.138	0.03	[−0.12 to 0.17]	.713
Other race	0.02	[−0.06 to 0.09]	.637	−0.06	[−0.15 to 0.04]	.255	0.09	[0.01 to 0.16]	**.019**	−0.03	[−0.15 to 0.09]	.603
Random effects												
σ^2	0.14			0.26		0.12				0.34		
τ_{00}	$0.10_{trackid}$			$0.10_{trackid}$		$0.09_{trackid}$				$0.28_{trackid}$		
ICC	0.41			0.28		0.43				0.45		
N	$986_{trackid}$			$958_{trackid}$		$981_{trackid}$				$987_{trackid}$		

Predictors	Loneliness			Coping while stress			Depression			Social anxiety		
	Estimates	CI	*p*	Estimates	CI	*p*	Estimates	CI	*p*	Estimates	CI	*p*
Observations	1353.00			1307.00			1347.00			1355.00		
Marginal R^2/ conditional R^2	0.250/0.560			0.094/0.350			0.351/0.631			0.148/0.529		