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Does Your Smartphone Make You Unhappy?
The Effects of Digital Media and Social Media on Well-Being

A Dissertation submitted in partial satisfaction
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by

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ABSTRACT OF THE DISSERTATION

Does Your Smartphone Make You Unhappy?
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Dr. Sonja Lyubomirsky, Chairperson

Both scientists and laypeople have become increasingly concerned about smartphones, especially their associated digital media (e.g., email, news, gaming, and dating apps) and social media (e.g., Facebook, Instagram, Snapchat). Recent correlational research that relies heavily on self-reported time estimates links substantial declines in Gen Z well-being to digital and social media use (Twenge et al., 2018), yet other work suggests the effects are small and unnoteworthy (Orben & Przybylski, 2019a). Such mixed results call for additional research—both investigations comparing self-report vs. objective indicators of screen time and experiments to disentangle correlation from causation and better elucidate the strength and direction of effects.

How accurate is self-report? Are smartphones making young people unhappy? I aimed to address these questions in two studies. In Study 1, I recruited undergraduate students (*N* = 414; 98.3% Gen Z) and examined correlations among psychosocial well-being and screen time. Overall, most participants were unable to accurately estimate how much time they spent on their smartphones and social media. The more participants objectively used their smartphones, the less happy they were. However, some smartphone apps were associated with greater well-being (e.g., Camera, News, Snapchat), some were associated with lower well-being (e.g., Facebook, Reddit, Tinder), and some were not meaningfully linked to well-being (e.g., Clock, Hulu, WhatsApp).

Study 2 involved a pre-registered experimental deprivation study with a subset of the same undergraduate students from Study 1 (*N* = 338; 97.9% Gen Z), who were randomly assigned to one of four conditions: (1) restrict digital media use, (2) restrict social media use, (3) restrict water use (active control), or (4) restrict nothing (measurement-only control). Relative to controls, participants restricting digital media reported a variety of benefits, including higher life satisfaction, mindfulness, autonomy, competence, and self-esteem, and reduced loneliness and stress. In contrast, those assigned to restrict social media reported relatively few benefits (increased mindfulness) and even some costs (more negative emotion).

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

"Along with the attendant growth of social media, the proliferation of smartphones—more than 10 billion have been sold—has had a sweeping influence on almost every aspect of life and culture. It has given a new texture and tempo to our days. It has upset social norms and relations. It has reshaped the public square and the political arena." — Nicholas Carr

"Every once in a while, a revolutionary product comes along that changes everything," said Steve Jobs, CEO of Apple Inc., during his keynote address at the MacWorld Conference and Expo in 2007 (Schroter, 2011). Minutes later, he announced the advent of the iPhone, a new device that combined music listening, mobile phone, and Internet browsing technologies—the world's first smartphone. Several other companies (e.g., Google, Samsung, Huawei) followed suit and released their own devices, many of which were so affordable that adoption rates quickly soared (Davidson, 2019).

In little more than a decade, the smartphone has become a ubiquitous and essential tool for more than 3.6 billion individuals (O'Dea 2021a), changing people's lives in both predictable and unanticipated ways—impacting how they connect with others (e.g., Messages, Facebook), find romantic partners (e.g., Tinder, Bumble), entertain themselves (e.g., YouTube, Netflix), listen to music (e.g., Spotify, Pandora), shop (e.g., Amazon, Etsy), commute (e.g., Google Maps, Waze), order food (e.g., DoorDash, UberEats), book travel (e.g., Airbnb, Kayak), and more. At the time of this writing, the smartphone is still altering the world's physical and digital landscapes.

In the wake of this dramatic societal technological shift has come a "techlash" blaming the smartphone and related apps for everything from traffic accidents to ethnic cleansing (Davidson, 2019). More recently, psychological scientists and lay audiences have been debating whether digital technologies are addictive and harmful to well-being, physical health, and longevity (Alter, 2017; Chiu, 2018; Grady, 2019; Lanier, 2018; Moby, 2016; Orben & Przybylski, 2019a, 2019b; Twenge, 2017; Twenge et al., 2017, 2018; Wu, 2016). Are smartphones and their associated digital media (e.g., social media, email, news, text, gaming, sports, entertainment, dating, and music apps) making people unhappy?

To address this question, I conducted a "shortitudinal" experiment that tasked participants with restricting their smartphone (i.e., digital media) and/or social media use in daily life (Dormann & Griffin, 2015). The following chapters present two studies from this data collection effort. Study 1 examines baseline data from this experiment to examine differences between self-report estimates and objective indicators of screen time. It also explores whether non-screen activities are associated with greater well-being than screen activities, as well as differences among specific smartphone apps and categories. Study 2 reports the results of the shortitudinal deprivation experiment in which participants restricted their digital media use, social media use, water use (active control), or nothing (measurement-only control). Will restricting digital media and social media use as much as possible for about a week improve psychological well-being and related constructs?

Chapter 2: Study 1

"Smartphones have become our constant companions. Social media has insinuated itself into everything we do." — Nicholas Carr

"Phones are neither good nor bad, they are just lifeless machines that were invented to serve humankind …" — Abhijit Naskar

The smartphone has spread faster than any technology in human history (DeGusta, 2012). With its rise, narratives about the addictiveness and harmfulness of technology use have seeped into global discourse, infiltrating both our digital and corporeal worlds. Concerns about digital technology can be glimpsed in an avalanche of news articles, books, Netflix documentaries, t-shirts, YouTube videos, street signs, podcasts, and memes that warn people to "beware of smartphone zombies," provide "ten arguments for deleting your social media accounts right now," and pose questions about whether "smartphones destroyed a generation" (Alter, 2017; Anderson et al., 2018; Arnold et al., 2019; Brooker & Wright, 2018; Dmodepl, 2019; Lanier, 2018; Moby, 2016; reMarkable, 2018; Twenge, 2017a). A general, gnawing anxiety about smartphones and social media has emerged and ironically gone viral on these very devices and platforms. Yet empirical psychological research is still debating whether digital technology use impairs psychosocial well-being.

In annual surveys from 1991 to 2016, Twenge and colleagues (2017, 2018) examined several large-scale datasets (*N* = 506,820 to 1.1 million) of U.S. adolescents, comprising the generation known as Gen Z (or iGen), and found that they experienced substantial declines in psychological well-being and increases in depressive symptoms from 2010 onwards. The researchers linked these declines in mental health to increased digital technology use (e.g., smartphones and social media). A key finding from that paper examined correlations between happiness and self-reported time spent on various types of activities. Specifically, non-screen activities (e.g., exercise, in-person social interaction, attending religious services, doing homework) were positively correlated with happiness (*r*s = .02 to .16). However, screen activities (e.g., texting, social media, gaming, Internet browsing) were negatively correlated with happiness (*r*s = –.11 to .00). The researchers concluded that Gen Z individuals who spent more time on screen activities and less time on non-screen activities had lower well-being. In other words, their analyses suggested digital technology use may harm happiness.

However, after conducting follow-up analyses, Orben and Przybylski (2019a) argued that worries about digital technology use may be unwarranted. These researchers applied specification curve analysis across three large-scale datasets (total N = 355,358) and found that the association between self-reported screen time and adolescent well-being was negative but small ($\beta = -0.042$)—comparable to that of eating potatoes or wearing glasses, both relatively benign non-screen activities (Orben & Przybylski, 2019a). In two additional large-scale datasets in the U.S. and Ireland (total N = 17,247), Orben and Przybylski (2019b) also examined associations between well-being and self-reported ($\beta = -0.08$), as well as time-use-diary measures ($\beta = -0.02$), of screen time. Again, they concluded that digital technology use is not meaningfully linked to Gen Z well-being, depression, or self-esteem.

In addition to Twenge and colleagues' (2018) findings that greater screen time predicts greater depression, other researchers have found that greater depression predicts greater screen time use (Zink et al., 2019), that the two influence each other reciprocally (Houghton et al., 2018), or that there is no significant relationship (George et al., 2018). Most of the mixed and inconclusive correlational work yields mostly small associations between screen time and well-being (including related constructs like self-esteem and loneliness) and relies heavily on measures of digital technology use that are retrospective and self-reported (Etchells et al., 2016; Parkes et al., 2013; Orben & Przybylski 2019a; Przybylski & Weinstein, 2017; Smith et al., 2018; Twenge et al., 2017, 2018). However, previous research suggests that people often misreport (i.e., overestimate or underestimate) the amount of time they spend on specific activities, especially screen activities (Grondin, 2010; Scharkow, 2016). Collecting objective indicators of screen time from smartphone devices is a promising approach to address this measurement issue (Orben & Przybylski, 2019b).

As such, researchers have begun to examine objective indicators of screen time using a variety of methods, such as mobile network provider data, smartphone tracker apps, battery use screenshots, and Apple's Screen Time function (Andrews et al., 2015; Boase & Ling, 2013; David et al., 2018; Deng et al., 2019; Elhai et al., 2018; Gower et al., 2018; Johannes et al., 2020; Ohme et al., 2020; Sewall et al., 2020; Shaw et al. 2020; Vanden Abeele et al., 2013). Notably, this work has shown that users spend about 2.5 to 5 hours and make over 100 app switches per day on their smartphones (Andrews et al., 2015; David et al., 2018; Deng et al., 2015; Ohme et al., 2020; Sewall et al., 2020). People also tend to make self-report errors when asked to estimate their actual smartphone and social media use—usually overestimating time spent (Andrews et al., 2015; Deng et al., 2019; Sewall et al., 2020), but occasionally underestimating it (Ohme et al., 2020). Additional research suggests light users tend to overestimate their actual screen time, while heavy users underestimate it (Araujo et al., 2017).

Finally, recent research suggests that it may not be the amount of screen time that impacts well-being, but how, when, and where individuals spend that time (Hancock et al., 2020; Kushlev & Leitao, 2020; Masciantonio et al., 2020; Verduyn et al., 2017; David et al., 2018). As such, some types of screen time may be better for psychosocial well-being than others (e.g., using Facebook passively vs. actively, using gaming apps vs. productivity apps). Thus, broad correlations that examine only overall screen time and well-being may present an oversimplified view of a complex relationship.

The Present Study

In sum, correlational research suggests that self-reported non-screen activities (e.g., exercise, in-person social interaction) may boost well-being, while self-reported screen activities (e.g., online news, social media, gaming) may harm it (Twenge et al., 2018). Yet other research shows that the effects of self-reported and time-use-diary screen time on well-being are small and unnoteworthy (Orben & Przybylski 2019a, 2019b). I wanted to explore whether this pattern of results replicated with objective indicators of smartphone screen time, as well as compare my findings with those of extant objective indicator studies.

To this aim, I recruited Gen Z individuals to complete a survey of well-being-related outcome measures (e.g., positive emotions, life satisfaction, depression), while also collecting Screen Time screenshots from their iPhones. I did not pre-register hypotheses for Study 1, but merely aimed to investigate the cross-sectional data in an exploratory manner. Specifically, I had three research questions: How accurate is self-reported screen time relative to objective indicators? Are non-screen activities associated with higher subjective well-being than screen activities? Finally, are some specific smartphone apps associated with higher psychosocial well-being than others? Data, materials, and R code are available for Study 1 at https://osf.io/vpekx/.

Method

Participants

I recruited participants from the University of California, Riverside psychology department's online research participation system and offered them course credit as compensation. Eligibility criteria included the following: To join the study, participants had to be at least 18 years old, read and write English fluently, own an iPhone running iOS 12 or later with "Screen Time," and use social media at least four to six times per week.

Study 1 used data collected in the lab during a single time point, which was obtained as part of a larger experimental study with two time points (see Study 2), yielding a total sample of 414 participants (M_{age} = 19.1, *SD* = 2.2; 75.1% female). Almost all (98.3%) belonged to Gen Z (also referred to as iGen), which was the first generation to grow up with smartphones (Turner, 2015; Twenge, 2017b). Participants came from various ethnic backgrounds, such as Asian (40.8%), Hispanic (33.1%), White (11.1%), Black (4.1%), other (5.1%), and more than one (5.8%). The majority were single (63.8%) and many worked part-time (30.4%). They also reported a range of household incomes: 25.6% reported that their families earned less than $30,000 a year; 22% earned between $30,001 and $60,000; 18.1% earned between $60,0001 and $100,000; 21.3% earned over $100,000; and 13% did not know their household income.

Procedure

To limit demand effects, I recruited participants for a "Daily Habits Study"—that is, a study exploring daily habits (e.g., exercise, sleep), behaviors (e.g., reading, volunteering, smartphone use), thoughts, and emotions. The data for Study 1 (comprising the first time point of Study 2) were collected in-person in the Positive Activities and Well-Being Laboratory from February 19, 2019 to February 24, 2020. All data collection was finished before the university transitioned to online learning due to the COVID-19 pandemic.

Upon visiting the lab, participants signed a consent form, and were directed to a private computer to complete an online survey of measures and demographic information. Immediately afterward, research assistants (RAs) helped participants capture screenshots of the *Screen Time* section of their iPhones, which were saved for later transcription, coding, and analysis. Screen Time is a feature of Apple's iPhone mobile operating system (iOS 12 and later) that provides various user characteristics (e.g., time spent on the device, pickups, notifications; see Figure 1). The remainder of the procedure (including additional measurements and time point) is described in Study 2.

Measures

For the present investigation, I focused on the following measures. For each measure, participants were asked to rate their experience(s) over the "past week (last 7 days)."

Positive and Negative Emotions

To assess hedonic well-being, I used a 12-item adapted version of the Affect-Adjective Scale (Diener & Emmons, 1985; Shin et al., 2021). This scale assesses a range of low and high arousal positive emotions (e.g., happy, peaceful/serene) and negative emotions (angry/hostile, dull/bored) on 7-point Likert scales (1 = *not at all*, 7 = *extremely*). Scale reliabilities (McDonald's omegas [ωs]) were .89 for positive affect and .77 for negative affect.

Life Satisfaction

To gauge a relatively more stable, cognitive type of well-being, I also administered the Satisfaction With Life Scale (SWLS; Diener et al., 1985). Participants were asked to rate five items (e.g., "The conditions of my life are excellent") on 7-point

Likert-type scales (1 = *strongly disagree*, 7 = *strongly agree*). The scale reliability for life satisfaction was ω = .85.

Depression

I measured depressive symptoms with six items (e.g., “The future often seems hopeless”) from the Bentler Inventory of Depression (Newcomb et al., 1981), with response choices varying from 1 (*disagree*) to 5 (*agree*). The scale reliability for depression was ω = .87.

Loneliness

Participants also completed a 6-item loneliness scale (e.g., “A lot of times I feel lonely”) from Monitoring the Future, a big longitudinal survey of American adolescents (Johnston et al., 2017). They were given 5-point Likert scales (1 = *disagree*; 5 = *agree*), and the reliability for loneliness was ω = .62.

Self-Esteem

To assess feelings of self-worth, I asked participants to rate their agreement (1 = *strongly disagree*; 5 = *strongly agree*) on the 6-item Rosenberg Self-Esteem scale (Rosenberg, 1965). An example item includes: “I take a positive attitude toward myself.” The reliability for self-esteem was ω = .84.

Daily Habits/Non-Screen Time Activities

I also asked participants to report on their daily habits (or non-screen activities) during the past week. The following items were rated by frequency (1 = *never*; 5 = *daily*): exercising, spending time outdoors or in nature, relaxing (e.g., meditating, getting a spa treatment), attending religious services, and volunteering at a non-profit organization or charity. Participants were also asked to report their time spent (in hours and minutes) on other activities, such as: reading for leisure, sleeping, working for pay, doing homework/studying for school, and socially interacting with others (e.g., friends, family, co-workers).

Self-Reported Smartphone and Social Media Time

Before capturing iPhone Screen Time screenshots as an objective measure (see below), participants were asked to self-report how much time they spent on their iPhone (in hours and minutes). Specifically, I asked them, “As accurately as possible, please estimate the total amount of time you spend using your smartphone on average per day.” I did the same for social media by asking, “As accurately as possible, please estimate the total amount of time you spend using social media apps/sites on average per day. Please include time spent on all types of social media (e.g., Facebook, Instagram, Twitter, Snapchat) on all types of devices (e.g., iPhones, iPads, computers).”

Objective Smartphone and Social Media Time

As mentioned in the procedure above, RAs worked with participants to capture screenshots of the Screen Time section of their iPhones (see Figure 1). The screenshots were then transcribed, coded, checked, double-checked, and subsequently joined with survey data for analyses. During data collection, Apple updated its mobile operating system from iOS 12 to iOS 13, which changed the original time scale slightly, varying the duration from 3 to 13 days, depending on the participant. Thus, I used Screen Time’s

“Weekly Total” estimate to create a daily average objective smartphone time composite.

I also summed time spent on several social media apps (e.g., Facebook, Snapchat, Twitter, Instagram) to create a daily average objective social media time composite. I did not use Screen Time’s “Social Networking” app category because it contains apps that are generally not classified as social media (e.g., Messages, Phone, FaceTime). Importantly, my objective social media composite only gauged time spent on participants’ iPhones, which does not include social media time on other devices (e.g., computers, tablets). However, most social media site visits (79%) come from mobile devices (Tankovska, 2021a), so this composite still provides a useful assessment of objective social media time.

Other Screen Time User Characteristics

Using Screen Time screenshots, I was also able to collect various other iPhone user characteristics, such as app categories (e.g., dating apps, gaming apps, education apps), specific apps (e.g., Snapchat, Camera, Gmail, Tinder, Mail, Facebook), how often users picked up their iPhones (i.e., pickups), and how often they received notifications.

Exploratory Analyses

Due to the iOS 12 vs. iOS 13 time-scaling differences mentioned above, all iPhone Screen Time user characteristics were computed as daily averages (e.g., average dating app use per day, average pickups per day). Because I collected Screen Time data on 194 apps, I only ran correlations for the 35 most used apps (i.e., apps with a mean of at least ~1 minute per day).

Time use variables (e.g., volunteering, reading, self-reported smartphone time, objective social media time, gaming apps, productivity apps, Instagram, Hulu, Safari, Photos) that were right-skewed and kurtoic were log-transformed before computing zero-order Pearson correlations and paired-sample t tests, as has been done in previous studies (Boase & Ling, 2013; Sewall et al., 2020; Vanden Abeele et al., 2013). However, I calculated summary statistics (e.g., *M*, *SD*, *Mdn*) of the raw (untransformed) variables (in minutes).

I also computed a few composites for specific analyses. First, I created a non-screen activities composite that accounted for combined time spent on daily habits like exercising, volunteering, working, studying, etc. I also computed a standardized subjective well-being composite (Positive Emotions – Negative Emotions + Life Satisfaction) to examine how screen time cumulatively impacts the three main components of subjective well-being suggested by empirical psychological literature (Diener et al., 1999; Medvedev & Landhuis, 2018).

Results

Table 1 provides the summary statistics for Study 1 outcome, daily habits (i.e., non-screen), and screen time variables, presented in raw (untransformed) format for ease of interpretation.

Self-Report vs. Objective Screen Time

How accurate is self-report? To examine this question, I conducted zero-order Pearson correlations and paired-sample *t* tests that assessed differences between self-report and objective smartphone and social media time estimates (see Figure 2). I also examined histograms of discrepancy scores subtracting the objective indicators from the self-reported estimates (see Figure 3).

Surprisingly, participants' average self-reported smartphone time (M = 323.09, SD = 155.15) and objective smartphone time (M = 321.53, SD = 106.66) estimates (in minutes) were highly similar (a difference of only 1.56 minutes). They were also strongly and significantly positively correlated (r = .55, p < .001). The results of a paired-sample *t* test showed that there was no significant difference between mean self-reported and objective smartphone time, $t(408) = –0.27$, p = .789. On average, participants appeared to be relatively accurate in estimating their smartphone time. However, the histogram of smartphone discrepancy scores showed a wide spread of error in people's estimates. About half of the sample underestimated their use, while the other half overestimated it. Taking an absolute value (i.e., transforming the negative numbers to positive numbers) of the discrepancy scores revealed that people misestimated their daily smartphone time by an average of 91.52 minutes (SD = 95.17). Overall, most participants (54.5%) misestimated their smartphone time by an hour or more per day.

Participants' average self-reported social media time (M = 230.96, SD = 113.43) and objective social media time (M = 113.07, SD = 62.13) estimates (in minutes) were also alike, but much less so (a difference of 117.89 minutes). These estimates were positively, significantly correlated (r = .25, p < .001). However, the results of a paired-sample t test showed a significant difference between the self-report and objective estimates, $t(401)$ = 21.20, p < .001. The histogram of social media discrepancy scores also showed a wide spread of error in people's estimates, with most overestimating their use. Looking at the absolute value of discrepancy scores, people misestimated their average daily social media time by an average of 129.18 minutes (SD = 98.94). Overall, most participants (71.9%) misestimated their objective social media time by an hour per day or more.

Screen vs. Non-Screen Activities

Are non-screen activities linked to higher well-being than screen activities? Table 2 and Figure 4 show correlations for screen and non-screen activities with the standardized subjective well-being composite. Several non-screen activities were positively associated with well-being, including time spent relaxing (r = .24, p < .001), outdoors (r = .19, p < .001), exercising (r = .18, p < .001), volunteering (r = .15, p = .003), socially interacting with others (r = .12, p = .013), and attending religious services (r = .10, p = .037). However, some non-screen activities were not associated with greater well-being, such as studying (r = –.04, p = .4) and working (r = –.05, p = .304). To assess the overall effects of non-screen activities, I examined the non-screen time composite (e.g., combined time spent relaxing, volunteering, working) and found that it was not significantly associated with subjective well-being (r = .05, p = .293).

Moving on to screen activities, some were positively correlated with well-being (e.g., gaming apps [$r = .23$, $p = .071$], news app [$r = .12$, $p = .02$]), while others were negatively correlated, such as Apple's "other" apps category ($r = –.26$, $p = .033$), social networking apps ($r = –.21$, $p < .001$), and dating apps ($r = –.17$, $p = .001$). Notably, the gaming app effect size was larger ($r = .23$) than other screen activities, but likely did not reach significance because I had a smaller number of participants who frequently used apps in this category ($n = 64$). Average daily pickups ($r = –.02$) and notifications ($r = –.05$) correlations were close to zero (*p*s > .2). Self-reported smartphone time well-being correlations (especially for positive and negative emotions) were similar in magnitude to objective indicators. Sometimes, correlations with objective indicators were slightly stronger than for self-report. Overall, to assess the effects of screen activities, I examined objective smartphone time and found that it was significantly associated with lower well-being ($r = –.16$, $p = .001$).

I also examined correlations for other related psychosocial constructs, such as depression, loneliness, and self-esteem (see Table 2). Spending more time outdoors, exercising, and relaxing (non-screen activities) were consistently associated with greater self-esteem (*r*s = .14 to .19), as well as less depression (*r*s = –.09 to –.16) and loneliness (*r*s = –.16 to –18) (almost all *p*s < .01). Spending time socially interacting with others in-person was also associated with less loneliness ($r = –.16$, $p = .001$), and marginally greater self-esteem ($r = .08$, $p = .088$). Overall, combined non-screen activity correlations were negative for depression (*r* = –.09, *p* = .077), close to zero for loneliness (*r* = –.02, *p* = .667), and positive for self-esteem (*r* = .15, *p* = .002).

Examining screen activities, some appeared to be associated with higher levels of loneliness, depression, and self-esteem (e.g., pickups, notifications), while several others were consistently associated with lower levels (e.g., other apps, social networking apps, dating apps). Yet many other screen activities were close to zero and non-significant (e.g., entertainment apps, productivity apps). Self-reported smartphone and social media time showed slightly larger correlations for loneliness, depression, and self-esteem (*r* magnitudes of .10 to .19) than objective indicators (.08 to .11). Overall, objective smartphone (i.e., screen time) correlations were positive for depression (*r* = .11, *p* = .029) and loneliness (*r* = .10, *p* = .054), and negative for self-esteem (*r* = –.08, *p* = .086).

Examining Specific Apps

Are some specific smartphone apps associated with higher psychosocial well-being than others? To address this question, I also examined correlations for the most used iPhone apps (e.g., News, Facebook, Calculator, Photos). As Table 2 shows, some apps may be better for well-being than others.

Some apps were associated with greater psychosocial well-being, suggesting the more these apps were used, the better off participants were. For example, using the camera app was associated with greater life satisfaction (*r* = .14, *p* = .006), and lower depression (*r* = –.12, *p* = .019). The “Find My Friends” app was associated with higher positive affect ($r = .12$, $p = .02$) and lower depression ($r = –.11$, $p = .026$) and loneliness ($r = –.12$, $p = .014$). Apple's News app was associated with greater positive affect ($r = .12$, $p = .016$) and life satisfaction ($r = .12$, $p = .013$). The Phone app was associated with greater life satisfaction ($r = .10$, $p = .048$) and self-esteem ($r = .12$, $p = .018$), as well as lower depression ($r = –.12$, $p = .015$). Finally, Snapchat was associated with higher positive affect ($r = .15$, $p = .003$), and self-esteem ($r = .10$, $p = .049$), as well as less loneliness ($r = –.11$, $p = .021$).

Other apps were negatively associated with psychosocial well-being, suggesting the more these apps were used, the worse off participants were. For example, Facebook was associated with less positive affect ($r = –.11$, $p = .025$), more depression ($r = .14$, $p = .006$), and lower self-esteem ($r = –.15$, $p = .002$). Reddit was associated with lower life satisfaction ($r = –.12$, $p = .014$) and self-esteem ($r = –.13$, $p = .007$), as well as higher depression ($r = .10$, $p = .039$). Tinder was associated with lower life satisfaction ($r = –.17$, $p = .001$) and self-esteem ($r = –.14$, $p = .004$) and higher depression ($r = .16$, $p = .001$).

Additionally, several apps were not significantly correlated with psychosocial well-being and had *r*s close to zero. For example, the Clock app (*r*s = –.06 to .02, *p*s >.1), Dictionary app (*r*s = –.03 to .00, *p*s >.1), GroupMe (*r*s = –.07 to .04, *p*s >.1), Hulu (*r*s = –.04 to .07, *p*s >.1), Music (*r*s = –.04 to .06, *p*s >.1), Settings (*r*s = –.01 to .06, *p*s >.1) and WhatsApp (*r*s = –.03 to .08, *p*s >.1).

Discussion

On average, Gen Z individuals used their smartphones about 5 hours and 21 minutes, picked up their phones 135 times, and received 187 notifications per day. Overall, most participants were relatively inaccurate in estimating how much time they spent on their smartphones and social media apps, which replicates previous work (Andrews et al., 2015; Sewall et al., 2020). Participants both overestimated and underestimated their smartphone time, but mostly overestimated their social media time. Social media time may have been more systematically overestimated because I asked participants to report time spent "on all types of devices (e.g., iPhones, iPads, computers)," and the objective indicator only picked up time on iPhone. However, given that mobile now accounts for 79% of social media site visits in the U.S., this seems unlikely to fully account for the difference (Tankovska, 2021a).

Combined non-screen activities, like exercising, spending time outdoors, reading, and working, were not associated with substantially better or worse well-being (r = .05). However, the more screen time participants engaged in (i.e., the more they objectively interacted with their smartphones), the less happy they were (r = –.16). Notably, this effect is much larger than eating potatoes or wearing glasses, and may be about as harmful to well-being as volunteering is helpful (r = .15). Yet the correlation between smartphone use and well-being still constitutes a small effect size (r = –.10 to –.30) (Cohen, 1992). Thus, it probably should not prompt excessive panic about smartphones.

However, small effects can aggregate over time to meaningfully impact outcomes (Funder & Ozer, 2019).

Finally, my analyses suggest that some apps may support psychosocial well-being more than others. Specifically, the more time participants spent on the Camera, Find My Friends, News, Phone, and Snapchat apps, the better off they were (e.g., greater positive affect and life satisfaction, lower depression and loneliness). The more time participants spent on the Facebook, Reddit, and Tinder apps, the worse off they were. Notably, several apps (e.g., Clock, Dictionary, GroupMe, Hulu, Settings, WhatsApp) were not meaningfully linked to well-being. Notably, these analyses just look at time spent on specific apps, and previous research suggests how people use an app (e.g., passively scrolling the newsfeed vs. posting photos on Facebook) may alter its effects on well-being (Verduyn et al., 2015).

My results parallel findings from previous correlational research. Like Twenge and colleagues (2018), I found that non-screen activities were (on average) linked to higher well-being than screen activities. However, in contrast, not all screen activities were linked to lower well-being. For example, spending time on gaming apps, Apple's News app, Snapchat, and the camera app were associated with greater well-being (e.g., happiness, life satisfaction). Further, the effects of many apps on well-being were close to zero, as Orben and Przybylski (2019a, 2019b) argued. Previous research suggests that subjective reports may overinflate correlations between screen time and mental health (Sewall et al., 2020; Shaw et al., 2020). I found this to be the case for depression, loneliness, and self-esteem, but not for emotional (positive and negative affect) and subjective well-being, which produced relatively similar effect size magnitudes. My study also demonstrates that specific apps (e.g., Snapchat vs. Tinder) are differentially linked to well-being. Yet future experimental work is needed to determine the types of use (e.g., when, how, why) for each app that might positively or negatively impact psychosocial well-being. Overall, my correlational findings add to the growing body of work suggesting that it may not be general screen time that negatively impacts well-being, but how people spend that time (Hancock et al., 2020; Kushlev & Leitao, 2020).

Limitations and Future Directions

This study is subject to several limitations that may seed future work. Although Study 1 was able to assess objective time spent on screen activities (via Apple iPhone Screen Time screenshots), I still relied on retrospective self-reports of non-screen activities, which people frequently estimate inaccurately (Grondin, 2010). A future study with more objective indicators of non-screen activities may provide an even clearer picture of the differential well-being effects of screen vs. non-screen activities. For example, previous smartphone sensing research has used objective sensor data from smartphones to assess time spent sleeping, exercising, and socializing (Wang et al., 2014).

Additionally, my results represent merely a snapshot of specific individuals (Gen Z undergraduate students) using a specific device (iPhone) with specific apps (e.g., Snapchat, News) in a specific location (California) during a specific time period (early

2019 to early 2020; pre-COVID-19 pandemic). Future studies should expand these findings to other populations (e.g., Boomers, Millennials), nations (e.g., Brazil, Thailand), devices (e.g., Android smartphones), apps (e.g., shopping apps [Amazon, Target], reading apps [Books, Kindle], music apps [Spotify, Pandora], gaming apps [CandyCrush, BrawlStars]), and timeframes (post-COVID-19). Further, with developers constantly updating their digital technology services (as happened during my data collection when Apple updated its mobile operating system from iOS 12 to iOS 13), future research may find divergent effects even with similar samples.

Further, although my sample size was fairly large (N = 414), the previous correlational research that has relied on self-report frequently deploys massive sample sizes (Ns = 17,247 to 1.1 million). Collecting big data on objective smartphone use would allow future researchers to estimate effect sizes more robustly, including small effects (Funder & Ozer, 2019). However, the approach taken in the present study with manual screenshots is likely not easily scalable. If future researchers deploy a big data, Many Labs, and/or Psychological Science Accelerator approach, combined with a smartphone sensing app (e.g., Aware, Beiwe, CrossCheck, StudentLife), such work may substantially push the field forward (Carpenter et al., 2016; Jones et al., 2021; Klein et al., 2014, 2018; Nishiyama, 2021; Torous et al., 2016; Wang et al., 2014, 2020).

Finally, it bears repeating that the analyses presented here are correlational, and therefore cannot indicate the direction of causality. For example, the negative correlation reported between smartphone time and subjective well-being (r = –.16) could be explained in a few different ways: (a) higher smartphone use may lower well-being, (b) people with already low well-being may use their smartphones more, or (c) a third variable (e.g., introversion) could be driving both higher smartphone use and lower well-being. An experiment is necessary to better illuminate the causal direction of the relationship between screen time and well-being. Study 2 aims to address this gap in the empirical literature.

Chapter 3: Study 2

"Teens who spend more time on screen activities are more likely to be unhappy, and those who spend more time on non-screen activities are more likely to be happy." — Jean Twenge

"The association of well-being with regularly eating potatoes was nearly as negative as the association with technology use, and wearing glasses was more negatively associated with well-being."
— Amy Orben & Andrew Przybylski

In many industrialized and developing nations today, most residents use smartphones. Approximately 3.6 billion people own a smartphone worldwide, with the number growing every year (O'Dea, 2021a). As of 2021, smartphone penetration rates exceeded 50% in many countries, including Brazil (51.4%), Thailand (54.3%), Mexico (54.4%), Japan (59.9%), Turkey (61.7%), Iran (62.9%), China (63.4%), Russia (68.5%), South Korea (76.5%), France (77.6%), Germany (77.9%), and the United States (81.6%) (O'Dea, 2021b).

Clearly, smartphones have become a ubiquitous aspect of daily life for many people around the globe, as has the ever present on-demand digital media that come packaged with these devices, such as social media, email, news, text, gaming, sports, entertainment, dating, and music apps. Smartphones allow individuals to message friends and family anytime from anywhere, find driving directions to new locations, reply to work emails from a beach in Mexico, and video conference relatives living in Singapore. Although these technologies are incredibly valuable and convenient in myriad ways, recent research suggests that they may come with some associated costs.

Digital Media and Well-Being

In annual surveys from 1991 to 2016, Twenge and colleagues (2018) found that 8th, 10th, and 12th graders in the U.S. (N = 1.1 million) experienced substantial declines in psychological well-being (e.g., happiness, life satisfaction) in 2012 and beyond. These Gen Z/iGen adolescents also reported substantial drops in self-esteem, self-satisfaction, and domain satisfaction (e.g., satisfaction with education, friends, etc.). In attempting to account for these declines, the researchers reported that adolescents who spent more time on screen activities (e.g., social media, the Internet, texting, gaming) and less time on non-screen activities (e.g., in-person social interactions, exercise, homework) reported lower well-being. Adolescents who spent a small amount of time on screens were the happiest. For 8th and 10th graders, partial correlations between happiness and screen time activities (including demographic controls) ranged from r = –0.01 (reading news online) to r = –0.11 (Internet use).

A follow-up investigation also showed that U.S. teens' (N = 506,820) depressive symptoms, suicide-related outcomes, and suicide rates increased from 2010 to 2015 (Twenge et al, 2017). Again, adolescents (8th, 10th, and 12th graders) who spent more time on screen activities were relatively more likely to report mental health problems, and those who spent more time on non-screen activities were less likely.

Notably, the observed rise in depressive symptoms (in 2010) and subsequent decline in well-being (in 2012) closely followed the rise of smartphone technology. The first iPhone was introduced in 2007 (DeGusta, 2012), and among U.S. adolescents, smartphone ownership leapt from 37% in 2012 to 73% in 2015 (Lenhart, 2015).

The above correlational studies suggest that digital media—specifically, time spent on smartphone-related screen activities—may be harmful to well-being. Yet in a few recent empirical articles, Orben and Przybylski (2019a, 2019b) argued that digital media use may have small effects on well-being and related constructs (e.g., depression, self-esteem). In one study, these researchers analyzed three large-scale datasets (Monitoring the Future, the Youth Risk and Behaviour Survey, and the Millennium Cohort Study; total N = 355,358) and found a negative but small association (β = –0.042) between digital media use and well-being (Orben & Przybylski, 2019a). Comparing this association to other activities, they concluded that digital media's negative effect on well-being was comparable to that of eating potatoes (β = –0.042) and wearing eye glasses (β = –0.061).

Another recent investigation by Orben and Przybylski examined two additional large-scale datasets (Growing Up in Ireland and the United States Panel Study of Income Dynamics) to generate hypotheses, then tested those hypotheses on the Millenium Cohort Study, with a total N across the three datasets of 17,247 (Orben & Przybylski, 2019b). This time, they analyzed both self-report and time-use diary measures and again concluded that digital media use is not meaningfully linked to Gen Z well-being, depression, or self-esteem. In aggregate, the median association between self-reported screen time and well-being was β = –0.08, but time-use diary measures reduced this estimate to close to zero (β = –0.02).

Due to the difficulty in inferring causality from correlational research, a few experimental studies have begun to test the effects of restricting smartphone use, at least during short time periods or in particular circumstances. In two recent experiments, college students were directed to find a campus library with or without their smartphone. Relative to those using their smartphones, students not using their smartphones arrived at the building feeling more socially connected, but it took them longer to find the building and the difficulty of the task appeared to make them less happy (Kushlev et al., 2017). In another investigation, groups of three to five friends or family members out to dinner at a local café were directed to keep their phones on them or put them on silent and set them in a locked, closed container on the table. The diners who kept their phones reported more distraction, as well as lower interest, enjoyment, and well-being during dinner (Dwyer et al., 2018).

Other studies have tested the effects of limiting smartphone use in specific, targeted ways. In one study, participants maximized phone interruptions for 1 week by keeping push notification alerts on and their phones within their reach or sight (Kushlev et al., 2016). The next week, participants minimized phone interruptions by keeping alerts off and their phones away. Participants reported higher levels of inattention and hyperactivity when alerts were on than when alerts were off. Higher levels of inattention, in turn, predicted lower productivity and well-being. Another experiment sought to determine whether batching smartphone notifications might improve happiness (Fitz et al., 2018). Relative to receiving notifications as usual, hourly, or no notifications at all, batching smartphone notifications 3 times per day increased well-being.

In sum, correlational research on digital media has yielded two competing messages. Some psychological scientists conclude that digital media use may harm well-being, while others infer that digital media has no meaningful impact. However, their disagreements appear to be less about the evidence (as both present similar, small correlational estimates: r = –0.01 to –0.11 in Twenge et al., 2017; *β = –0.02 to* –0.08 in Orben & Przybylski, 2019b) than about how to interpret it.

The experimental research so far has found that limiting digital media in targeted ways (e.g., at dinner, batching notifications) often bolsters well-being, but limiting it sometimes backfires (e.g., when trying to find an unknown building). To my knowledge, no one experiment has yet restricted overall digital media (i.e., smartphone) use in daily life for a week or more to assess its downstream effects on well-being. Such a "shortitudinal" investigation (Dorman & Griffin, 2015) is necessary to disentangle correlation from causation, and better elucidate the direction and strength of the relationship between digital media and well-being.

Social Media and Well-Being

Broadly, social media is a type of digital media that allows individuals to create and share user-generated content (Kaplan & Haenlein, 2010), such as blog posts, tweets, and YouTube videos. The most prevalent examples of social media are often referred to as social networking sites (SNS; Verduyn et al., 2017)—for example, Facebook, Twitter, Instagram, and Snapchat. Three key characteristics usually define SNS: (1) users have a personal profile that is constantly updated with user-generated content, (2) each user has a publicly displayed list of connections (aka friends or followers), and (3) the service is centered around a scrolling stream of frequently updated content (e.g., Facebook's News Feed) (Verduyn et al., 2017). Social media services can be accessed via computers and tablets, but a majority of the most popular SNS employ mobile apps and are predominantly used on smartphones. As of 2019, mobile accounted for 79% of social media site visits in the U.S. (Tankovska, 2021a).

Like smartphones, social media use has become pervasive. As of 2021, 72% of U.S. adults used social networking sites—up from 5% in 2005 when social media usage tracking began (Pew Research Center, 2021). At the current rate of growth, it is projected that 4.4 billion people will be using social media worldwide in 2025 (Tankovska, 2021b).

In light of its ubiquity, it is worth noting that emerging evidence suggests that social media may be an especially harmful component of digital media, exerting adverse effects on well-being. Several studies have specifically focused on prompting users to reduce the amount of time they spend on Facebook. One of the most frequently cited studies ("The Facebook Experiment") recruited Danish individuals (*N* = 1,095), and randomly assigned them to keep using Facebook as usual or stop using Facebook for a week (Tromholt, 2016). Participants who gave up Facebook experienced increases in life satisfaction, and their emotions became more positive. Effects were greatest for users who initially used Facebook heavily, reported feeling high Facebook envy, and typically used Facebook passively (i.e., scrolling their news feeds).

A recent, longer Facebook deprivation study found similar effects. The researchers measured 2,743 Facebook users' willingness to deactivate their accounts for 4 weeks, then paid a randomly selected subset to do so (Allcott et al., 2019). At posttest, the users who deactivated their accounts reported increases in positive emotions, subjective happiness, and life satisfaction, relative to those who did not deactivate their accounts. In another study (a natural experiment), an Israeli company banned employees from using Facebook altogether at the office, then later differentially restricted its use (Arad et al., 2017). Employees who continued to use Facebook engaged in more social comparison and showed diminished happiness. However, these effects only applied to the younger half of the sample, and only if those young people believed others had more positive experiences than they did.

Other studies have attempted to assess whether using social media in specific ways may produce different well-being outcomes. One study brought participants into the lab and directed them to either use Facebook passively (e.g., by scrolling through their newsfeed and looking at friends' pages), or to use Facebook actively (e.g., by posting status updates or directly messaging friends) (Verduyn et al., 2015). Neither passive nor active group participants demonstrated changes in affective well-being immediately following the manipulation. However, participants in the passive use group showed a significant drop in affective well-being at the end of the day.

The studies reviewed above suggest that restricting Facebook provides well-being benefits (e.g., Allcott et al., 2019; Tromholt, 2016). What about other social media services? Facebook is the top social network in the U.S., with 169.8 million unique monthly visitors, but numerous other SNS are extremely popular, such as Instagram (121.2M monthly users), Twitter (81.5M monthly users), Pinterest (66.88M monthly users), Reddit (47.9M monthly users), and Snapchat (46M monthly users), among others (Statista Research Department, 2021).

Limiting Facebook alone likely does not restrict all (or even most) social media use, because participants directed to restrict Facebook may just begin to use Twitter or Instagram instead. Moreover, Facebook is no longer the most popular social media platform among Gen Z individuals (Anderson & Jiang, 2018)—the age group about whom much of the concern about screen time and mental health has focused. Teens are abandoning Facebook at an ever-increasing rate in favor of alternative social media, such as YouTube, Instagram, and Snapchat. Thus, examining other social media platforms is a compelling next step for the field.

Recently, a few notable additional studies directing participants to restrict other types of social media have emerged. One study assigned undergraduates to either limit Facebook, Instagram, and Snapchat use to 10 minutes per platform per day, or to use social media as usual for 3 weeks (Hunt et al., 2018). Relative to controls, the participants assigned to limit their social media use showed significant reductions in loneliness and depression. However, there were no significant differences between the two groups for social support, anxiety, self-esteem, or autonomy. Notably, this study left a number of other social media services unrestricted (e.g., Twitter, Pinterest), which participants could have used instead. The researchers also did not assess some of the most commonly used subjective well-being measures in the psychological literature (e.g., positive emotions, life satisfaction). In another article with three experiments (total $N = 600$), participants were assigned to one of two conditions: a normal-use social media day or an abstinence day (Przybylski et al., 2020). Taking a short 1-day break from social media did not significantly improve positive affect, negative affect, or self-esteem; and appeared to actually exhibit some backfiring effects—harming feelings of social relatedness (a type of need satisfaction) and satisfaction with one's day. These findings are compelling, but only apply to a single day.

Taken together, previous research indicates that restricting social media in general (i.e., do not use Facebook, Instagram) or in specific ways (i.e., using social media actively instead of passively) may yield psychological benefits (e.g., increased well-being, reduced loneliness and depression). Notably, most experimental studies deploy a "use social media as usual" vs. "stop using social media" approach. Participants who are told to use social media as usual may not represent a strong control group that accounts for experimental demand effects. The present study sought to build on previous findings by restricting all social media in daily life while employing an alternative activity control condition. Using this approach, I assessed subsequent effects on well-being and related psychosocial constructs.

Theoretical Mechanisms

More recently, activists have begun issuing calls to alter or reduce screen time with the aim of improving mental health. Their suggestions include changing smartphone settings (e.g., turning off notifications, setting the screen to grayscale), carving out technology-free times and spaces, creating barriers to unintentional use, undergoing short periods of abstinence (i.e., "digital detoxes"), and deleting social networking accounts altogether (BBC News, 2018; Center For Humane Technology, 2019; Ghaffary, 2019; Lanier, 2018; Montgomery, 2020; Price, 2018; Turkle, 2011). Yet few of these approaches have been empirically tested.

Why might restricting digital and/or social media improve well-being and mental health? Several theoretical mechanisms have been proposed. The Goldilocks hypothesis suggests that digital technology use at high levels may harm well-being but that a "just right amount" of moderate tech use maximizes well-being (Etchells et al., 2016; Parkes et al., 2013; Przybylski et al., 2014; Przybylski & Weinstein, 2017). The interference hypothesis posits that the pervasive presence of smartphones in daily life may interfere with concurrent activities (e.g., receiving disruptive text messages while having lunch with a friend) (Kushlev et al., 2019; Kushlev & Leitao, 2020; Sbarra et al., 2019). The displacement hypothesis suggests that screen time may displace other more rewarding or beneficial non-screen activities like exercising, volunteering, cooking, gardening, reading, and interacting face-to-face (Montgomery, 2020; Neuman, 1988; Przybylski et al., 2020).

Alternatively, the complementarity hypothesis proposes that smartphones may improve well-being by offering access to information, communication, and experiences that would otherwise be unavailable (Kushlev & Leitao, 2020). By this logic, restricting digital and social media use may prompt backfiring effects, worsening mental health outcomes.

Notably, human beings are hard-wired to socially interact in-person, not digitally (Sbarra et al., 2019). Although scrolling Facebook or Instagram may act as a social surrogate to fulfill belonginess needs (Derrick et al., 2019), such surrogacy may be akin to social junk food—providing empty calories without the essential nutrients. Alternately or additionally, reducing social media use may remove aversive experiences, such as envy (e.g., coveting an influencer's posh trip to the Maldives), social comparison (e.g., viewing perfect-looking, photoshopped images of models) and fear of missing out (e.g., seeing friends at a party one was not invited to) (Appel et al., 2016; Roberts & David, 2020; Verduyn et al., 2020).

The Present Study

In Study 2, I sought to explore the effects of digital media and social media on well-being by experimentally manipulating it in daily life. Instead of asking participants to limit their media use for a short period of time (e.g., at dinner, for one day) or in specific, targeted ways (e.g., batching smartphone notifications), I asked them to actively restrict their digital media and social media use for about 8 days. To this end, I recruited undergraduate students, and randomly assigned them to one of four conditions in a between-subjects design: (1) restrict digital media use (Digital Diet), (2) restrict social media use (Social Diet), (3) restrict water use as an active control (Water Diet), or (4) restrict nothing as a measurement-only control (No Diet). Will restricting digital media and social media use as much as possible for about a week improve psychological well-being and related constructs? I pre-registered my hypotheses for this study on the Open Science Framework (OSF). Pre-registration, data, materials, and R code are available at https://osf.io/vpekx/.

Hypotheses

I tested the pre-registered hypotheses listed below. Overall, I hypothesized that restricting digital media and social media would have psychological benefits. However, given the debate in the correlational literature mentioned above, I anticipated the possibility of finding null or even backfiring effects, as such effects would be valuable and informative.

Hypothesis 1. Relative to controls (Water Diet, No Diet), participants assigned to restrict their smartphone digital media use (e.g., gaming, social media, entertainment, online news apps; Digital Diet) will demonstrate greater increases in positive affect, happiness, life satisfaction, mindful attention, self-esteem, self-reported health, connectedness, autonomy, and competence, as well as larger decreases in negative affect, depression, stress, and loneliness.

Hypothesis 2. Relative to controls (Water Diet, No Diet), participants assigned to restrict their social media use (e.g., Facebook, Instagram, Twitter, Snapchat; Social Diet) will demonstrate greater increases in positive affect, happiness, life satisfaction, mindful attention, self-esteem, self-reported health, connectedness, autonomy, and competence, as well as larger decreases in negative affect, depression, stress, and loneliness.

Method

Participants

I recruited undergraduate students from the University of California, Riverside psychology department's online research participation system. The study required the following eligibility criteria: Participants had to be at least 18 years old, read and write English fluently, own an iPhone running iOS 12 or later with *Screen Time*, and use social media at least four to six times per week. Students received course credit as compensation for their participation. Those who completed the entire study and reported putting at least minimal effort toward their assigned activity instructions received an extra $10 Amazon digital gift card bonus.

A total of 414 participants completed at least one survey (Time 1/pretest). To help ensure the credibility of responses, I also pre-registered a few exclusion criteria. Specifically, participants were excluded from analyses if they answered 15 simultaneous questions with the same response (3 excluded), reported they did not restrict their digital media, social media, or water use at all (11 excluded), and/or their daily average

Time 2 media use exceeded their Time 1 use (33 excluded in the Digital Diet and Social Diet conditions only).

I also originally planned to exclude participants if they answered “No” to the following question: “In your honest opinion, should we use your data in our analyses in this study?” (Self-Reported Single Item [SRSI] question; Meade & Craig, 2012). Surprisingly, a large number of participants (32) answered “No” to this question—more than in previous studies—and given its ambiguous interpretation, I decided to discard the SRSI question exclusion criteria and keep those participants in the analyses. Finally, some participants (34) did not complete the Time 2/posttest survey. Notably, a few participants were filtered out because they matched multiple exclusion criteria (e.g., answering 15 questions with the same response and not restricting at all), yielding a final sample of N = 338.

Among the 338 participants (M_{age} = 19.4, SD = 2.4), almost all (97.9%) were born 1995 or later, meaning they belonged to the generation known as Gen Z (or iGen), the first generation to enter adolescence with smartphones (Twenge, 2017). I chose to sample Gen Z individuals because they tend to experience high rates of social isolation, loneliness, fear of missing out, and poor mental health outcomes—and have been the focus of much of the correlational research described earlier (Orben & Przybyslki, 2019a, 2019b; Twenge et al., 2017, 2018). The majority of participants were also predominantly female (78.1% female) and single (64.2%). They came from a variety of ethnicities, including Asian (40.5%), Hispanic (34.9%), White (10.7%), Black (3.8%), other

(3.9%), and more than one (6.2%). Participants also reported a range of household incomes: 26.4% reported that their families earned less than $30,000 a year; 20.1% earned between $30,001 and $60,000; 19.8% earned between $60,0001 and $100,000; 20.7% earned over $100,000; and 13% did not know their household income. A number of the student participants also worked part-time (31.4%).

Procedure

Figure 5 presents an overview of the Study 2 timeline. To reduce demand effects, participants were ostensibly recruited for a "Daily Habits Study"—a study examining daily habits (e.g., exercise, cigarette smoking), behaviors (e.g., reading, watching TV, smartphone use, water use), thoughts, emotions, and physical health. The study duration averaged 8 days (range = 7-13 days) with two time points. At both Time 1 (T_1) pretest and Time 2 (T_2) posttest, participants visited our lab in-person. Data collection ran from February 19, 2019 to March 2, 2020, just prior to the university's transition to online learning due to the COVID-19 pandemic.

Time 1 (T_1 / Pretest)

To begin the study, participants signed a consent form. Then research assistants (RAs) collected dried blood spots (DBS; 3-5 drops of blood) via finger prick for collection on protein saver cards for later laboratory analysis of leukocyte gene expression. The DBS analyses are beyond the scope of this dissertation and are not presented here. After DBS collection, participants were directed to a private computer to complete an online survey of outcome measures and demographic information.

At the end of the T_1 survey, participants were randomly assigned (using a Qualtrics randomizer block) to one of four conditions (Digital Diet, Social Diet, Water Diet, or No Diet) that varied with respect to their daily activity instructions. See Appendix A for condition instructions.

Participants in the Digital Diet condition (*n* = 76) were instructed to limit their digital media use on their smartphones as much as possible. They were allowed to use their smartphones for practical purposes (e.g., to obtain GPS directions, to answer work emails), but were instructed to restrict their use as much as possible and to stop using any non-necessary apps (e.g., Facebook, Tetris, Hulu, CNN).

Participants in the Social Diet condition (*n* = 67) were directed to stop using social media during the intervention period. I provided them with recommendations about how to accomplish this aim (e.g., set a Screen Time Social Networking app limit, delete social media apps off their iPhones), as well as a list of social media apps/sites (e.g., Facebook, Instagram, Twitter, Snapchat) to avoid.

I also included two control conditions. To confirm that restriction alone (e.g., feeling good about doing good) was not driving effects, my first control condition was a Water Diet (active control) group (*n* = 115), in which participants were directed to restrict their water use. That is, they were asked to use less water when they washed their hands, brushed their teeth, took showers, washed dishes, etc., but not to restrict how much water they drink.

My second control condition was a No Diet (measurement-only control) group (*n* = 80), in which participants only completed measures. They did not receive any instructions regarding their digital media, social media, or water use. The goal of this control condition (as well as the Water Diet group) was to include a subset of participants who continued using digital and social media as usual without prompting them to monitor and/or change their behavior. We made every effort to reduce the salience of tracking digital media use for these groups, as we were concerned that monitoring it may change it. For example, a systematic review of fitness tracking technologies (e.g., Fitbit, Nike+) found that self-tracking can prompt individuals to increase their physical activity levels (Jin et al., 2020).

Due to a Qualtrics randomizer block quirk that over-assigned participants to the Water Diet group, our condition *n*s were relatively uneven. However, attrition was fairly comparable across conditions, with the Social Diet group demonstrating the lowest attrition rate (2.3%) and the No Diet condition demonstrating the highest (11.1%).

After students finished the survey and received their condition instructions, RAs helped them take screenshots of the *Screen Time* section of their iPhone in their Settings app. Screen Time is a feature of Apple's mobile operating system (iOS 12 and later) that provides various iPhone user characteristics, such as the average amount of time users spend on their iPhone including time spent on specific apps, as well as the number of times users picked up their phones and received push notifications (see

Figure 1). Once captured, iPhone Screen Time screenshots were emailed to a general study email for later transcription, coding, and analysis.

Time 2 (T_2 / Posttest)

At T_2, participants returned to the lab for a visit that was similar to T_1 described above. Participants first provided another DBS sample, then completed a second posttest survey of outcomes. The survey asked them about their experiences during the past week and provided a debriefing statement. Finally, RAs collected a second set of Screen Time screenshots from participants' iPhones.

Measures

Participants completed the following measures at T_1 and T_2, rating each measure over the "past week (last 7 days)."

Brief Happiness and Satisfaction

Adapted from Monitoring the Future (MtF), a large, multi-decade longitudinal survey of U.S. adolescents (Bradburn, 1969; Johnston et al., 2017; Twenge et al., 2017), I measured recent happiness and satisfaction with two, brief single items. To measure happiness, participants were asked, "Taking all things together, how would you say things are these days—would you say you're very happy, pretty happy, or not too happy these days?" (1 = *not too happy*; 3 = *very happy*). To measure satisfaction, participants were asked, "How satisfied are you with your life as a whole these days?" (1 = *completely dissatisfied*; 7 = *completely satisfied*).

Positive and Negative Emotions

Affective well-being was assessed using a modified version of the Affect-Adjective Scale (Diener & Emmons, 1985; Shin et al., 2021). This 12-item measure taps a range of low and high arousal positive emotions (e.g., enjoyment/fun, relaxed/calm) and negative emotions (worried/anxious, dull/bored). Participants rated the extent to which they experienced each emotion in the past week on a 7-point Likert scale (1 = *not at all*, 7 = *extremely*). Scale reliabilities (McDonald's omegas [ωs]) ranged from .89 to .91 for positive affect and .75 to .82 for negative affect across timepoints.

Life Satisfaction

I used the Satisfaction With Life Scale (SWLS; Diener et al., 1985) to assess participants' current satisfaction with their life in general. The SWLS consists of five items (e.g., "In most ways my life is close to my ideal," "I am satisfied with my life"), which are rated on 7-point Likert-type scales (1 = *strongly disagree*, 7 = *strongly agree*). SWLS reliabilities ranged from ω = .85 to .88 across timepoints.

Mindful Attention

Mindfulness (i.e., the extent to which participants mindfully attended to the present moment) was measured with a 5-item short form of the Mindful Attention Awareness Scale (MAAS-Short; Brown & Ryan, 2003; Kushlev et al., 2016). Example items include, "I found it difficult to stay focused on what was happening in the present" and "I found myself doing things without paying attention" (both reverse coded).

Participants rated how they felt on a 6-point Likert scale (1 = *almost never*, 6 = *almost always*). MAAS-Short reliabilities ranged from ω = .80 to .85 across timepoints.

Need Satisfaction

I assessed three types of need satisfaction (feelings of autonomy, competence, and connectedness [or relatedness]) with a shortened version of the Balanced Measure of Psychological Needs (BMPN; Sheldon et al., 2001). This questionnaire includes a total of 9-items to assess autonomy (3 items), competence (3 items), and connectedness (3 items). Example items include, "I felt free to do things my own way" (autonomy), "I felt very capable in what I did" (competence), and "I felt a sense of contact with people who care for me" (connectedness). Participants rated their level of agreement with each item on a 5-point Likert-type scale (1 = *not at all*, 5 = *much agreement*). Across timepoints, autonomy reliabilities were ω = .74 to .80, competence reliabilities were ω = .76 to .77, and connectedness reliabilities were ω = .88 to .89.

Depressive Symptoms

Depressive symptoms were measured with six items (e.g., "Life often seems meaningless," "I feel that I can't do anything right") from the Bentler Inventory of Depression (Newcomb et al., 1981). Response choices ranged from 1 (*disagree*) to 5 (*agree*). Scale reliabilities for depression were ω = .87 to .90 across timepoints.

Loneliness

To measure loneliness, I administered a 6-item scale from MtF (Johnston et al., 2017). Participants indicated their level agreement on a 5-point Likert-type scale (1 =

disagree; 5 = *agree*). Example items include "A lot of times I feel lonely" and "I usually have a few friends around that I can get together with" (reverse scored). Scale reliabilities for loneliness ranged from ω = .61 to .73 across timepoints.

Self-Esteem

I also used the 6-item Rosenberg Self-Esteem scale (Rosenberg, 1965). Participants indicated their level of agreement (1 = *strongly disagree*; 5 = *strongly agree*) on items such as "Sometimes I think that I am no good at all" (reverse scored) and "I am able to do things as well as most other people." Reliabilities for self-esteem ranged from ω = .84 to .87 across timepoints.

Stress

I assessed participants' stress levels with a 4-item short form of the 14-item Perceived Stress Scale (Cohen et al., 1983). Example items include, "How often have you felt you were unable to control the important things in your life?" and "How often have you felt things were going your way?" (reverse coded) Participants were asked to indicate how often they felt a certain way on a 5-point Likert-type scale (1 = *never*, 5 = *very often*). Reliabilities for stress ranged from ω = .74 to .76 across timepoints.

Self-Reported Health

Participants were also asked to report on their health-related quality of life using an adapted 5-item version of the SF-36 Health Survey (Ware, 1999). Participants rated their views about their health on 5- and 6-point Likert scales. Example items include "Overall, how would you rate your health during the past week?" (1 = *very poor*, 6 =

excellent) and “How much bodily pain have you had during the past week?” (1 = *none*; 6 = *very severe*; reverse coded). Because the SF-36 uses different scale points (e.g., 5-point and 6-point), each item was recoded on a value of 0 to 100 to create composites. Scale reliabilities for health were ω = .76 at both timepoints.

Self-Reported Digital Media Time and Social Media Time

Prior to collecting objective time indicators (see below), we asked participants to estimate how much time they spent using digital media (i.e., smartphone time) in hours and minutes. To assess self-reported digital media (i.e., smartphone) time, we asked participants, “As accurately as possible, please estimate the total amount of time you spend using your smartphone on average per day.” We also asked participants to provide a self-reported estimate of how much time they spent using social media. Specifically, we asked, “As accurately as possible, please estimate the total amount of time you spend using social media apps/sites on average per day. Please include time spent on all types of social media (e.g., Facebook, Instagram, Twitter, Snapchat) on all types of devices (e.g., iPhones, iPads, computers).”

Objective Digital Media Time and Social Media Time

To objectively assess how much time participants spent using digital media and social media on their iPhones over the past 7 days at pretest and posttest, RAs helped participants capture screenshots of the *Screen Time* section of the Settings app on participants’ iPhones (see Figure 1). RAs transcribed, coded, checked, and double-checked these Screen Time usage metrics on a shared Google Sheet, which I downloaded and appended to survey data for my analyses. Because the collected screenshots came from two different operating systems (iOS 12 and iOS 13) with various time durations (e.g., 3 to 13 days), I used Screen Time's "Weekly Total" estimate to create a daily average composite as an objective indicator of smartphone time. Additionally, I summed total time spent on various social media apps (e.g., Facebook, Snapchat, Twitter, Instagram), and created a daily average composite to assess objective social media time. I did not use iPhone's "Social Networking" app category because it often includes time spent on apps generally not classified as social media (e.g., Messages, Phone, FaceTime). Notably, this measure only assessed objective social media time on participants' iPhones, which does not include time spent on other devices (e.g., computers, tablets). However, as mentioned earlier, a majority of people accessing social media services do so from their smartphones.

Pre-Registered Analytic Plan

To test Hypothesis 1, I subset the data to exclude the Social Diet group, then dummy coded condition to compare: (1) Digital Diet vs. Water Diet, (2) Digital Diet vs. No Diet, and (3) Digital Diet vs. Both Controls—with the Water Diet and No Diet control conditions coded as the reference group. To test Hypothesis 2, I used a similar process, but this time omitted the Digital Diet condition to compare: (1) Social Diet vs. Water Diet, (2) Social Diet vs. No Diet, and (3) Social Diet vs. Both controls.

I used two statistical techniques to test my hypotheses: (1) Regressed change: Condition dummy codes predicting T_2 scores, controlling for T_1 scores, and (2) second-order latent growth models: Condition dummy codes predicting growth (i.e., slope) extracted from second-order latent growth models.

In my regressed change models, regression coefficients were converted to partial correlations for ease of interpretation and comparability between models. In my second-order latent growth models (SOLGMs; see Figure 6), measurement invariance was imposed in the model. Residuals between the same item over time were correlated. I set the variance of the intercept latent variable to 1 and gave it an intercept of 0. The latent variables representing each time point had 0 residual variance as they were fully predicted by the intercept and slope latent variables. I then extracted values of the slope latent variable and predicted those extracted values from condition dummy codes as described above.

SOLGM analyses were only conducted for multi-item variables, and thus are not presented for single items (e.g., objective digital media time, brief happiness). The self-report and objective digital media and social media time use variables that were right-skewed and kurtotic were log-transformed before running regressed change analyses and computing Pearson correlations, as past studies have done (Boase & Ling, 2013; Sewall et al., 2020; Vanden Abeele et al., 2013).

Because both the regressed change and SOLGM statistical techniques produced highly similar results, I focus primarily on the regressed change analyses below, and indicate how the SOLGM analyses differed. In the interests of parsimony, I also focus primarily on comparisons testing the effects of the treatment conditions relative to both controls (Digital Diet vs. Both Controls, Social Diet vs. Both Controls). However, all of the individual comparisons (e.g., Digital Diet vs. Water Diet, Social Diet vs. No Diet) are presented in the associated tables for further inspection.

Results

Table 3 presents the Study 2 means and standard deviations by condition, and Table 4 presents the Study 2 bivariate correlations.

Manipulation Checks

Did participants change their behavior as directed? I first wanted to determine whether participants assigned to the Digital Diet and Social Diet conditions restricted their digital and social media use accordingly. Figure 7 shows pre-post difference scores by condition, and Table 5 presents the regressed change models for both self-report and objective time use variables.

Digital Diet participants successfully reduced their digital media use. Participants in the Digital Diet group showed greater decreases in both self-reported digital media time (partial $r = -.51$, $p < .001$; an average of –113 minutes/day) and objective digital media time (partial $r = -.57$, $p < .001$; an average of –115 minutes/day), relative to both controls. The other individual condition comparisons (Digital Diet vs. Water Diet and Digital Diet vs. No Diet) were also statistically significant at ps < .001. The similarities between the self-report and objective digital media (i.e., smartphone) time manipulation checks are not surprising given their strong, positive correlation in Study 1 ($r = .55$, $p < .001$).

Social Diet participants also successfully reduced their social media use. Participants in the Social Diet group showed greater decreases in both self-reported social media time (partial $r = -.62$, $p < .001$; an average of –152 minutes/day) and objective social media time (partial $r = -.66$, $p < .001$; an average of –68 minutes/day), relative to both controls. The other individual condition comparisons (Social Diet vs. Water Diet and Social Diet vs. No Diet) were also statistically significant at ps < .001. Notably, self-report and objective social media time were also positively correlated in Study 1 ($r = .25$, $p < .001$).

Hypothesis 1. The Effects of Restricting Digital Media

According to my regressed change models (see Table 6 and Figure 8), restricting digital media did appear to improve a variety of psychological outcomes. In support of my first hypothesis, participants in the Digital Diet group reported greater increases in life satisfaction (partial $r = .21$, $p < .001$), mindful attention (partial $r = .21$, $p < .001$), autonomy (partial $r = .17$, $p = .006$), competence (partial $r = .15$, $p = .011$), and self-esteem (partial $r = .25$, $p < .001$), as well as greater decreases in loneliness (partial $r = -.13$, $p = .03$) and stress (partial $r = -.17$, $p = .006$), relative to both controls. They also reported marginally greater increases in health (partial $r = .10$, $p = .097$). I did not find statistically significant differences between the Digital Diet group and both control conditions for brief happiness (partial $r = .03$, $p = .611$), brief satisfaction (partial $r = .06$, $p = .321$), positive emotions (partial $r = -.02$, $p = .773$), negative emotions (partial $r = -.05$, $p = .416$), connectedness (partial $r = .03$, $p = .665$), or depression (partial $r = -.08$, $p =$

.196). The other individual regressed change condition comparisons (Digital Diet vs. Water Diet and Digital Diet vs. No Diet) showed a nearly identical pattern of results (see Table 6), as did the SOLGM analyses (see Tables 7 for SOLGM fit statistics and 8 for SOLGM results). See Figure 9 for pre-post difference scores by condition for four key mental health outcomes (positive emotions, negative emotions, life satisfaction, and depression).

Hypothesis 2: The Effects of Restricting Social Media

Restricting social media (Hypothesis 2) appeared to provide limited benefits, and even a few costs. According to my regressed change models (see Table 6 and Figures 9 and 10), restricting social media improved only mindful attention significantly (partial r = .16, p = .012) and life satisfaction marginally (partial r = .11, p = .079), relative to both controls. The Social Diet vs. Both Controls comparison was also marginal for negative emotions (partial r = .12, p = .06)—but in the opposite direction of the hypothesis. In other words, participants who restricted social media reported marginally higher levels of anger, sadness, boredom, etc. I did not find statistically significant differences for brief happiness (partial r = .07, p = .231), brief satisfaction (partial r = .06, p = .340), positive emotions (partial r = –.08, p = .213), autonomy (partial r = .01, p = .932), competence (partial r = .04, p = .507), connectedness (partial r = –.02, p = .805), depression (partial r = .01, p = .858), loneliness (partial r = –.02, p = .703), self-esteem (partial r = .02, p = .691), stress (partial r = –.04, p = .486), or health (partial r = –.04, p = .544).

The other individual regressed change condition comparisons (Social Diet vs. Water Diet and Social Diet vs. No Diet) showed a similar pattern of results (see Table 6), as did the SOLGM analyses (see Tables 7 for SOLGM fit statistics and 8 for SOLGM results). A few of the non-significant regressed change outcomes reported above became marginal or significant for the individual condition comparisons. For example, with regard to the brief happiness item, the regressed change Social Diet vs. Both Controls comparison was non-significant (partial r = .07, p = .231), but the Social Diet vs. Water Diet comparison was marginal (partial r = .14, p = .066). As with the Digital Diet comparisons, the Social Diet regressed change and SOLGM analyses were nearly identical, with virtually no discrepancies in significance between the two approaches.

Exploratory: Restricting Digital Media vs. Social Media

Given that participants in the Digital Diet condition experienced a number of benefits, while those in the Social Diet group did not, I compared the two conditions directly. Specifically, I conducted one final exploratory comparison: Digital Diet vs. Social Diet, with the Social Diet coded as the reference group (see Table 6). Those in the Digital Diet condition reported greater increases in autonomy (partial r = .17, p = .045), self-esteem (partial r = .24, p = .004), and health (partial r = .17, p = .045) than those in the Social Diet group, as well as greater decreases in negative emotions (partial r = –.17, p = .044). No significant differences between the two conditions emerged for brief happiness (partial r = –.03, p = . 728), brief satisfaction (partial r = –.02, p = .834), positive emotions (partial r = .07, p = .399), life satisfaction (partial r = .12, p = . 139), mindful attention (partial $r = .05$, $p = .531$), competence (partial $r = .11$, $p = .180$), connectedness (partial $r = .04$, $p = .613$), depression (partial $r = –.12$, $p = .140$), loneliness (partial $r = –.12$, $p = .168$), or stress (partial $r = –.14$, $p = .10$). Again, the SOLGM analyses were highly similar, with only a slight discrepancy regarding the results for competence ($b = .21$, $p = .095$) and health ($b = 3.39$, $p = .055$).

Intention-to-Treat Analyses

Because my analyses included some data exclusions (e.g., repetitive responders, those who did not restrict at all), I also ran intention-to-treat (ITT) regressed change analyses that included all participants randomized to condition (see Table 9). Some researchers argue that data exclusions that remove participants due to quality checks or intervention non-compliance variables (as I have done above) may inflate Type 1 error (i.e., false positives) (Fergusson et al., 2002). Alternatively, others advance the opposite approach, pointing out that ITT analyses that include all participants randomized to condition may minimize Type 1 error, but inflate Type 2 error (i.e., false negatives). However, as shown in Table 9, the debate is largely moot in this case, because the ITT results were very similar to the pre-registered analyses reported above, and only slightly weaker (i.e., reducing partial *r*s on average by –.01).

Discussion

In summary, Gen Z individuals who were asked to reduce their digital media or social media use for about a week appeared to carry out this charge relatively successfully. Participants assigned to restrict their digital media use (i.e., time spent on their smartphones) experienced a number of benefits, including higher life satisfaction, mindfulness, autonomy, competence, and self-esteem (*r*s = .15 to 25), as well as reduced loneliness and stress (*r*s = –.13 to –.17). In contrast, those assigned to restrict their social media use (i.e., time spent on Facebook, Instagram, Twitter, and Snapchat) experienced relatively few benefits (increased life satisfaction and mindfulness) and even some costs (more negative emotion) (*rs* = .11 to .16). The significant effects I found were small, but not miniscule. Notably, these effect sizes were often larger than those found in previous correlational research (Twenge et al., 2017, 2018; Orben & Przybylski, 2019a, 2019b). However, relative to controls, restricting digital or social media did not improve hedonic well-being (positive emotions and negative emotions) or depression—critical mental health outcomes frequently debated in the correlational literature. Partial *r* effect sizes for those mental health outcomes were indeed close to zero (*r*s = –.08 to .01), with the exception of negative emotions (partial *r* = .12, reflecting not a positive but adverse effect).

My study is one of a small handful of recent large, controlled experimental studies investigating the question of what happens when people deliberately restrict their screen time. Interestingly, my experimental findings dovetail with the nuanced and mixed results from the correlational work. Much more research is needed, including replications and studies with even larger sample sizes, but the accumulating evidence suggests that it may not be the amount of time spent on digital media or social media that meaningfully impacts well-being, but how, why, when, and where one spends that time (Hancock et al., 2020; Kushlev & Leitao, 2020).

Although reducing time spent on digital media did have some meaningful positive effects, the present investigation does not lead to the conclusion that smartphones and social media are extremely harmful to young people. Thus, the pervasive vilification and anxiety surrounding these new technologies may be unwarranted. It may be the case that smartphones and social media are merely the latest victims of widespread technophobia. Historically, new inventions (e.g., novels, radios) have often prompted socially contagious technology panics (Orben, 2017). In 1680, philosopher and mathematician Gottfried Wilhem von Leibniz questioned the usefulness of the printing press, suggesting that "the horrible mass of books that keeps growing might lead to a fall back into barbarism" (Stephens, 1998). In 1926, a global Catholic organization, the Knights of Columbus, wondered: "Does the telephone break up home life and the old practice of visiting friends?" (Thompson, 2016). Clearly, concern about new technologies is nothing new. Yet many new technologies are ultimately adopted into daily life, and go on to provide myriad benefits to humanity, such as improved health, wealth, education, and consumer products (Pinker, 2018).

Limitations, and Future Directions

My study examined the effects of restricting digital and social media on Gen Z individuals (mostly ages 18-25). Future experimental restriction studies should recruit adolescent minors (younger than 18), as well as older adults (ages 26 and older) from other generations (e.g., Millennials, Gen Xers, Boomers), to examine effects on people from different age groups and cohorts. For example, younger people might benefit more than older people from restricting social media because they may be more susceptible to social influence (Arad et al., 2017) or are heavier users (Andone et al., 2016). To increase generalizability, such studies also need to be conducted in different cultures (e.g., individualist vs. collectivist, tight vs. loose), settings (e.g., urban vs. rural), and languages, as such variables could moderate technology's effects. For example, vertical collectivism (i.e., positioning oneself hierarchically within an in-group) is positively associated with nomophobia (fear of being without one's smartphone) (Arpaci, 2019). Thus, members of collectivist cultures may experience backfiring effects when restricting digital media use.

Furthermore, although relatively large for a high-effort shortitudinal intervention ($N \geq 250$), my sample size may still not have been large enough. After all, Twenge and colleagues (2018) reported partial correlations between screen time activities and well-being of r = –0.01 to –0.11. Orben and Przybylski (2019b) reported associations between screen time and well-being of β = –0.02 to –0.08. Both these groups of investigators used exceptionally large samples sizes (N = 17,247 to 1.1 million). As statistical significance depends on both effect size and sample size (Funder & Ozer, 2019), my sample (N = 338) may have been too small to significantly detect the very small effects generally observed in the correlational literature. Of course, even if those small effect sizes are made detectable, the debate about whether such effects matter will likely continue. Regardless, researchers might consider using a big data, Many Labs, and/or Psychological Science Accelerator approach in the future to achieve even greater generalizability and statistical power, as well as to obtain more robust effect size estimates (Carpenter et al., 2016; Jones et al., 2021; Klein et al., 2014, 2018).

Although the participants in my study did successfully restrict the amount of time they spent on their smartphones and social media apps, they did not restrict as much as I would have wished. Participants' Screen Time screenshots showed that those in the Digital Diet condition restricted their iPhone use by an average of 115 minutes per day. However, they were still using their iPhones for about 211 minutes per day at posttest. Similarly, participants in the Social Diet condition restricted their social media use by –68 minutes per day, but they were still using social media for an average of 50 minutes per day at posttest. If participants had reduced their digital and social media use to near zero, the effects may have been stronger or dramatically different. Future researchers may identify ways to induce individuals to reduce their screen time more effectively.

To be sure, future studies should experimentally restrict digital media for longer periods of time (e.g., 1 month, 3 months, or 6 months; e.g., see Allcott et al., 2019; Hunt et al., 2021). Some writers and researchers have argued that smartphones and social media are addictive, and designed to hopelessly hook users (Alter, 2017; Lanier, 2018; Wu, 2016). By this reasoning, it is possible that participants who restricted their social media use may have reported greater levels of negative emotions (e.g., anger, sadness) than controls because they were experiencing something akin to withdrawal symptoms. If these participants were followed for longer periods of time, perhaps restricting social media would have yielded greater benefits if they replaced it with non-screen habits like exercising and socially interacting with others.

Notably, this study was conducted prior to the COVID-19 pandemic. Restricting digital media and social media before COVID-19 may have provided different benefits and costs than had it been attempted during the pandemic. Restricting media use likely prompted my participants to engage in more pleasurable activities, such as spending time outdoors and socially interacting with others. Yet people engaging in social distancing have limited such opportunities. Further, social media lurking (e.g., scrolling the news feed, but not commenting) can act as a social surrogate that individuals use to meet their belongingness needs (Derrick et al., 2019). Thus, removing social media while social distancing may produce backfiring effects, subsequently harming well-being. Alternatively, recent research suggests that teens undergoing quarantine in 2020 reported lower rates of depression and loneliness than a similar pre-pandemic cohort in 2018 (Twenge et al., 2020). The researchers concluded that quarantining teens might have fared relatively better because they spent less time on screen activities, like social media and gaming, and more time sleeping and connecting with family.

Past research demonstrates that there are situations in which smartphones can be helpful or harmful to well-being (Dwyer et al., 2018; Kushlev et al., 2017). Likely content and context matter more than the amount of time spent (Hancock et al., 2020).

Future studies could explore these issues more deeply so that investigators can determine how, why, when, and where to best use smartphones and social media to optimize well-being and related constructs. Device manufacturing, operating system, and app design companies would likely benefit from such research, allowing them to remodel their technologies to better support user well-being. Happier customers likely translate into higher sales and better engagement, potentially facilitating an improved digital environment for all.

Chapter 4: General Conclusion

"Anything can change, because the smartphone revolution is still in its early stages." —Tim Cook

Most people want to be happy (Diener, 2000), and many people across the globe report being happier with a smartphone than without one (Crabtree et al., 2018). Perhaps this is why smartphones have spread faster than any technology in human history (DeGusta, 2012).

My results show that, at a particular point in time, smartphone and social media use—indicated by both self-report and objective measures—are associated with lower well-being. Notably, however, restricting smartphone use for a week appears to grant some benefits (e.g., greater life satisfaction, decreased loneliness), but reducing social media use (not just Facebook, but also Instagram, Snapchat, Twitter, etc.) appears to provide very few benefits (greater mindfulness) and even some costs (greater negative emotion). Overall, the effect sizes were generally larger than what has been reported in previous correlational research. However, they were still relatively small, suggesting that digital technology use may minimally change psychosocial well-being and related constructs. Further, the type of digital technology use likely matters. For example, some apps and app categories (e.g., gaming apps, Snapchat, News, Camera) were associated with greater well-being, while others were associated with lower well-being (e.g., social networking apps, dating apps, Tinder, Safari).

Despite a plethora of memes, news articles, books, YouTube videos, movies, TV shows, and podcasts disparaging digital and social media (Alter, 2017; Anderson et al., 2018; Arnold et al., 2019; Brooker & Wright, 2018; Lanier, 2018; Moby, 2016; reMarkable, 2018), my results suggest that smartphone users may be better off keeping calm and carrying on.

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Appendix A

Digital Diet Condition Instructions

We all have small habits that can have a big impact on our daily lives and the world around us. This week, we want you to **restrict your iPhone screen time** (such as time spent on gaming, social media, entertainment, and online news apps). You may use your iPhone for necessary daily activities, such as for GPS navigation, work, school, or to call or message friends or family. But we would like you to limit how much time you spend on your iPhone as much as possible. The more you can limit your overall screen time, the better. We want you to do your best to restrict any non-necessary screen time.

These are the apps that it would be OK to use only as absolutely necessary (at most a few minutes at a time):

- Phone Messaging apps (e.g., Messages, Messenger, WhatsApp)
- Email apps (e.g., Apple Mail, Gmail)
- GPS/Navigation (e.g., Apple Maps, Google Maps, Waze)
- Weather
- Calendar
- Calculator
- Contacts
- Camera
- Notes
- Other apps you need to obtain necessary information or to do necessary school/work/personal tasks

Please do NOT use these non-necessary apps (or use them as little as possible) this week:

- Social media apps (e.g., Facebook, Twitter, Instagram, Snapchat)
- Gaming apps (e.g., Minecraft, Candy Crush, Angry Birds)
- Entertainment apps (e.g., Netflix, Hulu, HBO)
- News apps (e.g., Apple News, CNN, Buzzfeed)
- Web browsing apps (e.g., Safari, Chrome) [Unless you need to obtain necessary info]
- Dating apps (e.g., Tinder, OkCupid, Match.com)
- Exercise, health, and relaxation apps (e.g., Fitbit, Lose It!, Calm)
- Reading/books apps (e.g., iBooks, Audible, Amazon Kindle)
- Education apps (e.g., Khan Academy, Duolingo)

Restricting your screen time this week can be made easier by doing some of the following:

- Set a Screen Time app limit of 1 min for all apps and add necessary apps (such as Phone, Messages) to "Always Allowed"
- Delete non-necessary apps off your phone
- Turn off push notifications for non-necessary apps
- Place non-necessary apps into a separate folder on your phone and place that folder on a screen you don't usually look at
- Log out of non-necessary apps on your iPhone

Please limit your iPhone usage/screen time as much as possible this week—starting tomorrow when you wake up and continuing until your next lab visit. These instructions will be emailed to you to make them easier to follow them throughout the week.

Social Diet Condition Instructions

We all have small habits that can have a big impact on our daily lives and the world around us. This week, we want you to **restrict your social media use** as much as possible. Specifically, stay off social media apps/sites (such as Facebook, Instagram, Twitter, and Snapchat) on your iPhone, computer, iPad, and other e-devices this week.

Examples of social media apps/sites/services that we would like you to avoid entirely include:

- Facebook (NOT including Facebook Messenger or WhatsApp)
- Instagram
- Twitter
- Snapchat
- Google+
- Pinterest
- LinkedIn
- YouTube
- Tumblr
- Sina Weibo
- WeChat
- Naver
- Line
- Qzone
- Kakao Talk
- Dating apps (such as OkCupid, Coffee Meets Bagel, Bumble, Tinder, Grindr, Hinge, Match.com, eHarmony, PlentyOfFish/POF Dating, etc.)

Restricting your social media usage this week can be made easier by doing some of the following:

- Set a Screen Time app limit for 1 min for Social Networking apps
- Delete social media apps off your phone
- Turn off push notifications for those apps
- Place social media apps into a separate folder on your phone and place that folder on a screen you don't usually look at
- Remove social media bookmarks from your computer web browser
- Log out of social media sites on your devices

We request that you do not look at social media at all this week. However, you may log-in to a service such as Facebook briefly if you need to obtain specific information (e.g., check details for an event), but we ask that you then log-out immediately.

Please limit your social media usage as much as possible this week—starting when you wake up tomorrow until your next lab visit. These instructions will be emailed to you to make them easier to follow throughout the week.

Water Diet Condition Instructions

We all have small habits that can have a big impact on our daily lives and the world around us. This week, we want you to **restrict your water usage**, such as by taking shorter showers and using less water when you wash dishes or brush your teeth. However, please do not change the amount of water that you *drink*.

We would like you to conserve the water you use as much as possible. Here are some things we recommend that you do this week:

- Turn off the water when you are not using it. Don't let it run while you brush your teeth, shave, or wash your hands, dishes, or fruit and vegetables.
- Take shorter showers. Try to cut 1 to 5 minutes off your shower time
- Take baths instead of showers. If you like to linger, a partially filled tub uses less water than a shower.
- Use appliances efficiently. Run full loads in the dish or clothes washer, or, if your appliance has one, use a load selector (e.g., "low water").
- Water the lawn and garden only when necessary. Early morning or evening are the best times.
- Wash your car sensibly. Clean the car with a pail of soapy water and use the hose only for a quick rinse.

Please limit your water usage (but not how much you drink) as much as possible this week — starting when you wake up tomorrow and continuing until your next lab visit.

These instructions will be emailed to you to make them easier to follow throughout the week.

No Diet Condition Instructions
[Participants did not receive any condition instructions. They just completed measures.]

Tables

Table 1

Study 1 Summary Statistics

Variable	*n*	*M*	*SD*	*Mdn*	Min	Max
Positive Emotions	414	4.48	1.10	4.50	1.50	7.00
Negative Emotions	414	2.98	0.95	2.83	1.17	6.17
Life Satisfaction	414	4.55	1.17	4.60	1.00	7.00
Well-Being	414	0.00	1.00	0.01	-3.25	2.23
Depression	414	2.03	0.81	1.83	1.00	4.83
Loneliness	414	2.30	0.76	2.33	1.00	4.50
Self-Esteem	414	3.66	0.74	3.67	1.33	5.00
Exercising	414	2.80	1.13	3.00	1.00	5.00
Outdoors	414	2.88	1.19	3.00	1.00	5.00
Relaxation	414	1.57	0.91	1.00	1.00	5.00
Religious Services	414	1.41	0.76	1.00	1.00	5.00
Volunteering	414	1.38	0.82	1.00	1.00	5.00
Reading	414	33.79	50.33	15.00	0.00	425.00
Sleeping	414	406.43	101.03	420.00	0.00	900.00
Working	414	102.00	187.08	0.00	0.00	1320.00
Studying	414	219.11	134.34	180.00	20.00	1080.00
Social Interaction	414	236.08	175.48	180.00	1.00	1440.00
Self-Report Smartphone Time	414	323.09	155.15	300.00	60.00	1200.00
Self-Report Social Media Time	414	230.96	113.43	220.00	5.00	630.00
Objective Smartphone Time	409	321.53	106.66	315.00	70.00	779.00
Objective Social Media Time	402	113.07	62.13	107.80	0.00	485.00
Dating Apps	402	1.52	7.95	0.00	0.00	113.30
Creativity Apps	100	30.63	25.73	22.50	0.00	130.43
Education Apps	7	25.66	13.90	21.14	10.86	53.67
Entertainment Apps	284	68.19	58.57	51.09	4.00	387.00
Gaming Apps	64	57.70	51.71	43.97	7.29	327.29
Other Apps	65	28.27	18.75	23.00	5.43	120.86
Productivity Apps	118	25.06	26.77	17.20	1.00	170.00
Reading & Reference Apps	113	38.48	34.39	27.00	4.86	170.43
Social Networking Apps	405	152.32	74.28	143.86	19.43	595.00
Pickups	409	135.33	49.90	131.00	0.00	366.00
Notifications	405	187.10	124.89	163.00	10.56	872.00

Table 1 (Continued)

Variable	*n*	*M*	*SD*	*Mdn*	Min	Max
Blackboard App	403	1.28	3.31	0.00	0.00	34.00
Calculator App	408	0.99	2.77	0.23	0.00	42.44
Camera App	409	2.22	3.27	1.29	0.00	32.14
Chrome App	405	1.91	10.24	0.00	0.00	155.43
Clock App	408	1.51	5.93	0.50	0.00	76.14
Dictionary App	402	1.63	22.64	0.00	0.00	420.00
Facebook App	406	7.65	18.13	0.70	0.00	151.22
FaceTime App	404	1.50	7.02	0.00	0.00	92.29
Find My Friends App	405	0.50	1.45	0.00	0.00	15.43
Gmail App	408	2.28	3.09	1.43	0.00	26.00
Google Maps App	408	3.08	9.65	0.00	0.00	98.57
GroupMe App	405	1.36	3.89	0.05	0.00	40.86
Hulu App	402	2.34	11.08	0.00	0.00	108.57
Instagram App	409	45.95	40.86	39.00	0.00	458.00
Mail App	405	1.80	3.15	0.29	0.00	26.64
Maps App	408	3.75	7.99	0.57	0.00	62.57
Messages App	411	30.00	28.52	21.86	0.00	254.00
Messenger App	407	2.90	9.47	0.00	0.00	104.86
Music App	403	1.99	5.84	0.00	0.00	56.00
Netflix App	405	10.17	28.49	0.00	0.00	238.86
News App	406	0.15	1.26	0.00	0.00	16.86
Notes App	407	1.25	2.75	0.29	0.00	31.57
Phone App	402	2.87	5.24	1.22	0.00	57.29
Photos App	410	5.14	5.75	3.29	0.00	40.57
Reddit App	403	2.16	11.72	0.00	0.00	168.57
Safari App	409	16.04	19.71	10.86	0.00	167.00
Settings App	409	1.32	1.79	0.86	0.00	23.73
Snapchat App	409	30.22	28.75	24.43	0.00	202.80
Spotify App	406	3.99	7.68	0.77	0.00	71.00
TikTok App	403	3.99	15.02	0.00	0.00	128.86
Tinder App	402	1.03	5.43	0.00	0.00	57.86
Twitter App	405	19.01	26.24	5.56	0.00	163.57
WeChat App	405	5.50	28.31	0.00	0.00	254.57
Weibo App	402	1.12	11.90	0.00	0.00	207.57
WhatsApp	403	0.97	6.34	0.00	0.00	102.14
YouTube App	407	27.72	39.98	10.00	0.00	257.00

Note. For ease of interpretation, screen and non-screen activity variables are presented in raw (not log-transformed) form (in minutes).

Table 2

Study 1 Zero-Order Pearson Correlations

	Pos Aff	Neg Aff	Life Sat	SWB	Depress	Lonely	Self-Est
Non-screen Activities:							
Exercising	0.18***	-0.18***	0.09†	0.18***	-0.09†	-0.18***	0.14**
Outdoors	0.19***	-0.12*	0.16**	0.19***	-0.13**	-0.14**	0.18***
Relaxation	0.23***	-0.15**	0.21***	0.24***	-0.16***	-0.16***	0.19***
Religious Services	0.08†	-0.05	0.12*	0.10*	-0.07	-0.15**	0.10*
Volunteering	0.14**	-0.04	0.17***	0.15**	-0.12*	-0.03	0.15**
Reading	0.04	0.04	0.03	0.02	-0.05	0.02	0.07
Sleeping	0.09†	-0.06	0.00	0.06	0.02	0.00	0.05
Working	-0.03	0.07	-0.02	-0.05	0.01	0.04	0.06
Studying	-0.06	0.06	0.02	-0.04	-0.03	0.07	-0.03
Social Interaction	0.19***	-0.03	0.09†	0.12*	-0.06	-0.16**	0.08†
Combined Non-screen	0.09	0.05	0.09†	0.05	-0.09†	-0.02	0.15**
Screen Activities:							
SR Smartphone Time	-0.06	0.19***	-0.10†	-0.14**	0.14**	0.12*	-0.10*
SR Social Media Time	-0.08†	0.21***	-0.13**	-0.17***	0.19***	0.16***	-0.10*
Obj Smartphone Time	-0.12*	0.21***	-0.06	-0.16**	0.11*	0.10†	-0.08†
Obj Social Media Time	-0.11*	0.21***	-0.07	-0.16**	0.08	0.11*	-0.11*
Dating Apps	-0.10*	0.13*	-0.19***	-0.17***	0.19***	0.12*	-0.13**
Creativity Apps	-0.02	-0.08	-0.05	0.01	-0.09	-0.03	0.17†
Education Apps	-0.18	-0.11	0.36	0.07	-0.35	0.07	0.35
Entertainment Apps	-0.03	0.01	0.02	-0.01	-0.06	0.02	0.03
Gaming Apps	0.26*	-0.16	0.14	0.23†	-0.08	-0.18	0.06
Other Apps	-0.23†	0.29*	-0.16	-0.26*	0.31*	0.22†	-0.33*
Productivity Apps	-0.08	0.00	-0.03	-0.05	-0.02	0.07	0.01
Reading & Reference Apps	-0.16†	0.06	-0.07	-0.12	0.06	0.12	-0.07
Social Networking Apps	-0.17***	0.27***	-0.10*	-0.21***	0.13**	0.11*	-0.12*
Pickups	0.03	0.10†	0.00	-0.02	-0.04	-0.09†	0.02
Notifications	0.03	0.14**	-0.02	-0.05	0.00	-0.11*	-0.04

Table 2 (Continued)

	Pos Aff	Neg Aff	Life Sat	SWB	Depress	Lonely	Self-Est
Screen Activities (continued):							
Blackboard App	-0.05	0.08	-0.09†	-0.09†	0.08	0.09†	-0.08
Calculator App	-0.06	-0.03	0.05	0.01	-0.10†	0.05	0.08†
Camera App	0.05	-0.06	0.14**	0.10*	-0.12*	-0.08	0.06
Chrome App	0.00	-0.08	0.02	0.04	-0.03	-0.05	0.04
Clock App	-0.06	0.02	0.05	-0.02	0.00	-0.01	-0.03
Dictionary App	-0.01	-0.03	0.03	0.02	0.02	0.01	0.02
Facebook App	-0.11*	0.07	-0.04	-0.09†	0.14**	0.06	-0.15**
FaceTime App	0.03	0.09†	0.03	-0.01	-0.01	-0.01	0.00
Find My Friends App	0.12*	0.02	0.10†	0.08	-0.11*	-0.12*	0.04
Gmail App	0.08†	-0.06	0.02	0.07	-0.11*	0.02	0.08
Google Maps App	-0.05	-0.02	0.00	-0.01	0.09†	0.10*	-0.09†
GroupMe App	-0.07	0.04	0.02	-0.04	-0.01	0.02	-0.05
Hulu App	0.02	0.02	0.00	0.00	-0.04	-0.04	0.07
Instagram App	-0.01	0.10†	0.00	-0.04	0.00	0.03	0.00
Mail App	-0.09†	0.11*	-0.04	-0.10†	0.00	0.09†	0.00
Maps App	0.00	0.14**	0.05	-0.04	-0.05	0.04	0.07
Messages App	-0.03	0.09†	0.00	-0.05	0.02	-0.04	-0.01
Messenger App	-0.02	0.00	-0.05	-0.03	0.08	-0.02	-0.15**
Music App	0.03	0.01	0.04	0.03	-0.04	0.00	0.06
Netflix App	0.02	-0.03	-0.02	0.01	-0.06	0.08	0.03
News App	0.12*	-0.04	0.12*	0.12*	-0.05	-0.01	0.09†
Notes App	0.01	0.00	0.02	0.01	-0.07	0.06	0.03
Phone App	0.02	0.04	0.10*	0.03	-0.12*	-0.02	0.12*
Photos App	0.00	0.04	0.08	0.02	-0.01	-0.02	0.02
Reddit App	-0.03	0.03	-0.12*	-0.07	0.10*	-0.02	-0.13**
Safari App	-0.09†	0.15**	-0.06	-0.12*	0.04	0.09†	-0.05
Settings App	0.06	-0.01	-0.02	0.02	-0.03	-0.01	-0.01
Snapchat App	0.15**	-0.02	0.09†	0.10*	-0.09†	-0.11*	0.10*
Spotify App	-0.04	0.12*	-0.02	-0.07	0.00	-0.03	-0.06
TikTok App	-0.03	-0.04	-0.11*	-0.04	0.00	0.01	0.02
Tinder App	-0.10†	0.09†	-0.17***	-0.14**	0.16**	0.08	-0.14**
WeChat App	-0.07	0.04	-0.06	-0.07	0.05	0.09†	-0.09†
Weibo App	-0.06	0.00	-0.05	-0.04	0.01	0.06	-0.04
WhatsApp	0.00	0.01	0.08	0.03	-0.03	0.04	0.03
YouTube App	-0.02	-0.03	-0.02	-0.01	0.04	0.02	-0.09†

Note. Screen and non-screen time activity variables that were right-skewed and kurtotic were log-transformed. Pos Aff = Positive affect/emotions; Neg Aff = Negative affect/emotions; Life Sat = Life satisfaction; SWB = Standardized subjective well-being composite (PA – NA + LS); Depress = Depression, Lonely = Loneliness, Self-Est = Self-esteem; SR = Self-report; Obj = Objective. †*p* < .10. **p* <.05. ***p* < .01. ****p* < .001.

Table 3

Study 2 Means and Standard Deviations by Condition (N = 338)

	Digital Diet	Social Diet	Water Diet	No Diet
Outcome	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*
T_1 SR Digital Media Time	312.62 (131.8)	340.19 (135.35)	327.91 (164.77)	330.54 (169.34)
T_2 SR Digital Media Time	199.64 (115.98)	301.3 (162.68)	352.2 (196.16)	384.86 (203.56)
T_1 Obj Digital Media Time	323.25 (100.28)	330.67 (107.83)	333.89 (114.55)	328.21 (108.28)
T_2 Obj Digital Media Time	211.37 (105.78)	275.25 (104.92)	340.75 (117.44)	315.75 (113.52)
T_1 SR Social Media Time	228.01 (129.98)	242.1 (113.97)	228.04 (109.73)	237.6 (105.14)
T_2 SR Social Media Time	112.32 (106.53)	89.91 (101.2)	228.18 (136.09)	247.75 (149.29)
T_1 Obj Social Media Time	101.28 (58.82)	114.71 (62.47)	117.67 (61.61)	127.68 (70.47)
T_2 Obj Social Media Time	57.71 (59.09)	50.32 (50.27)	120.7 (68.08)	117.31 (61.77)
T_1 Brief Happiness	2.03 (0.46)	1.85 (0.58)	1.92 (0.5)	1.98 (0.48)
T_2 Brief Happiness	2.08 (0.48)	2.03 (0.6)	1.93 (0.6)	2.1 (0.54)
T_1 Brief Satisfaction	5.28 (1.09)	4.91 (1.26)	4.82 (1.35)	5.15 (1.2)
T_2 Brief Satisfaction	5.43 (1.07)	5.25 (1.21)	5.02 (1.32)	5.29 (1.3)
T_1 Positive Emotions	4.59 (0.96)	4.46 (1.03)	4.22 (1.17)	4.5 (1.25)
T_2 Positive Emotions	4.75 (0.99)	4.54 (1.14)	4.45 (1.19)	4.85 (1.13)
T_1 Negative Emotions	2.87 (0.87)	2.94 (0.88)	3.03 (0.99)	3.26 (1)
T_2 Negative Emotions	2.63 (0.89)	2.95 (1.03)	2.92 (1.02)	2.87 (1.11)
T_1 Life Satisfaction	4.59 (1.23)	4.52 (1.09)	4.35 (1.23)	4.65 (1.08)
T_2 Life Satisfaction	5.02 (1.08)	4.8 (1.06)	4.45 (1.33)	4.76 (1.16)
T_1 Mindful Attention	3.78 (0.98)	3.77 (0.9)	3.58 (0.9)	3.42 (0.91)
T_2 Mindful Attention	4.15 (0.83)	4.06 (0.91)	3.62 (0.95)	3.64 (0.95)
T_1 Autonomy	3.64 (0.85)	3.77 (0.71)	3.54 (0.78)	3.82 (0.79)
T_2 Autonomy	3.96 (0.69)	3.81 (0.75)	3.63 (0.82)	3.88 (0.79)
T_1 Competence	3.39 (0.86)	3.43 (0.83)	3.34 (0.76)	3.44 (0.83)
T_2 Competence	3.67 (0.7)	3.55 (0.82)	3.42 (0.83)	3.51 (0.86)
T_1 Connectedness	3.93 (0.88)	3.96 (0.81)	3.74 (0.91)	3.95 (1)
T_2 Connectedness	4.01 (0.82)	3.96 (0.9)	3.8 (1.03)	4.04 (0.93)
T_1 Depression	1.88 (0.77)	1.99 (0.79)	2.22 (0.86)	2.02 (0.83)
T_2 Depression	1.75 (0.75)	1.95 (0.74)	2.14 (0.91)	1.94 (0.85)
T_1 Loneliness	2.24 (0.75)	2.28 (0.76)	2.48 (0.79)	2.28 (0.72)
T_2 Loneliness	2.06 (0.65)	2.2 (0.82)	2.44 (0.86)	2.17 (0.74)
T_1 Self-Esteem	3.71 (0.7)	3.63 (0.71)	3.53 (0.8)	3.65 (0.78)
T_2 Self-Esteem	3.98 (0.65)	3.69 (0.83)	3.56 (0.8)	3.73 (0.82)
T_1 Stress	2.64 (0.74)	2.82 (0.6)	2.88 (0.69)	2.8 (0.65)
T_2 Stress	2.41 (0.6)	2.65 (0.72)	2.78 (0.68)	2.65 (0.68)
T_1 Health	75.13 (14.1)	72.06 (16.43)	73.47 (13.85)	71.54 (16.92)
T_2 Health	77.49 (13.54)	71.43 (16.99)	72.66 (17.69)	73.53 (15.65)

Note. Values outside parentheses indicate outcome means, and parenthetical values represent standard deviations. For ease of interpretation, digital media time and social media time variables are presented in raw form (in minutes). SR = self-reported; Obj = objective.

Table 4

Study 2 Bivariate Correlations

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
1. T_1 SR Digital Media Time	—																																			
2. T_1 SR Social Media Time	0.64	—																																		
3. T_1 Obj. Digital Media Time	0.59	0.43	—																																	
4. T_1 Obj. Social Media Time	0.26	0.35	0.37	—																																
5. T_1 Brief Satisfaction	-0.11	-0.19	-0.11	-0.08	—																															
6. T_1 Brief Happiness	-0.10	-0.07	-0.07	-0.04	0.54	—																														
7. T_1 Positive Emotions	-0.04	-0.09	-0.10	-0.12	0.57	0.59	—																													
8. T_1 Negative Emotions	0.17	0.21	0.19	0.21	-0.50	-0.49	-0.52	—																												
9. T_1 Life Satisfaction	-0.11	-0.15	-0.04	-0.06	0.58	0.52	0.61	-0.55	—																											
10. T_1 Mindful Attention	-0.13	-0.13	-0.12	-0.17	0.31	0.25	0.34	-0.55	0.36	—																										
11. T_1 Autonomy	-0.04	-0.07	-0.02	-0.04	0.42	0.41	0.60	-0.39	0.56	0.36	—																									
12. T_1 Competence	-0.17	-0.20	-0.13	-0.15	0.43	0.33	0.44	-0.32	0.48	0.38	0.57	—																								
13. T_1 Connectedness	-0.06	-0.09	-0.02	-0.07	0.46	0.43	0.58	-0.36	0.49	0.30	0.54	0.41	—																							
14. T_1 Depression	0.15	0.20	0.10	0.07	-0.57	-0.47	-0.53	0.55	-0.64	-0.46	-0.46	-0.47	-0.46	—																						
15. T_1 Loneliness	0.13	0.16	0.08	0.09	-0.39	-0.38	-0.51	0.44	-0.49	-0.35	-0.38	-0.33	-0.57	0.54	—																					
16. T_1 Self-Esteem	-0.11	-0.13	-0.05	-0.12	0.53	0.49	0.55	-0.51	0.64	0.42	0.50	0.49	0.46	-0.78	-0.47	—																				
17. T_1 Stress	0.12	0.15	0.08	0.16	-0.54	-0.44	-0.56	0.61	-0.58	-0.52	-0.50	-0.46	-0.36	0.60	0.49	-0.61	—																			
18. T_1 Health	-0.15	-0.19	-0.06	0.01	0.37	0.30	0.36	-0.45	0.36	0.32	0.23	0.21	0.13	-0.33	-0.24	0.34	-0.38	—																		
19. T_2 SR Digital Media Time	0.35	0.25	0.41	0.24	-0.07	0.02	-0.04	0.15	0.01	-0.18	0.03	0.01	-0.01	0.09	0.07	-0.07	0.12	-0.05	—																	
20. T_2 SR Social Media Time	0.23	0.28	0.27	0.21	-0.12	0.00	-0.07	0.17	-0.07	-0.13	-0.02	-0.07	-0.06	0.08	0.03	-0.09	0.11	-0.09	0.60	—																
21. T_2 Obj. Digital Media Time	0.41	0.32	0.68	0.34	-0.13	-0.05	-0.10	0.21	-0.05	-0.19	-0.01	-0.08	-0.05	0.08	0.08	-0.05	0.10	-0.10	0.59	0.45	—															
22. T_2 Obj. Social Media Time	0.16	0.18	0.29	0.41	-0.04	0.06	-0.03	0.11	-0.01	-0.12	0.03	-0.07	-0.03	0.02	0.02	-0.04	0.09	0.01	0.50	0.72	0.56	—														
23. T_2 Brief Satisfaction	-0.02	-0.12	-0.10	-0.02	0.53	0.38	0.49	-0.43	0.50	0.23	0.35	0.35	0.35	-0.48	-0.31	0.43	-0.44	0.33	-0.05	-0.13	-0.11	0.02	—													
24. T_2 Brief Happiness	-0.09	-0.17	-0.06	-0.06	0.52	0.48	0.53	-0.45	0.51	0.25	0.41	0.37	0.38	-0.49	-0.42	0.48	-0.47	0.31	-0.04	-0.10	-0.07	-0.01	0.59	—												
25. T_2 Positive Affect	0.01	-0.06	-0.03	-0.09	0.42	0.41	0.67	-0.43	0.53	0.26	0.50	0.39	0.46	-0.49	-0.40	0.49	-0.49	0.25	-0.01	-0.04	-0.02	0.03	0.64	0.67	—											
26. T_2 Negative Affect	0.13	0.22	0.18	0.13	-0.44	-0.36	-0.40	0.67	-0.47	-0.39	-0.28	-0.34	-0.32	0.52	0.40	-0.45	0.48	-0.40	0.15	0.16	0.16	0.07	-0.58	-0.53	-0.52	—										
27. T_2 Life Satisfaction	-0.12	-0.16	-0.07	-0.07	0.52	0.46	0.51	-0.50	0.81	0.31	0.49	0.45	0.45	-0.64	-0.46	0.59	-0.56	0.30	-0.10	-0.17	-0.11	-0.08	0.60	0.58	0.61	-0.56	—									
28. T_2 Mindful Attention	-0.06	-0.07	-0.03	-0.11	0.27	0.18	0.23	-0.38	0.39	0.60	0.23	0.29	0.23	-0.45	-0.33	0.35	-0.40	0.27	-0.23	-0.20	-0.15	-0.15	0.33	0.36	0.37	-0.53	0.48	—								
29. T_2 Autonomy	0.04	-0.03	0.02	-0.06	0.37	0.32	0.48	-0.35	0.56	0.21	0.60	0.44	0.43	-0.47	-0.35	0.52	-0.45	0.21	-0.04	-0.07	-0.02	-0.02	0.51	0.54	0.65	-0.46	0.64	0.39	—							
30. T_2 Competence	-0.10	-0.15	-0.10	-0.13	0.38	0.30	0.43	-0.34	0.45	0.27	0.47	0.64	0.39	-0.47	-0.35	0.51	-0.44	0.21	-0.09	-0.13	-0.07	-0.08	0.43	0.49	0.57	-0.48	0.56	0.41	0.66	—						
31. T_2 Connectedness	0.04	-0.02	0.09	0.02	0.35	0.37	0.47	-0.32	0.48	0.16	0.44	0.39	0.59	-0.45	-0.43	0.41	-0.37	0.15	0.06	0.01	0.07	0.07	0.49	0.49	0.61	-0.46	0.59	0.35	0.66	0.56	—					
32. T_2 Depression	0.08	0.16	0.07	0.09	-0.51	-0.42	-0.48	0.51	-0.62	-0.34	-0.40	-0.36	-0.45	0.82	0.51	-0.71	0.55	-0.29	0.11	0.11	0.07	0.03	-0.61	-0.57	-0.61	0.63	-0.76	-0.50	-0.62	-0.56	-0.57	—				
33. T_2 Loneliness	0.06	0.10	0.03	0.03	-0.40	-0.38	-0.46	0.44	-0.47	-0.29	-0.39	-0.32	-0.49	0.54	0.77	-0.46	0.49	-0.25	0.11	0.07	0.08	0.05	-0.40	-0.50	-0.50	0.55	-0.58	-0.46	-0.47	-0.42	-0.57	0.62	—			
34. T_2 Self-Esteem	-0.08	-0.11	-0.06	-0.09	0.57	0.46	0.51	-0.48	0.63	0.35	0.43	0.47	0.41	-0.77	-0.46	0.81	-0.59	0.30	-0.10	-0.11	-0.06	-0.02	0.55	0.54	0.57	-0.58	0.71	0.48	0.61	0.62	0.52	-0.83	-0.57	—		
35. T_2 Stress	0.10	0.17	0.09	0.17	-0.46	-0.35	-0.44	0.50	-0.54	-0.40	-0.42	-0.41	-0.33	0.55	0.41	-0.55	0.62	-0.34	0.18	0.20	0.17	0.11	-0.49	-0.57	-0.58	0.61	-0.66	-0.56	-0.59	-0.56	-0.47	0.66	0.54	-0.69	—	
36. T_2 Health	-0.15	-0.23	-0.13	-0.02	0.35	0.29	0.35	-0.40	0.36	0.30	0.21	0.13	0.25	-0.38	-0.32	0.33	-0.37	0.55	-0.11	-0.09	-0.15	0.01	0.40	0.44	0.46	-0.52	0.42	0.42	0.35	0.33	0.32	-0.44	-0.42	0.39	-0.48	—

Note. Correlations (Pearson *r*s) are based on ≤ 338 participants. Correlations .11 and above are significant at $p < .05$. Correlations between .09 and .11 are marginal at $p < .1$. Digital media time and social media time variables that were right-skewed and kurtotic were log-transformed. SR = self-reported; Obj = objective.

Table 5

Study 2 Manipulation Check Regressed Change Models

Manipulation Check Variable by Comparison	*b*	*b SE*	Partial *r*	Partial *r* 95% CI *LL*	Partial *r* 95% CI *UL*	*p*
Self-Reported Digital Media Time						
H1. Digital Diet vs. Water Diet	-0.68	0.09	-0.5	-0.58	-0.4	< .001
H1. Digital Diet vs. No Diet	-0.76	0.1	-0.53	-0.62	-0.42	< .001
H1. Digital Diet vs. Both Controls	-0.71	0.07	-0.51	-0.58	-0.43	< .001
H2. Social Diet vs. Water Diet	-0.22	0.07	-0.23	-0.36	-0.09	0.002
H2. Social Diet vs. No Diet	-0.31	0.08	-0.31	-0.44	-0.15	< .001
H2. Social Diet vs. Both Controls	-0.26	0.06	-0.24	-0.35	-0.13	< .001
E. Digital Diet vs. Social Diet	-0.46	0.12	-0.32	-0.45	-0.17	< .001
Objective Digital Media Time						
H1. Digital Diet vs. Water Diet	-124.67	11.53	-0.63	-0.69	-0.55	< .001
H1. Digital Diet vs. No Diet	-104.64	12.73	-0.56	-0.64	-0.46	< .001
H1. Digital Diet vs. Both Controls	-116.27	10.48	-0.57	-0.63	-0.49	< .001
H2. Social Diet vs. Water Diet	-60.5	11.68	-0.37	-0.48	-0.24	< .001
H2. Social Diet vs. No Diet	-40.49	12.8	-0.26	-0.4	-0.1	0.002
H2. Social Diet vs. Both Controls	-52.19	10.76	-0.29	-0.39	-0.18	< .001
E. Digital Diet vs. Social Diet	-64.34	13.84	-0.37	-0.5	-0.23	< .001
Self-Reported Social Media Time						
H1. Digital Diet vs. Water Diet	-1.2	0.15	-0.51	-0.59	-0.41	< .001
H1. Digital Diet vs. No Diet	-1.23	0.18	-0.49	-0.58	-0.37	< .001
H1. Digital Diet vs. Both Controls	-1.21	0.12	-0.52	-0.59	-0.44	< .001
H2. Social Diet vs. Water Diet	-1.61	0.16	-0.61	-0.68	-0.53	< .001
H2. Social Diet vs. No Diet	-1.63	0.19	-0.59	-0.66	-0.49	< .001
H2. Social Diet vs. Both Controls	-1.61	0.13	-0.62	-0.67	-0.55	< .001
E. Digital Diet vs. Social Diet	0.41	0.25	0.13	-0.03	0.29	0.109
Objective Social Media Time						
H1. Digital Diet vs. Water Diet	-1.19	0.15	-0.5	-0.59	-0.4	< .001
H1. Digital Diet vs. No Diet	-1.12	0.18	-0.46	-0.57	-0.34	< .001
H1. Digital Diet vs. Both Controls	-1.17	0.12	-0.51	-0.58	-0.43	< .001
H2. Social Diet vs. Water Diet	-1.59	0.17	-0.6	-0.67	-0.51	< .001
H2. Social Diet vs. No Diet	-1.52	0.19	-0.57	-0.65	-0.46	< .001
H2. Social Diet vs. Both Controls	-1.56	0.13	-0.6	-0.66	-0.53	< .001
E. Digital Diet vs. Social Diet	0.45	0.27	0.15	-0.03	0.31	0.096

Note. Hypothesized condition dummy codes predicting T_2 scores, controlling for T_1 scores. Digital media time and social media time variables that were right-skewed and kurtotic were log-transformed. CI = confidence interval; LL = lower limit; UL = upper limit.

Table 6

Study 2 Outcome Regressed Change Models

Variable	*b*	*b SE*	Partial *r*	Partial *r* 95% CI *LL*	Partial *r* 95% CI *UL*	*p*
Hypothesis 1. Digital Diet vs. Water Diet:						
Brief Happiness	0.09	0.07	0.09	-0.05	0.23	0.215
Brief Satisfaction	0.19	0.16	0.09	-0.06	0.23	0.227
Positive Emotions	0.06	0.13	0.03	-0.11	0.18	0.639
Negative Emotions	-0.18	0.11	-0.12	-0.25	0.03	0.113
Life Satisfaction	0.36	0.10	0.25	0.12	0.38	<.001
Mindful Attention	0.41	0.11	0.26	0.13	0.39	<.001
Autonomy	0.27	0.09	0.21	0.07	0.34	0.004
Competence	0.22	0.09	0.18	0.03	0.31	0.015
Connectedness	0.09	0.12	0.06	-0.09	0.20	0.447
Depression	-0.10	0.07	-0.09	-0.23	0.05	0.194
Loneliness	-0.19	0.07	-0.19	-0.32	-0.05	0.009
Self-Esteem	0.29	0.07	0.31	0.18	0.42	<.001
Stress	-0.23	0.08	-0.21	-0.34	-0.08	0.003
Health	3.77	2.01	0.14	-0.01	0.27	0.062
Hypothesis 1. Digital Diet vs. No Diet:						
Brief Happiness	-0.04	0.08	-0.04	-0.20	0.11	0.582
Brief Satisfaction	0.08	0.17	0.04	-0.12	0.20	0.619
Positive Emotions	-0.16	0.12	-0.10	-0.25	0.06	0.202
Negative Emotions	0.03	0.13	0.02	-0.14	0.18	0.815
Life Satisfaction	0.29	0.11	0.21	0.06	0.35	0.008
Mindful Attention	0.32	0.12	0.20	0.05	0.35	0.011
Autonomy	0.17	0.10	0.14	-0.02	0.29	0.076
Competence	0.19	0.09	0.16	0.00	0.31	0.046
Connectedness	-0.02	0.12	-0.02	-0.17	0.14	0.848
Depression	-0.08	0.08	-0.08	-0.23	0.08	0.321
Loneliness	-0.08	0.08	-0.09	-0.24	0.07	0.271
Self-Esteem	0.21	0.07	0.24	0.09	0.38	0.003
Stress	-0.16	0.08	-0.15	-0.30	0.01	0.061
Health	2.14	2.00	0.09	-0.07	0.24	0.286
Hypothesis 1. Digital Diet vs. Both Controls:						
Brief Happiness	0.03	0.07	0.03	-0.09	0.15	0.611
Brief Satisfaction	0.15	0.15	0.06	-0.06	0.18	0.321
Positive Emotions	-0.03	0.11	-0.02	-0.14	0.10	0.773
Negative Emotions	-0.08	0.10	-0.05	-0.17	0.07	0.416
Life Satisfaction	0.33	0.09	0.21	0.10	0.32	<.001
Mindful Attention	0.36	0.10	0.21	0.10	0.32	<.001
Autonomy	0.23	0.08	0.17	0.05	0.28	0.006
Competence	0.21	0.08	0.15	0.04	0.27	0.011
Connectedness	0.05	0.10	0.03	-0.09	0.15	0.665
Depression	-0.09	0.07	-0.08	-0.2	0.04	0.196
Loneliness	-0.15	0.07	-0.13	-0.25	-0.01	0.030
Self-Esteem	0.26	0.06	0.25	0.14	0.36	<.001
Stress	-0.19	0.07	-0.17	-0.28	-0.05	0.006
Health	3.00	1.80	0.10	-0.02	0.22	0.097

Table 6 (continued)

Variable	b	b SE	Partial r	Partial r 95% CI LL	Partial r 95% CI UL	p
Hypothesis 2. Social Diet vs. Water Diet:						
Brief Happiness	0.14	0.08	0.14	-0.01	0.27	0.066
Brief Satisfaction	0.19	0.16	0.08	-0.06	0.23	0.258
Positive Emotions	-0.06	0.14	-0.03	-0.18	0.11	0.648
Negative Emotions	0.10	0.11	0.07	-0.08	0.21	0.365
Life Satisfaction	0.20	0.11	0.14	-0.01	0.28	0.065
Mindful Attention	0.31	0.11	0.21	0.06	0.34	0.005
Autonomy	0.04	0.10	0.03	-0.12	0.17	0.706
Competence	0.07	0.10	0.05	-0.09	0.20	0.476
Connectedness	0.00	0.12	0.00	-0.14	0.15	0.979
Depression	0.00	0.07	0.00	-0.14	0.15	0.961
Loneliness	-0.07	0.08	-0.06	-0.21	0.08	0.406
Self-Esteem	0.05	0.07	0.06	-0.09	0.20	0.455
Stress	-0.08	0.08	-0.07	-0.21	0.07	0.333
Health	-0.31	2.23	-0.01	-0.16	0.14	0.891
Hypothesis 2. Social Diet vs. No Diet:						
Brief Happiness	0.00	0.08	0.00	-0.17	0.16	0.960
Brief Satisfaction	0.10	0.18	0.05	-0.12	0.21	0.559
Positive Emotions	-0.27	0.13	-0.17	-0.32	-0.01	0.043
Negative Emotions	0.34	0.12	0.23	0.07	0.37	0.006
Life Satisfaction	0.14	0.12	0.09	-0.07	0.25	0.264
Mindful Attention	0.21	0.13	0.13	-0.03	0.29	0.109
Autonomy	-0.03	0.10	-0.03	-0.19	0.14	0.737
Competence	0.05	0.10	0.04	-0.13	0.20	0.664
Connectedness	-0.09	0.12	-0.06	-0.22	0.11	0.485
Depression	0.03	0.08	0.03	-0.13	0.19	0.730
Loneliness	0.03	0.09	0.03	-0.13	0.19	0.701
Self-Esteem	-0.01	0.08	-0.01	-0.18	0.15	0.871
Stress	-0.01	0.09	-0.01	-0.17	0.15	0.900
Health	-2.37	2.26	-0.09	-0.24	0.08	0.297
Hypothesis 2. Social Diet vs. Both Controls:						
Brief Happiness	0.09	0.07	0.07	-0.05	0.19	0.231
Brief Satisfaction	0.15	0.16	0.06	-0.06	0.18	0.340
Positive Emotions	-0.15	0.12	-0.08	-0.20	0.04	0.213
Negative Emotions	0.19	0.10	0.12	-0.01	0.23	0.060
Life Satisfaction	0.18	0.10	0.11	-0.01	0.23	0.079
Mindful Attention	0.26	0.10	0.16	0.04	0.27	0.012
Autonomy	0.01	0.09	0.01	-0.12	0.13	0.932
Competence	0.06	0.09	0.04	-0.08	0.16	0.507
Connectedness	-0.03	0.11	-0.02	-0.14	0.11	0.805
Depression	0.01	0.07	0.01	-0.11	0.13	0.858
Loneliness	-0.03	0.07	-0.02	-0.14	0.10	0.703
Self-Esteem	0.03	0.07	0.02	-0.10	0.15	0.691
Stress	-0.05	0.07	-0.04	-0.16	0.08	0.486
Health	-1.21	1.98	-0.04	-0.16	0.08	0.544

Table 6 (continued)

Variable	*b*	*b SE*	Partial *r*	Partial *r* 95% CI *LL*	*UL*	*p*
Exploratory. Digital Diet vs. Social Diet:						
Brief Happiness	-0.03	0.08	-0.03	-0.19	0.14	0.728
Brief Satisfaction	-0.03	0.16	-0.02	-0.18	0.15	0.834
Positive Emotions	0.12	0.14	0.07	-0.10	0.23	0.399
Negative Emotions	-0.27	0.13	-0.17	-0.32	0.00	0.044
Life Satisfaction	0.16	0.11	0.12	-0.04	0.28	0.139
Mindful Attention	0.08	0.13	0.05	-0.11	0.22	0.531
Autonomy	0.21	0.10	0.17	0.00	0.32	0.045
Competence	0.14	0.10	0.11	-0.05	0.27	0.180
Connectedness	0.06	0.12	0.04	-0.12	0.21	0.613
Depression	-0.11	0.07	-0.12	-0.28	0.04	0.140
Loneliness	-0.12	0.08	-0.12	-0.27	0.05	0.168
Self-Esteem	0.23	0.08	0.24	0.08	0.38	0.004
Stress	-0.16	0.10	-0.14	-0.29	0.03	0.100
Health	4.55	2.25	0.17	0.00	0.32	0.045

Note. Hypothesized condition dummy codes predicting T_2 scores, controlling for T_1 scores. Positive *b*s suggest the treatment group (Digital Diet, Social Diet) reported greater increases than the reference group (Water Diet, No Diet, Both Controls, Social Diet). Negative *b*s suggest the treatment group reported greater decreases than the reference group. CI = confidence interval; LL = lower limit; UL = upper limit.

Table 7

Study 2 Fit Statistics of Second-Order Latent Growth Models

Construct	χ^2	df	CFI	TLI	RMSEA [90% CI]	SRMR
Hypothesis 1. Digital Diet vs. Water Diet:						
Positive Emotions	203.092	66	0.924	0.910	0.104 [0.088, 0.121]	0.073
Negative Emotions	162.918	66	0.898	0.880	0.088 [0.071, 0.105]	0.066
Life Satisfaction	71.250	44	0.982	0.977	0.057 [0.031, 0.080]	0.038
Mindful Attention	85.243	66	0.950	0.937	0.070 [0.047, 0.092]	0.051
Autonomy	10.466	12	1.000	1.006	0.000 [0.000, 0.066]	0.029
Competence	25.129	12	0.968	0.944	0.076 [0.033, 0.117]	0.050
Connectedness	27.107	12	0.980	0.964	0.081 [0.040, 0.122]	0.041
Depression	148.861	66	0.951	0.942	0.081 [0.064, 0.098]	0.053
Loneliness	302.270	66	0.813	0.779	0.137 [0.121, 0.153]	0.139
Self-Esteem	147.226	66	0.943	0.932	0.080 [0.063, 0.098]	0.047
Stress	42.487	26	0.970	0.959	0.058 [0.022, 0.088]	0.051
Health	100.324	44	0.902	0.877	0.082 [0.061, 0.103]	0.071
Hypothesis 1. Digital Diet vs. No Diet:						
Positive Emotions	169.293	66	0.926	0.913	0.100 [0.082, 0.119]	0.058
Negative Emotions	153.736	66	0.891	0.872	0.092 [0.073, 0.111]	0.066
Life Satisfaction	92.842	44	0.953	0.942	0.084 [0.060, 0.108]	0.060
Mindful Attention	88.902	66	0.932	0.915	0.081 [0.056, 0.105]	0.060
Autonomy	17.079	12	0.985	0.974	0.052 [0.000, 0.104]	0.044
Competence	17.558	12	0.984	0.972	0.054 [0.000, 0.106]	0.042
Connectedness	15.746	12	0.993	0.988	0.045 [0.000, 0.099]	0.037
Depression	120.322	66	0.957	0.949	0.073 [0.052, 0.093]	0.064
Loneliness	247.956	66	0.767	0.725	0.133 [0.116, 0.151]	0.100
Self-Esteem	105.791	66	0.964	0.958	0.062 [0.039, 0.084]	0.051
Stress	43.548	26	0.953	0.934	0.066 [0.028, 0.099]	0.058
Health	86.263	44	0.917	0.897	0.078 [0.054, 0.103]	0.068
Hypothesis 1. Digital Diet vs. Both Controls:						
Positive Emotions	235.513	66	0.936	0.924	0.097 [0.084, 0.111]	0.059
Negative Emotions	179.800	66	0.919	0.905	0.080 [0.066, 0.094]	0.054
Life Satisfaction	82.220	44	0.980	0.975	0.057 [0.037, 0.075]	0.037
Mindful Attention	105.095	66	0.948	0.935	0.072 [0.054, 0.089]	0.046
Autonomy	10.833	12	1.000	1.003	0.000 [0.000, 0.057]	0.026
Competence	16.979	12	0.992	0.986	0.039 [0.000, 0.079]	0.034
Connectedness	26.226	12	0.987	0.977	0.066 [0.031, 0.101]	0.032
Depression	170.993	66	0.954	0.946	0.077 [0.063, 0.091]	0.051
Loneliness	391.160	66	0.808	0.773	0.135 [0.122, 0.148]	0.133
Self-Esteem	145.644	66	0.961	0.953	0.067 [0.052, 0.081]	0.041
Stress	45.773	26	0.972	0.961	0.053 [0.026, 0.078]	0.046
Health	135.605	44	0.896	0.870	0.088 [0.071, 0.105]	0.069

Table 7 (Continued)

Construct	χ^2	df	CFI	TLI	RMSEA [90% CI]	SRMR
Hypothesis 2. Social Diet vs. Water Diet:						
Positive Emotions	180.423	66	0.934	0.922	0.098 [0.081, 0.115]	0.065
Negative Emotions	135.925	66	0.928	0.915	0.076 [0.058, 0.094]	0.062
Life Satisfaction	46.848	44	0.998	0.997	0.019 [0.000, 0.054]	0.037
Mindful Attention	62.521	66	0.977	0.971	0.048 [0.014, 0.074]	0.042
Autonomy	14.299	12	0.994	0.990	0.032 [0.000, 0.086]	0.041
Competence	21.360	12	0.977	0.959	0.065 [0.009, 0.110]	0.044
Connectedness	22.626	12	0.986	0.975	0.070 [0.021, 0.113]	0.035
Depression	140.265	66	0.950	0.941	0.079 [0.061, 0.097]	0.050
Loneliness	270.152	66	0.837	0.807	0.130 [0.114, 0.147]	0.147
Self-Esteem	112.979	66	0.965	0.959	0.063 [0.042, 0.082]	0.046
Stress	19.360	26	1.000	1.021	0.000 [0.000, 0.037]	0.041
Health	136.043	44	0.860	0.824	0.107 [0.087, 0.128]	0.089
Hypothesis 2. Social Diet vs. No Diet:						
Positive Emotions	163.364	66	0.930	0.917	0.100 [0.081, 0.120]	0.056
Negative Emotions	134.139	66	0.919	0.904	0.084 [0.063, 0.104]	0.066
Life Satisfaction	61.227	44	0.979	0.973	0.052 [0.009, 0.081]	0.055
Mindful Attention	89.487	66	0.933	0.917	0.084 [0.059, 0.109]	0.064
Autonomy	31.912	12	0.941	0.896	0.106 [0.062, 0.152]	0.060
Competence	17.315	12	0.984	0.973	0.055 [0.000, 0.108]	0.039
Connectedness	14.292	12	0.996	0.993	0.036 [0.000, 0.095]	0.037
Depression	109.664	66	0.959	0.952	0.067 [0.044, 0.089]	0.057
Loneliness	226.074	66	0.810	0.776	0.128 [0.110, 0.147]	0.130
Self-Esteem	101.318	66	0.968	0.962	0.060 [0.035, 0.083]	0.054
Stress	25.230	26	1.000	1.003	0.000 [0.000, 0.063]	0.046
Health	109.762	44	0.886	0.858	0.101 [0.077, 0.125]	0.083
Hypothesis 2. Social Diet vs. Both Controls:						
Positive Emotions	223.392	66	0.939	0.928	0.095 [0.082, 0.109]	0.055
Negative Emotions	163.534	66	0.932	0.920	0.075 [0.061, 0.090]	0.053
Life Satisfaction	58.973	44	0.991	0.989	0.036 [0.000, 0.058]	0.035
Mindful Attention	83.873	66	0.966	0.958	0.059 [0.039, 0.078]	0.041
Autonomy	19.516	12	0.988	0.979	0.049 [0.000, 0.087]	0.038
Competence	18.319	12	0.990	0.982	0.045 [0.000, 0.084]	0.031
Connectedness	22.058	12	0.991	0.984	0.057 [0.014, 0.093]	0.028
Depression	169.019	66	0.951	0.942	0.077 [0.063, 0.092]	0.048
Loneliness	367.386	66	0.824	0.792	0.132 [0.119, 0.145]	0.139
Self-Esteem	122.605	66	0.971	0.966	0.057 [0.041, 0.073]	0.040
Stress	24.577	26	1.000	1.003	0.000 [0.000, 0.046]	0.038
Health	166.086	44	0.873	0.841	0.103 [0.087, 0.120]	0.080

Table 7 (Continued)

Construct	χ^2	df	CFI	TLI	RMSEA [90% CI]	SRMR
Exploratory. Digital Diet vs. Social Diet:						
Positive Emotions	168.056	66	0.906	0.889	0.104 [0.085, 0.124]	0.067
Negative Emotions	146.272	66	0.880	0.858	0.092 [0.072, 0.112]	0.071
Life Satisfaction	61.125	44	0.981	0.976	0.052 [0.009, 0.082]	0.048
Mindful Attention	73.534	66	0.944	0.930	0.069 [0.039, 0.095]	0.057
Autonomy	19.033	12	0.973	0.953	0.064 [0.000, 0.116]	0.056
Competence	27.372	12	0.948	0.909	0.095 [0.047, 0.142]	0.052
Connectedness	24.685	12	0.972	0.951	0.086 [0.036, 0.134]	0.058
Depression	126.608	66	0.944	0.934	0.080 [0.059, 0.101]	0.061
Loneliness	216.652	66	0.803	0.768	0.126 [0.108, 0.145]	0.118
Self-Esteem	119.930	66	0.943	0.932	0.076 [0.054, 0.097]	0.057
Stress	50.497	26	0.932	0.906	0.081 [0.047, 0.114]	0.057
Health	86.280	44	0.911	0.889	0.082 [0.056, 0.107]	0.075

Note. CFI = Comparative Fit Index. TLI = Tucker-Lewis Index. RMSEA = Root Mean Square Error of Approximation. SRMR = Standardized Root Mean Square Residual.

Table 8

Study 2 Second-Order Latent Growth Models

Variable	*b*	*b SE*	*p*
Hypothesis 1. Digital Diet vs. Water Diet:			
Positive Emotions	0.06	0.13	0.655
Negative Emotions	-0.13	0.09	0.145
Life Satisfaction	0.32	0.11	0.002
Mindful Attention	0.44	0.12	<.001
Autonomy	0.24	0.09	0.007
Competence	0.25	0.10	0.014
Connectedness	0.08	0.11	0.482
Depression	-0.08	0.08	0.363
Loneliness	-0.17	0.07	0.016
Self-Esteem	0.30	0.07	<.001
Stress	-0.23	0.09	0.007
Health	3.16	1.99	0.112
Hypothesis 1. Digital Diet vs. No Diet:			
Positive Emotions	-0.16	0.12	0.173
Negative Emotions	0.01	0.13	0.951
Life Satisfaction	0.33	0.13	0.009
Mindful Attention	0.33	0.13	0.008
Autonomy	0.16	0.09	0.070
Competence	0.24	0.11	0.023
Connectedness	-0.04	0.11	0.733
Depression	-0.10	0.09	0.274
Loneliness	-0.13	0.11	0.246
Self-Esteem	0.22	0.08	0.005
Stress	-0.15	0.09	0.094
Health	1.48	1.70	0.384
Hypothesis 1. Digital Diet vs. Both Controls:			
Positive Emotions	-0.04	0.11	0.710
Negative Emotions	-0.08	0.09	0.375
Life Satisfaction	0.32	0.10	0.002
Mindful Attention	0.36	0.10	<.001
Autonomy	0.22	0.08	0.007
Competence	0.24	0.09	0.009
Connectedness	0.03	0.10	0.736
Depression	-0.09	0.08	0.273
Loneliness	-0.14	0.06	0.020
Self-Esteem	0.27	0.07	<.001
Stress	-0.17	0.07	0.024
Health	2.34	1.69	0.167

Table 8 (continued)

Variable	*b*	*b SE*	*p*
Hypothesis 2. Social Diet vs. Water Diet:			
Positive Emotions	-0.05	0.14	0.711
Negative Emotions	0.10	0.10	0.302
Life Satisfaction	0.21	0.12	0.073
Mindful Attention	0.30	0.11	0.006
Autonomy	-0.03	0.09	0.745
Competence	0.07	0.11	0.664
Connectedness	-0.02	0.11	0.887
Depression	0.02	0.08	0.845
Loneliness	-0.11	0.07	0.150
Self-Esteem	0.07	0.08	0.400
Stress	-0.07	0.09	0.431
Health	-0.22	1.94	0.909
Hypothesis 2. Social Diet vs. No Diet:			
Positive Emotions	-0.27	0.13	0.043
Negative Emotions	0.34	0.14	0.014
Life Satisfaction	0.19	0.14	0.179
Mindful Attention	0.15	0.10	0.159
Autonomy	-0.06	0.09	0.515
Competence	0.07	0.12	0.576
Connectedness	-0.10	0.11	0.368
Depression	0.03	0.08	0.767
Loneliness	-0.03	0.08	0.724
Self-Esteem	-0.02	0.09	0.856
Stress	-0.01	0.08	0.933
Health	-1.98	1.83	0.279
Hypothesis 2. Social Diet vs. Both Controls:			
Positive Emotions	-0.15	0.12	0.228
Negative Emotions	0.18	0.10	0.067
Life Satisfaction	0.20	0.11	0.074
Mindful Attention	0.23	0.10	0.018
Autonomy	-0.04	0.08	0.662
Competence	0.06	0.10	0.518
Connectedness	-0.04	0.10	0.691
Depression	0.02	0.08	0.832
Loneliness	-0.08	0.06	0.193
Self-Esteem	0.04	0.08	0.594
Stress	-0.04	0.07	0.595
Health	-1.14	1.73	0.507

Table 8 (continued)

Variable	*b*	*b SE*	*p*
Exploratory. Digital Diet vs. Social Diet:			
Positive Emotions	0.10	0.15	0.475
Negative Emotions	-0.25	0.13	0.047
Life Satisfaction	0.12	0.12	0.316
Mindful Attention	0.07	0.12	0.562
Autonomy	0.20	0.09	0.031
Competence	0.21	0.13	0.095
Connectedness	0.05	0.11	0.638
Depression	-0.09	0.07	0.236
Loneliness	-0.08	0.08	0.315
Self-Esteem	0.22	0.08	0.009
Stress	-0.16	0.10	0.113
Health	3.39	1.77	0.055

Note. Positive *b*s suggest the treatment group (Digital Diet, Social Diet) reported greater increases than the reference group (Water Diet, No Diet, Both Controls, Social Diet). Negative *b*s suggest the treatment group reported greater decreases than the reference group. SOLGM analyses were not conducted for single-item variables (e.g., Objective Digital Media Time, Brief Happiness).

Table 9

Study 2 Intention-to-Treat (ITT) Outcome Regressed Change Models

Variable	*b*	*b SE*	Partial *r*	Partial *r* 95% CI *LL*	Partial *r* 95% CI *UL*	*p*
ITT. Hypothesis 1. Digital Diet vs. Water Diet:						
Brief Happiness	0.09	0.07	0.09	-0.04	0.22	0.170
Brief Satisfaction	0.21	0.15	0.10	-0.04	0.23	0.154
Positive Emotions	0.11	0.12	0.06	-0.07	0.19	0.363
Negative Emotions	-0.13	0.11	-0.09	-0.22	0.05	0.212
Life Satisfaction	0.33	0.10	0.23	0.10	0.34	0.001
Mindful Attention	0.36	0.10	0.24	0.11	0.36	<.001
Autonomy	0.25	0.09	0.19	0.06	0.31	0.005
Competence	0.25	0.08	0.20	0.07	0.32	0.003
Connectedness	0.14	0.11	0.09	-0.05	0.22	0.207
Depression	-0.08	0.07	-0.08	-0.21	0.05	0.239
Loneliness	-0.15	0.07	-0.15	-0.28	-0.02	0.027
Self-Esteem	0.25	0.06	0.27	0.14	0.38	<.001
Stress	-0.22	0.07	-0.21	-0.33	-0.08	0.002
Health	3.33	1.79	0.13	-0.01	0.25	0.064
ITT. Hypothesis 1. Digital Diet vs. No Diet:						
Brief Happiness	-0.04	0.07	-0.05	-0.19	0.10	0.535
Brief Satisfaction	0.08	0.16	0.04	-0.11	0.18	0.621
Positive Emotions	-0.14	0.12	-0.09	-0.24	0.06	0.218
Negative Emotions	0.10	0.12	0.06	-0.09	0.21	0.425
Life Satisfaction	0.24	0.11	0.16	0.02	0.30	0.029
Mindful Attention	0.26	0.11	0.17	0.02	0.31	0.024
Autonomy	0.13	0.09	0.11	-0.04	0.25	0.159
Competence	0.20	0.09	0.18	0.03	0.31	0.020
Connectedness	0.00	0.11	0.00	-0.15	0.15	0.971
Depression	-0.05	0.07	-0.05	-0.20	0.10	0.511
Loneliness	-0.04	0.07	-0.04	-0.18	0.11	0.616
Self-Esteem	0.16	0.07	0.17	0.02	0.31	0.023
Stress	-0.13	0.08	-0.13	-0.27	0.02	0.094
Health	1.88	1.84	0.08	-0.07	0.22	0.308
ITT. Hypothesis 1. Digital Diet vs. Both Controls:						
Brief Happiness	0.03	0.06	0.03	-0.08	0.15	0.578
Brief Satisfaction	0.16	0.14	0.07	-0.05	0.18	0.243
Positive Emotions	0.00	0.10	0.00	-0.11	0.12	0.984
Negative Emotions	-0.03	0.10	-0.02	-0.13	0.10	0.766
Life Satisfaction	0.29	0.09	0.19	0.08	0.29	0.001
Mindful Attention	0.31	0.09	0.19	0.08	0.30	0.001
Autonomy	0.20	0.08	0.15	0.03	0.26	0.011
Competence	0.23	0.07	0.18	0.07	0.28	0.002
Connectedness	0.08	0.10	0.05	-0.06	0.16	0.381
Depression	-0.07	0.06	-0.06	-0.17	0.05	0.287
Loneliness	-0.10	0.06	-0.10	-0.21	0.02	0.100
Self-Esteem	0.21	0.06	0.21	0.10	0.32	< .001
Stress	-0.17	0.06	-0.16	-0.27	-0.05	0.006
Health	2.63	1.61	0.09	-0.02	0.21	0.104

Table 9 (continued)

Variable	*b*	*b SE*	Partial *r*	Partial *r* 95% CI *LL*	Partial *r* 95% CI *UL*	*p*
ITT. Hypothesis 2. Social Diet vs. Water Diet:						
Brief Happiness	0.12	0.07	0.11	-0.02	0.25	0.103
Brief Satisfaction	0.23	0.15	0.1	-0.03	0.24	0.138
Positive Emotions	-0.04	0.13	-0.02	-0.16	0.12	0.766
Negative Emotions	0.12	0.10	0.08	-0.06	0.21	0.262
Life Satisfaction	0.21	0.10	0.14	0	0.27	0.044
Mindful Attention	0.3	0.10	0.20	0.06	0.32	0.004
Autonomy	0.06	0.09	0.05	-0.09	0.18	0.494
Competence	0.15	0.09	0.11	-0.02	0.25	0.106
Connectedness	0.00	0.11	0.00	-0.14	0.14	0.991
Depression	0.00	0.07	0.00	-0.14	0.14	0.975
Loneliness	-0.06	0.08	-0.06	-0.19	0.08	0.419
Self-Esteem	0.07	0.07	0.07	-0.07	0.21	0.298
Stress	-0.08	0.08	-0.08	-0.21	0.06	0.273
Health	1.34	2.08	0.05	-0.09	0.18	0.520
ITT. Hypothesis 2. Social Diet vs. No Diet:						
Brief Happiness	-0.03	0.08	-0.03	-0.18	0.13	0.724
Brief Satisfaction	0.10	0.17	0.05	-0.11	0.20	0.547
Positive Emotions	-0.28	0.13	-0.17	-0.31	-0.01	0.032
Negative Emotions	0.38	0.12	0.25	0.10	0.38	0.002
Life Satisfaction	0.12	0.12	0.08	-0.07	0.23	0.307
Mindful Attention	0.18	0.12	0.12	-0.04	0.26	0.141
Autonomy	-0.03	0.10	-0.02	-0.18	0.13	0.774
Competence	0.11	0.10	0.09	-0.07	0.24	0.266
Connectedness	-0.11	0.12	-0.07	-0.22	0.08	0.358
Depression	0.03	0.07	0.03	-0.12	0.19	0.670
Loneliness	0.04	0.08	0.04	-0.11	0.19	0.592
Self-Esteem	-0.02	0.07	-0.02	-0.17	0.14	0.839
Stress	0.00	0.08	0.00	-0.15	0.16	0.985
Health	-0.55	2.19	-0.02	-0.18	0.13	0.765
ITT. Hypothesis 2. Social Diet vs. Both Controls:						
Brief Happiness	0.06	0.07	0.06	-0.06	0.17	0.348
Brief Satisfaction	0.18	0.14	0.07	-0.04	0.19	0.219
Positive Emotions	-0.14	0.11	-0.07	-0.19	0.04	0.226
Negative Emotions	0.22	0.10	0.13	0.02	0.25	0.024
Life Satisfaction	0.18	0.10	0.11	-0.01	0.22	0.066
Mindful Attention	0.24	0.10	0.15	0.03	0.26	0.011
Autonomy	0.03	0.08	0.02	-0.10	0.13	0.759
Competence	0.13	0.08	0.10	-0.02	0.21	0.108
Connectedness	-0.04	0.10	-0.02	-0.14	0.09	0.711
Depression	0.01	0.06	0.01	-0.11	0.13	0.877
Loneliness	-0.02	0.07	-0.02	-0.13	0.10	0.764
Self-Esteem	0.04	0.06	0.04	-0.08	0.15	0.555
Stress	-0.05	0.07	-0.04	-0.16	0.07	0.478
Health	0.51	1.83	0.02	-0.10	0.13	0.780

Table 9 (continued)

Variable	*b*	*b SE*	Partial *r*	Partial *r* 95% CI		*p*
				LL	*UL*	
ITT. Exploratory. Digital Diet vs. Social Diet:						
Brief Happiness	-0.01	0.07	-0.01	-0.16	0.13	0.867
Brief Satisfaction	-0.03	0.14	-0.02	-0.16	0.13	0.829
Positive Emotions	0.13	0.13	0.08	-0.07	0.22	0.293
Negative Emotions	-0.23	0.12	-0.14	-0.28	0.00	0.055
Life Satisfaction	0.12	0.10	0.09	-0.06	0.23	0.253
Mindful Attention	0.04	0.11	0.03	-0.12	0.17	0.692
Autonomy	0.16	0.09	0.13	-0.02	0.27	0.085
Competence	0.09	0.09	0.07	-0.08	0.21	0.338
Connectedness	0.11	0.11	0.07	-0.07	0.22	0.332
Depression	-0.08	0.06	-0.09	-0.23	0.06	0.220
Loneliness	-0.07	0.08	-0.07	-0.21	0.08	0.337
Self-Esteem	0.17	0.07	0.18	0.03	0.31	0.018
Stress	-0.13	0.08	-0.12	-0.26	0.03	0.115
Health	2.74	2.00	0.10	-0.05	0.24	0.172

Note. Intention-to-treat analyses include all participants randomized to condition. Hypothesized condition dummy codes predicting T_2 scores, controlling for T_1 scores. Positive *b*s suggest the treatment group (Digital Diet, Social Diet) reported greater increases than the reference group (Water Diet, No Diet, Both Controls, Social Diet). Negative *b*s suggest the treatment group reported greater decreases than the reference group. CI = confidence interval; LL = lower limit; UL = upper limit.

Figures

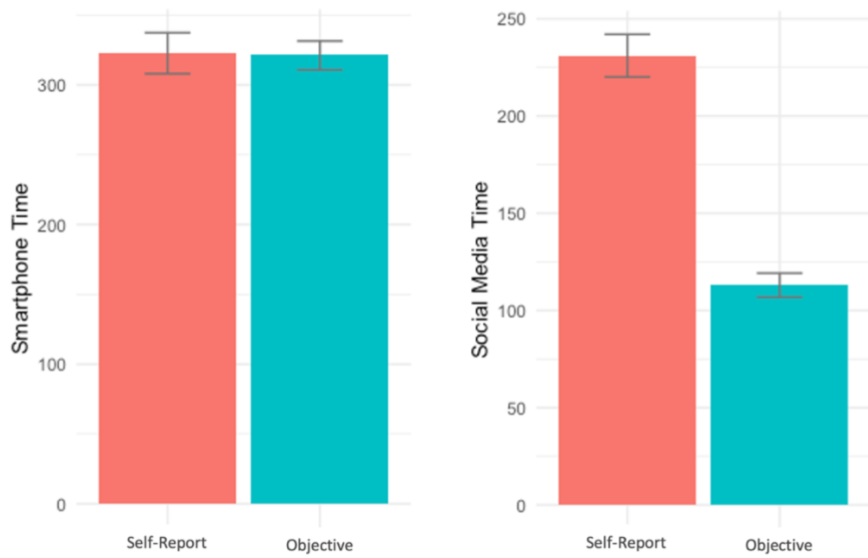
Figure 1

Example iPhone Screen Time Screenshots

Note. The above screenshots were collected using an Apple iPhone 7 Plus running mobile operating system iOS 12.

Figure 2

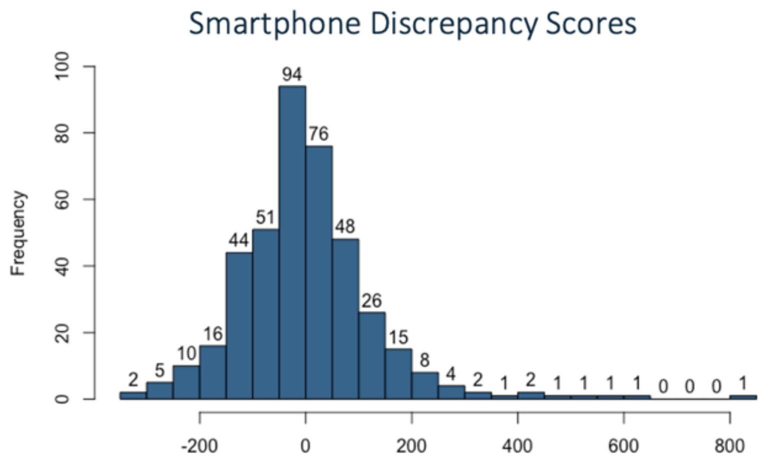
Study 1 Self-Report vs. Objective Time Means

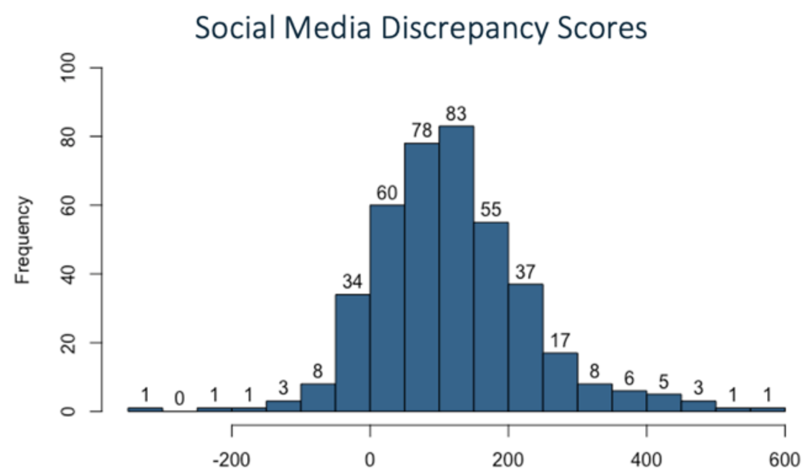


Note. Self-report vs. objective smartphone and social media time (in minutes). For ease of interpretation, means are presented in raw (not log-transformed) form.

Figure 3

Study 1 Self-Report vs. Objective Discrepancy Score Histograms

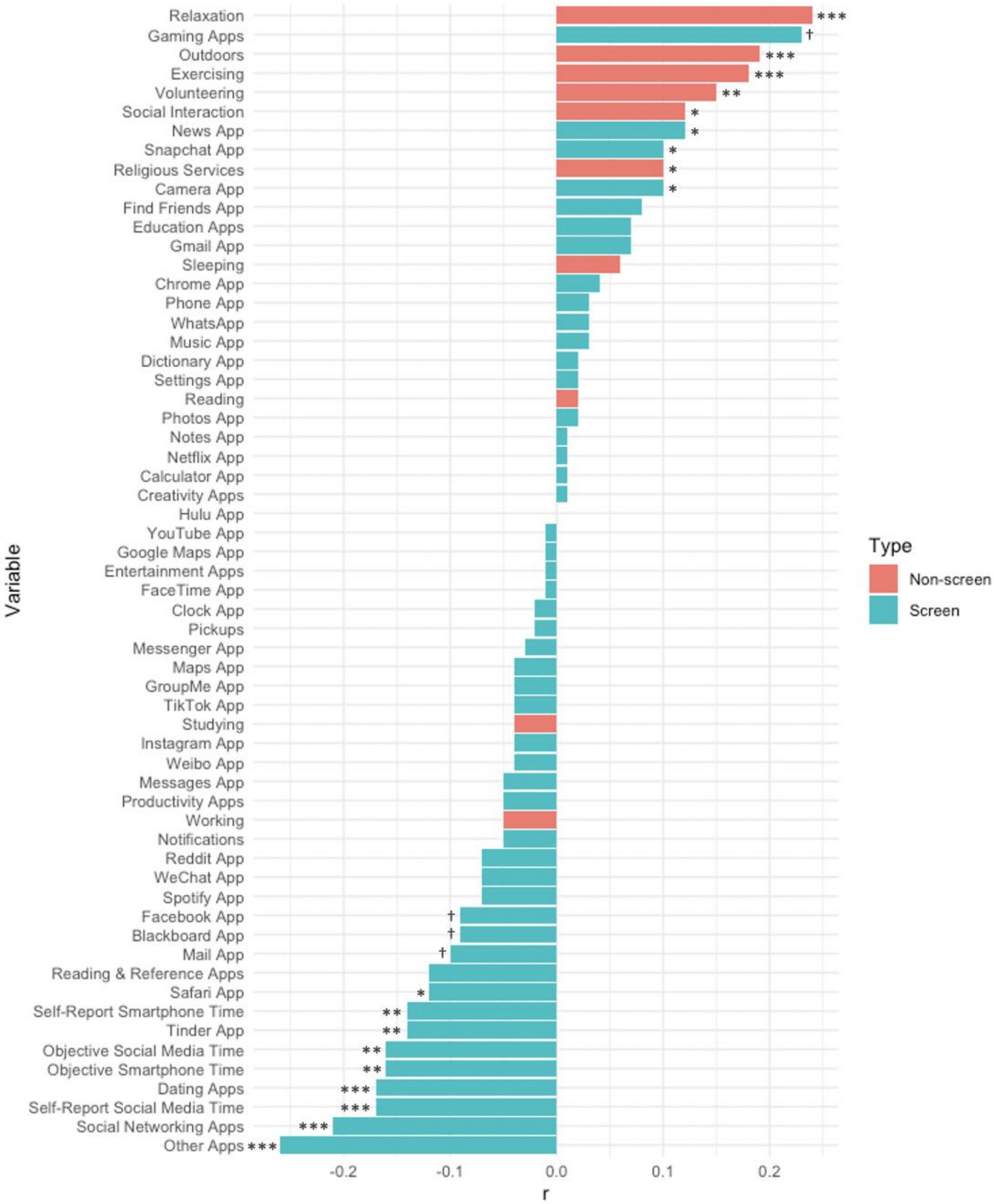




Note. Histograms of smartphone and social media time discrepancy scores (self-report – objective indicators) presented in raw (not log-transformed) form (in minutes).

Figure 4

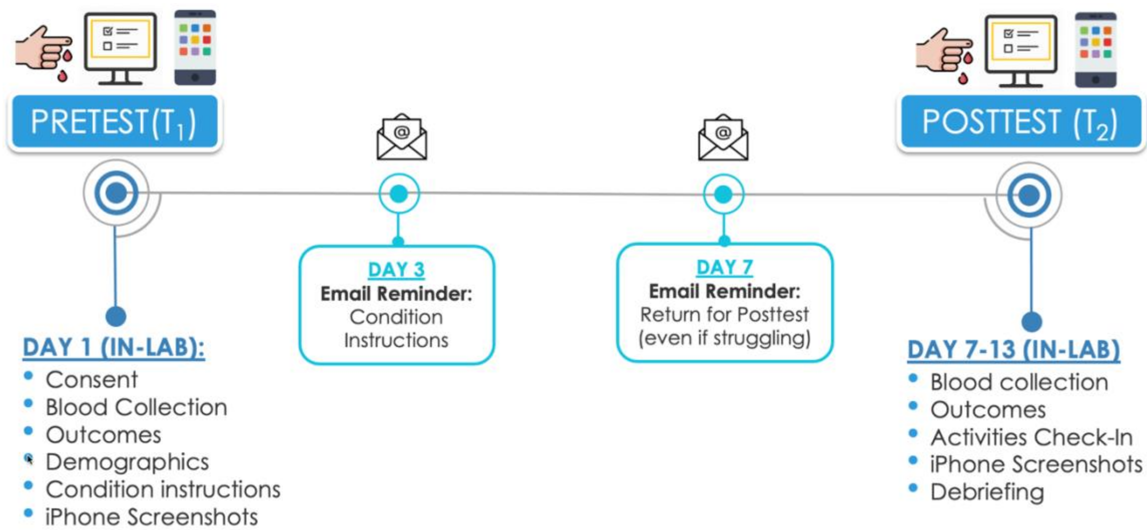
Study 1 Well-Being Correlations



Note. Standardized well-being composite correlations with non-screen activities (e.g., spending time relaxing, outdoors, volunteering; pink bars) and objective screen activities (e.g., gaming apps, Snapchat, Facebook; blue bars). †$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

Figure 5

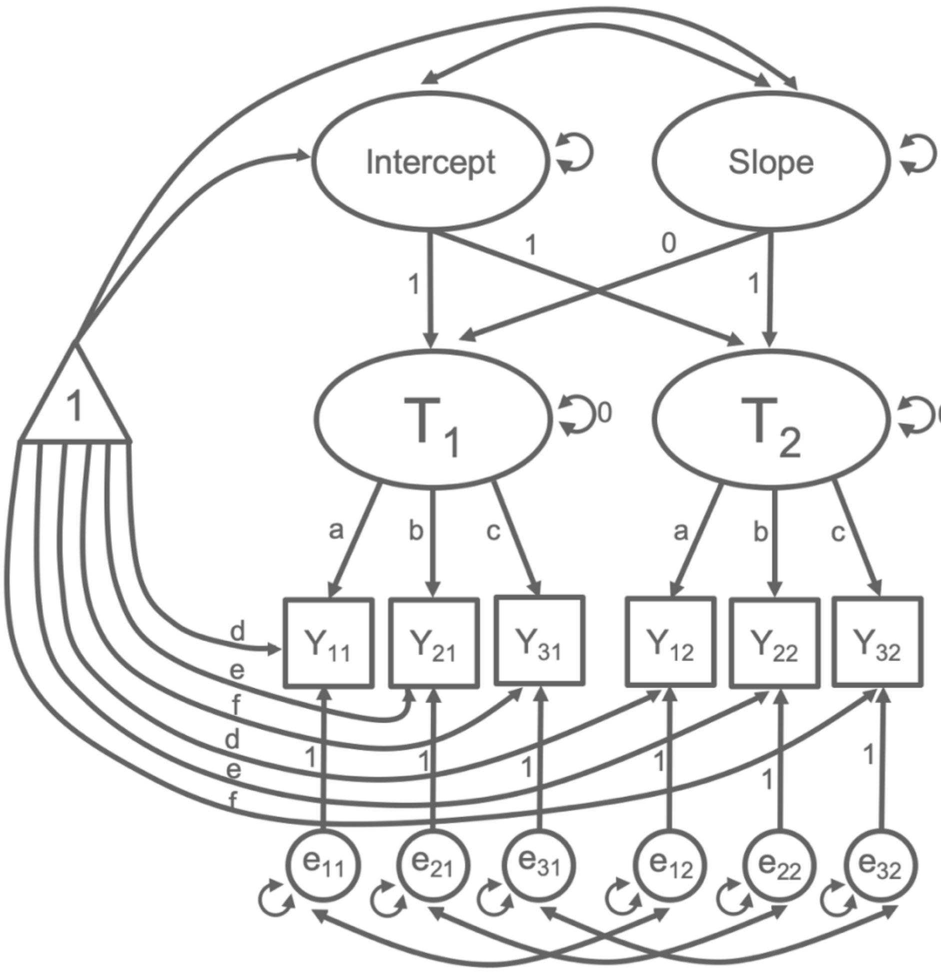
Study 2 Timeline



Note. Study 2 timeline with T_1 (pretest) on Day 1 and T_2 (posttest) on Day 7-13. Figure designed using resources from Flaticon.com

Figure 6

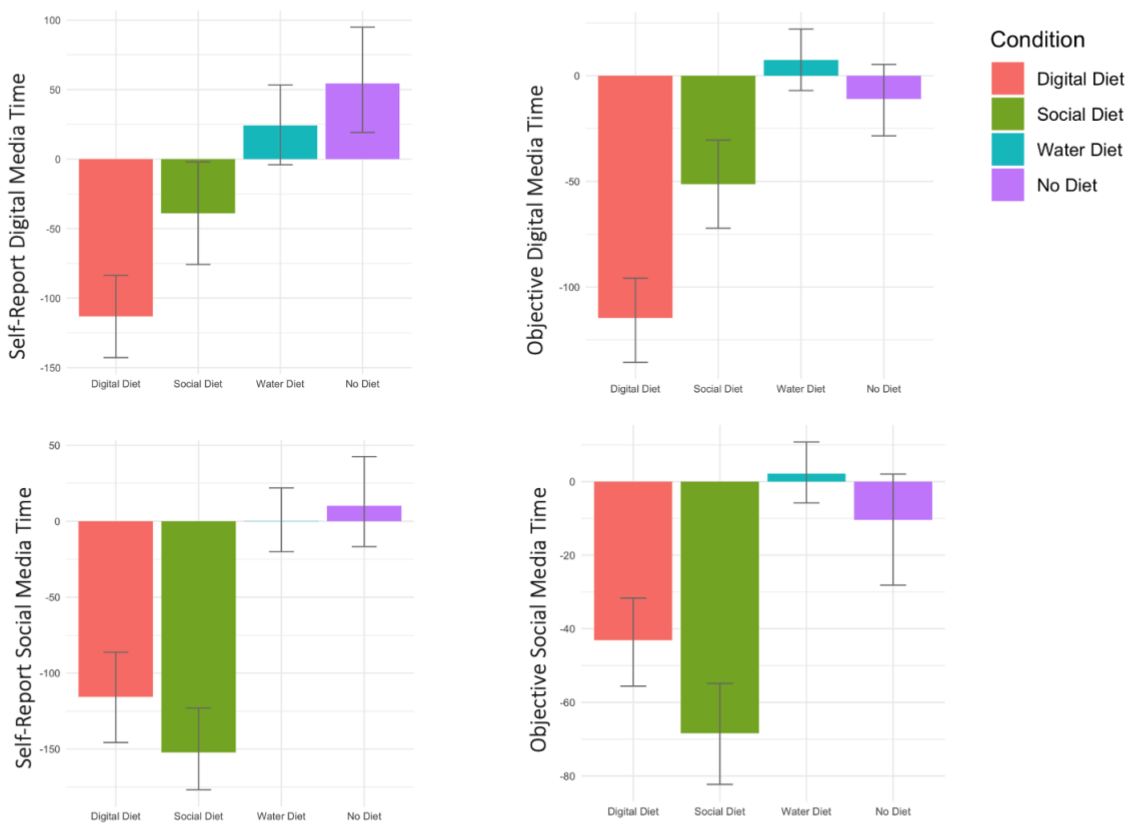
Example Second-Order Latent Growth Model



Note. Example second-order latent growth model used to model growth in outcome measures (e.g., positive affect, life satisfaction) from T_1 to T_2. Factor loadings were constrained to be equal across time. Correlations between the same items over the same duration were constrained to be equal and first-order latent variables had residual variances set to 0.

Figure 7

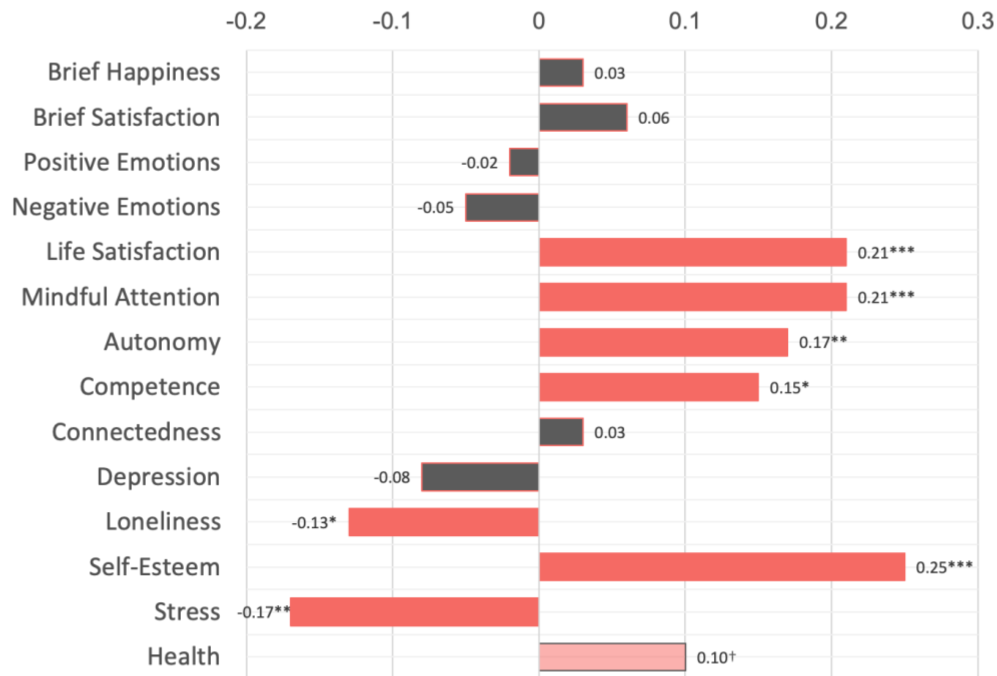
Study 2 Self-Report and Objective Time Difference Scores by Condition



Note. $T_2 - T_1$ difference scores for self-report and objective digital media time and social media time (in minutes). For ease of interpretation, difference scores are presented in raw (not log-transformed) form.

Figure 8

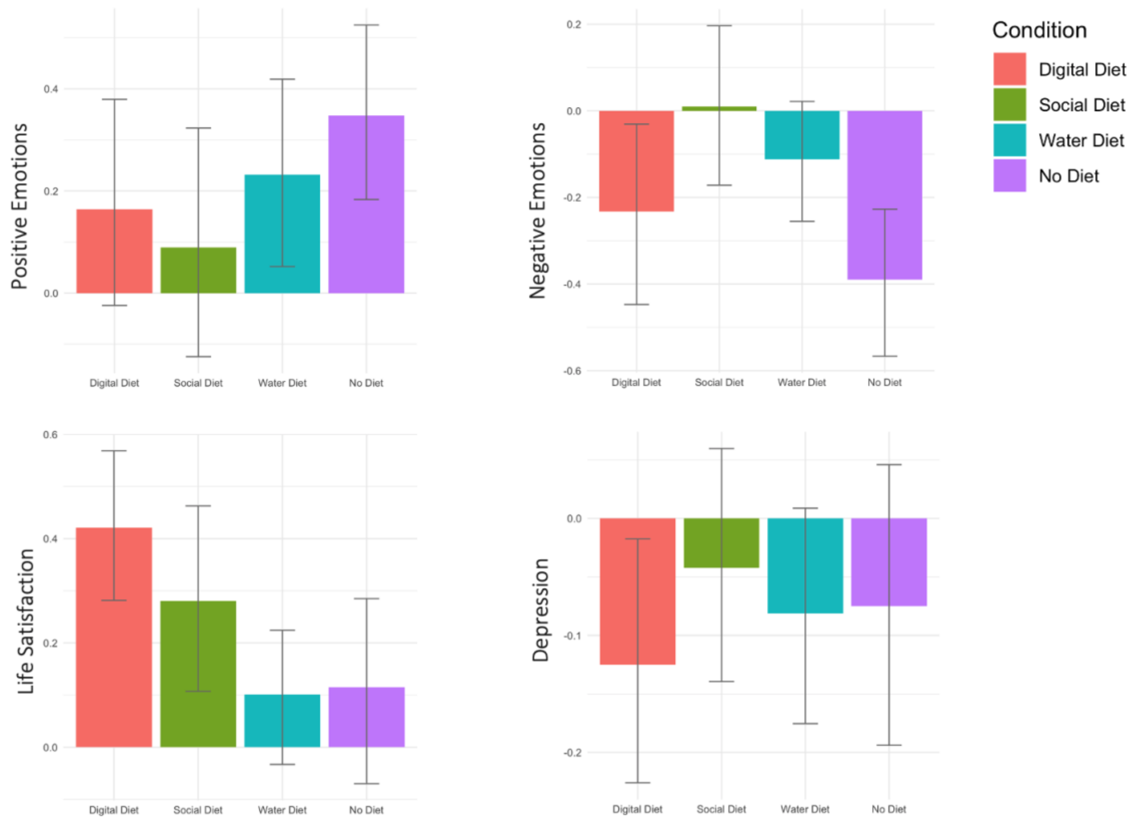
*Study 2 Hypothesis 1 Digital Diet vs. Both Controls Regressed Change Partial r*s



Note. Hypothesized condition dummy codes (Digital Diet vs. Both Controls) predicting T_2 scores, controlling for T_1 scores with *b*s converted to partial *r*s. Dark pink bars present significant regressed changed outcomes, light pink bars present marginal outcomes, and gray bars present non-significant outcomes. †p < .1; *p <.05; **p < .01; ***p < .001.

Figure 9

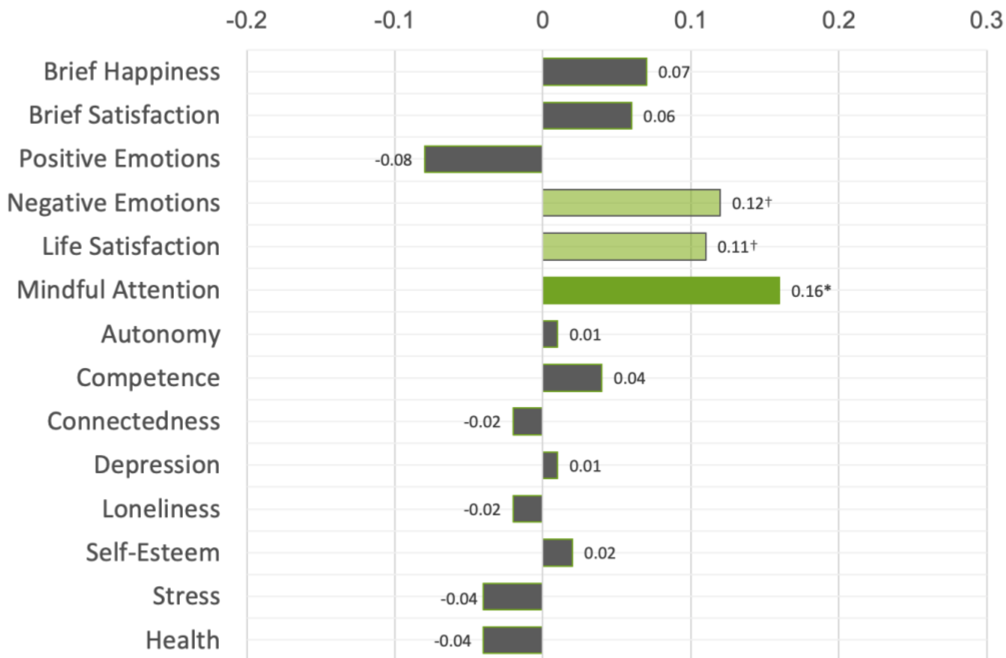
Study 2 Primary Mental Health Outcome Difference Scores by Condition



Note. $T_2 - T_1$ difference scores by condition for four key mental health outcomes: positive emotions, negative emotions, life satisfaction, and depression.

Figure 10

*Study 2 Hypothesis 2 Social Diet vs. Both Controls Regressed Change Partial r*s



Note. Hypothesized condition dummy codes (Social Diet vs. Both Controls) predicting T_2 scores, controlling for T_1 scores with *b*s converted to partial *r*s. Dark green bars present significant regressed changed outcomes, light green bars present marginal outcomes, and gray bars present non-significant outcomes. †p < .1; *p <.05; **p < .01; ***p < .001.