Does Putting Away Your Smartphone Make You Happier?
The Effects of Restricting Digital Media and Social Media on Well-Being

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Abstract

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 links substantial declines in Gen Z well-being to digital and social media use, yet other work suggests the effects are small and unnoteworthy. To further disentangle correlation from causation and better elucidate the strength and direction of effects, we conducted a pre-registered 8-day experimental deprivation study with Gen Z individuals ($N = 338$). Participants 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). (163 words)

Keywords: digital technology, smartphone, social media, well-being

Does Putting Away Your Smartphone Make You Happier?

The Effects of Restricting Digital Media and Social Media on Well-Being

Smartphones are ubiquitous in industrialized and developing nations alike. There are approximately 6.4 billion smartphone users worldwide, and that number is expected to grow by several hundred million in the next few years (O'Dea, 2021a). Smartphone penetration rates have exceeded 50% in many countries, including Brazil (51.4%), Iran (62.9%), China (63.4%), France (77.6%), and the United States (81.6%; O'Dea, 2021b). Clearly, smartphones have permeated every aspect of daily life for many people around the globe, as has the ever-present digital media that come packaged with them. These devices allow for nearly infinite possibilities, from listening to an obscure band on-demand, messaging friends on the go, finding a date for Saturday night, and getting up-to-date movie times and election results to searching for driving directions to unfamiliar locations, sharing photos on social media, replying to work emails while out of office, and Zooming with relatives living abroad. Although the technologies are valuable, rewarding, and convenient in myriad ways, recent research suggests that they may come with some associated costs.

Digital Media and Well-Being

In several correlational studies, Twenge and colleagues (2018a, 2018b) found that Gen Z (or iGen) adolescents in the U.S. ($Ns = 506,820$ to 1.1 million) experienced decreases in psychological well-being and increases in depressive symptoms (including a rise in suicide rates) from 2010 onward. These adolescents also reported drops in self-esteem and domain satisfaction. To account for these shifts, the researchers observed that adolescents who spent

more time on screen activities (e.g., scrolling social media, texting, browsing the Internet, gaming) and less time on non-screen activities (e.g., socializing, exercising, doing homework) reported lower well-being and higher depression. Adolescents who spent a small amount of time on screens were happiest. Partial correlations between happiness and screen activities (including demographic controls) ranged from $r = -0.01$ (reading news online) to $r = -0.11$ (Internet use).

Notably, the observed rise in depressive symptoms and decline in well-being 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 investigations suggest that digital media—specifically, time spent on smartphone-related screen activities—may be harmful to well-being.

Notably, however, drawing on additional correlational studies, 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 (total $N = 355,358$) and found a negative but small association ($\beta = -0.042$) between digital media use and well-being. Comparing this association to other activities, they concluded that digital media's negative effect on well-being was comparable to that of eating potatoes ($\beta = -0.042$) and wearing eyeglasses ($\beta = -0.061$).

Another follow-up investigation by Orben and Przybylski 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 $\beta = -0.08$, but time-use diary measures reduced this estimate to close to zero ($\beta = -0.02$).

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. For example, in two experiments, college students were directed to find a campus library with or without their smartphone. Relative to those using their smartphones, students not using them 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: $r_s = -0.01$ to -0.11 in Twenge et al., 2017; $\beta_s = -0.02$ 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 unfamiliar location). To our 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 (Verduyn et al., 2017)—for example, Facebook, Instagram, TikTok, Snapchat, and Twitter. Although these sites can be accessed via computers and tablets, a majority of the

most popular social networking sites 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 (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 1,095 Danish individuals, and randomly assigned them to stop using Facebook for a week or keep using it as usual (Tromholt, 2016). Participants who gave up Facebook experienced increases in life satisfaction, and their emotions became more positive. Effects were strongest 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 either to use Facebook passively (e.g., by scrolling through their newsfeed and looking at friends' pages) or actively (e.g., by posting status updates or directly messaging friends; Verduyn et al., 2015). Neither group 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. 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 social networking sites are extremely popular, such as Instagram (121.2M monthly users), Twitter (81.5M monthly users), Snapchat (46M monthly users), and TikTok (6.24M 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 Instagram, Snapchat, and TikTok (Auxier & Anderson, 2021). 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, no significant differences emerged between the two groups for social support, anxiety, self-esteem, or autonomy. Notably, this study left several other social media services unrestricted (e.g., Twitter, Reddit), which participants could have turned to instead. Also, some of the most commonly used subjective well-being measures in the psychological literature (e.g., positive emotions, life satisfaction) were not assessed. 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 display 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 fully restricting specific social networking sites (e.g., just restrict Facebook) or in specific ways (e.g., use social media actively

vs. passively) may yield psychological benefits (e.g., increased well-being, reduced loneliness). Notably, most experimental studies deploy a “use social media as usual” vs. “stop using social media” approach. However, participants instructed 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, we 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). By contrast, 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 & Leita, 2020; Sbarra et al., 2019), while the displacement hypothesis suggests that screen time may displace other more rewarding or beneficial non-screen activities like exercising, volunteering, 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 & Leita, 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 belongingness needs (Derrick et al., 2019), such surrogacy may be akin to social junk food—providing empty calories without the essential nutrients. Alternatively 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 peers) 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 the present study, we 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), we asked them to actively restrict their digital media and social media use for about 8 days. To this end, we recruited Gen Z individuals, 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? We preregistered our hypotheses for this study on the Open Science Framework (OSF). Preregistration, data, materials, and R code are available at [redacted pending peer review and publication].

Preregistered Hypotheses

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

Hypothesis 1

Relative to our two control groups (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

We recruited undergraduate students from the psychology department's online participant pool at a large public university. 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, we also preregistered several 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).

We also originally planned to exclude participants who 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, we decided to discard the SRSI question exclusion criteria and keep those participants in the analyses. Finally, 34 participants 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 in 1995 or later, placing them in the generation known as Gen Z (or iGen), the first generation to enter adolescence with smartphones (Twenge, 2017). We 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 & Przybylski, 2019a, 2019b; Twenge et al., 2018a, 2018b). The 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. Many student participants also worked part-time (31.4%).

Procedure

Figure 1 presents an overview of the study timeline. To reduce demand effects, participants were ostensibly recruited for a “Daily Habits Study”—a study examining daily habits (e.g., drinking, eating, exercising), behaviors (e.g., reading, watching TV, smartphone use, water use), thoughts, emotions, and physical health. The duration of the study 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 began in February 19, 2019 and ended on 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 investigation 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 Supplemental Materials for condition instructions.

Participants in the Digital Diet condition ($n = 76$) were instructed to limit their digital media use on their smartphones. 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. We 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.

We also included two control conditions. To confirm that restriction alone (e.g., putting effort into doing something worthwhile and feeling good about it) was not driving effects, our 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.

Our 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 *ns* were somewhat 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 2). Once captured, iPhone Screen Time screenshots were emailed to a general study email for later transcription, coding, and analysis.

Time 2 (T₂ / Posttest)

At T₂, participants returned to the lab for a visit that was similar to the T₁ visit 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 T₁ and T₂, rating each measure over the "past week (last 7 days)." See Supplemental Materials for additional exploratory moderator measures not reported here.

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), we 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 [ω s]) ranged from .89 to .91 for positive affect and .75 to .82 for negative affect across timepoints.

Life Satisfaction

We 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 $\omega = .85$ to .88 across timepoints.

Mindful Attention

Mindfulness (i.e., the extent to which participants are mindfully attending 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 $\omega = .80$ to .85 across timepoints.

Need Satisfaction: Autonomy, Competence, and Connectedness

We assessed three types of need satisfaction (feelings of autonomy, competence, and connectedness [or relatedness]) with a shortened 9-item version of the Balanced Measure of Psychological Needs (BMPN; Sheldon et al., 2001). This questionnaire includes 3 items each to assess autonomy (e.g., "I felt free to do things my own way"), competence (e.g., "I felt very

capable in what I did”), and connectedness (e.g., “I felt a sense of contact with people who care for me”). 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, the reliabilities were $\omega = .74$ to .80 for autonomy, $\omega = .76$ to .77 for competence, and $\omega = .88$ to .89 for connectedness.

Depressive Symptoms

Depressive symptoms were measured with 6 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 $\omega = .87$ to .90 across timepoints.

Loneliness

To measure loneliness, we 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 $\omega = .61$ to .73 across timepoints.

Self-Esteem

We 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 $\omega = .84$ to .87 across timepoints.

Stress

Participants' stress levels were assessed 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 $\omega = .74$ 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). 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 $\omega = .76$ 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, participants were asked, "As accurately as possible, please estimate the total amount of time you spend using your smartphone on average per day." They were also required 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 both the pretest and posttest visits, RAs helped participants capture screenshots of the *Screen Time* section of the Settings app on participants' iPhones (see Figure 2). RAs transcribed, coded, checked, and double-checked these Screen Time usage metrics on a shared Google Sheet, which we appended to survey data for 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), we used Screen Time's “Weekly Total” estimate to create a daily average composite as an objective indicator of smartphone time. Additionally, we 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. We did not use iPhone's “Social Networking” app category because it 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.

Preregistered Analytic Plan

We preregistered our analytic plan on the OSF. To test Hypothesis 1, we 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, we followed 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. In the interest of parsimony, we focus primarily on comparisons testing the effects of the relevant treatment conditions relative to both controls (i.e., Digital Diet vs. Both Controls and 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 Table 1 for further inspection.

We used two preregistered statistical techniques to test our hypotheses: (1) Regressed change: Condition dummy codes predicting T_2 scores, controlling for T_1 scores, and (2) second-order latent growth models (SOLGM): Condition dummy codes predicting growth (i.e., slope) extracted from second-order latent growth models. Because both the regressed change and SOLGM statistical techniques produced highly similar (and often nearly identical) results, we focus solely on the regressed change analyses below. See Supplemental materials for the SOLGM results.

In our regressed change models, regression coefficients were converted to partial correlations for ease of interpretation and comparability between models. Following past studies (Boase & Ling, 2013; Sewall et al., 2020), 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.

Results

See Supplemental Materials for means and standard deviations by condition (Table S1) and bivariate correlations (Table S2).

Manipulation Checks

Did our participants change their behavior as directed? We first wanted to determine whether participants assigned to the Digital Diet and Social Diet conditions restricted their digital and social media use accordingly. Figure 3 shows pre-post difference scores by condition 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 similarities between the self-report and objective digital media (i.e., smartphone) time manipulation checks may not be surprising given our previous finding of their strong, positive correlation ($r = .55, p < .001$; Walsh et al., 2021).

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. Notably, self-report and

objective social media time were also positively correlated in Walsh et al. (2021) ($r = .25, p < .001$).

See Supplemental Materials for manipulation check individual condition comparisons (Table S3). Notably, the other individual condition comparisons (Digital Diet vs. Water Diet, Digital Diet vs. No Diet, Social Diet vs. Water Diet, Social Diet vs. No Diet) were also statistically significant at mostly $ps < .001$.

Hypothesis 1. The Effects of Restricting Digital Media

According to our regressed change models (see Table 1 and Figure 4), restricting digital media did appear to improve a variety of psychological outcomes. In support of our 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 $r = .10, p = .097$). We 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 showed a similar pattern of results (see Table 1).

Hypothesis 2: The Effects of Restricting Social Media

By contrast, restricting social media (Hypothesis 2) appeared to provide limited benefits, and even a few costs. According to our regressed change models (see Table 1 and Figure 5), 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. We 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 showed a mostly similar pattern of results (see Table 1).

Exploratory: Restricting Digital Media vs. Social Media

We also compared the Digital Diet and Social Diet conditions directly. We preregistered these analyses as “exploratory” because we did not have specific a priori hypotheses about which condition might outperform the other. Given that participants in the Digital Diet condition experienced a number of benefits not shared by the Social Diet group, we coded the Social Diet as the reference group (see Table 1). 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 bigger 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 $r = -.14$, $p = .10$).

Intention-to-Treat Analyses

Because our analyses included some data exclusions (e.g., repetitive responders, those who did not restrict at all), we also ran intention-to-treat (ITT) regressed change analyses that included all participants randomized to condition (see Supplemental Materials for ITT analyses). 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 a little over a week appeared to carry out this charge relatively successfully. Notably, 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; $r_s = .11$ to $.16$). Overall, the significant effects were small, but not miniscule. Indeed, the 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 emotional well-being 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 for participants restricting social media (partial $r = .12$, reflecting not a positive but adverse effect). Notably, our social media restriction findings are intriguingly consistent with Przybylski and colleagues' (2020) one-day social media fast study, which also found backfiring effects. Further, our results are especially interesting considering recent correlational analyses we conducted with the same participants, which revealed social media use to be negatively associated with subjective well-being ($r = -.16$; Walsh et al., 2021). In other words, when Gen Z individuals entered our study, the more social media they reported using, the less happy they were. However, prompting them to reduce their social media use did not make them any happier.

Our 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, our experimental findings dovetail with the nuanced and mixed results from the correlational work. Much more research is needed, including replications and mechanism

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 & Leita, 2020; Twenge & Farley, 2021).

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 especially harmful to young people. However, as recent revelations from *The Wall Street Journal's* (2021) "Facebook Files" demonstrate, social media platforms are not always optimized for user well-being. For example, internal company documents showed that teens who struggle with mental health report that Instagram makes it worse (Wells et al., 2021). But not all social networking sites elicit identical effects. Baseline correlational findings with the same participants in this study showed that Facebook use is associated with lower well-being ($r = -.09$), while Snapchat use is associated with higher well-being ($r = .10$; Walsh et al., 2021). In other words, smartphone apps can be designed to increase (or decrease) user happiness.

Thus, vilification of these new technologies may be unwarranted. Smartphone apps may merely represent tools that can be tailored for better or worse. Historically, new inventions (e.g., novels, radios) have often prompted socially contagious technology panics (Orben, 2020). For example, in 1680, philosopher and mathematician Gottfried Wilhelm 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). Yet despite early concerns, many new technologies are ultimately adopted into daily life, and go on to provide myriad

benefits to humanity, such as improved health and wealth (Pinker, 2018).

Limitations and Future Directions

This study is subject to several limitations that may seed future work. Because our aim was to examine 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 observe 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 effects. For example, vertical collectivism (i.e., positioning oneself hierarchically within an ingroup) 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 ($N \geq 250$), our sample size may still not have been large enough. After all, for their reports of associations between screen time and well-being, Twenge and colleagues (2018b) and Orben and Przybylski (2019b) relied on exceptionally large samples sizes, with N s between 17 thousand and more than a million. As statistical significance depends on both effect size and sample size, our 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 big data, Many Labs, and/or Psychological Science Accelerator approaches 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 our study did successfully restrict the amount of time they spent on their smartphones and social media apps, they did not restrict as much as we would have wished. For example, participants' Screen Time screenshots revealed that the Digital Diet group 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, the Social Diet group 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 negligible levels, the effects may have been stronger or reversed. Future researchers may identify new ways to induce individuals to reduce their screen time more effectively. Some studies have also tried paying users to deactivate specific social media accounts (Allcott et al., 2019; Corrigan et al., 2018), but this requires recruiting self-selected participants willing to reduce their use. It is important to note that our participants did not self-select into the intervention. Thus, individuals in natural settings who wish to limit their screen time and actively take steps to do so may also experience stronger benefits.

To be sure, future studies should experimentally restrict digital media for longer periods of time (e.g., 1, 3, 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 had restricted social media for longer periods of time, they may have started to replace it with non-screen habits like exercising and gathering with friends, and thus may have ultimately enjoyed greater benefits. Alternatively, if the complementarity hypothesis is correct, restricting social media over longer periods may have produced even larger backfiring effects, as it would have limited individuals' access to enjoyable experiences.

Past research spotlights that smartphones can be helpful or harmful to well-being, depending on the situation (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.

Conclusion

Most people across the globe want to be happy (Diener, 2000) and many 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), prompting anxiety about their effects on human happiness and health. Is there value and virtue in reducing individuals' reliance on screens? Our results show that restricting smartphone use for a week does appear 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 advantages (greater mindfulness) and even some costs (more negative emotion). Overall, the effect sizes were generally larger than what has been reported in previous correlational research, yet still relatively small. Despite a plethora of memes, news articles, books, videos, movies, TV shows, and podcasts disparaging digital and social media, our results suggest that smartphone users may be better off keeping calm and carrying on.

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Table 1
Outcome Regressed Change Models

Variable	<i>b</i>	<i>b SE</i>	Partial <i>r</i>	Partial <i>r</i> 95% CI		<i>p</i>
				<i>LL</i>	<i>UL</i>	
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 1 (continued)

Variable	<i>b</i>	<i>b SE</i>	Partial <i>r</i>	Partial <i>r</i> 95% CI		<i>p</i>
				<i>LL</i>	<i>UL</i>	
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 1 (continued)

Variable	<i>b</i>	<i>b SE</i>	Partial <i>r</i>	Partial <i>r</i> 95% CI		<i>p</i>
				<i>LL</i>	<i>UL</i>	
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 T₂ scores, controlling for T₁ scores. Positive *bs* suggest the treatment group (Digital Diet, Social Diet) reported greater increases than the reference group (Water Diet, No Diet, Both Controls, Social Diet). Negative *bs* suggest the treatment group reported greater decreases than the reference group. CI = confidence interval; LL = lower limit; UL = upper limit.

Figure 1*Study Timeline*

Note. Study timeline with T₁ (pretest) on Day 1 and T₂ (posttest) on Day 7-13. Figure designed using resources from

Flaticon.com

Figure 2

Example iPhone Screen Time Screenshots

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

Figure 3*Self-Report and Objective Time Difference Scores by Condition*

Note. T₂ - T₁ 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 4*Hypothesis 1 Digital Diet vs. Both Controls Regressed Change Partial rs*

Note. Hypothesized condition dummy codes (Digital Diet vs. Both Controls) predicting T_2 scores, controlling for T_1 scores with bs converted to partial rs . 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 5

Hypothesis 2 Social Diet vs. Both Controls Regressed Change Partial rs

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