**The Association Between Well-Being and
Objectively Measured Versus Self-Reported Smartphone Time**

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Draft preprint version 8/5/20. This paper has not yet been peer reviewed.

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We have no known conflicts of interest to disclose. This article is based on the dissertation completed by Walsh (2021). Preregistration, data, materials, and R code are available on the Open Science Foundation (OSF) at [redacted pending peer review and publication].

We would like to thank the following people for their useful comments, suggestions, and contributions to this project: Steve Cole, William L. Dunlop, Megan M. Fritz, Sharath Chandra Guntuku, Seth Margolis, Chris C. Martin, Kate Sweeny, Lyle Ungar, and David A. Walsh. We would also like to thank Gabrielle Celaya, our undergraduate research coordinator, as well as our team of undergraduate research assistants, who dedicated innumerable hours to collecting these data and coding screenshots: Gabriela Alaniz, Estefanie Altuna, Fiorella Atoche Fernandez, Alana Barr, Joshua Bateman, S. Gokce Boz, Tia Calhoun, Ritz Cardona, Elizabeth Castellanos, Desire Cervantes, Elizabeth Dawson, Tia Elpusan, Arlene Enriquez-Rizo, Alvin Fong, Alec Frias, Monica Guirgus, Alan Guo, Victor Hill Jr., Margaret Lobermann, Taraji Long, Mary Mansour, Ashley Marin, Juliana Mena, Soumil Nariani, Vi Nguyen, Chuka Okolie, Shreya Parthiban, Yocelyn Ramirez-Pena, Jasmine Ramos, Samantha Rodriguez, Julie Salama, Mei Takeda, Samantha Thomas, and Christin Timmons.

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Abstract

Recent correlational research links smartphone and social media use to lower well-being among Gen Z youth, yet other work suggests that the effects are small and unnoteworthy. However, these findings rely heavily on self-report. How accurate is self-reported smartphone time and are objectively measured screen activities associated with lower well-being than nonscreen activities? Finally, are some smartphone uses “better” for well-being than others? We addressed these questions by examining correlations among psychosocial well-being and smartphone time in 414 Gen Z participants. Although objective smartphone use (i.e., assessed via Apple’s Screen Time function) and self-reports were correlated at $r=.55$, most participants were unable to accurately estimate their smartphone time. Furthermore, the more they used their smartphones—whether assessed objectively or via self-report—the less happy they were ($rs=-.14$ to $.17$). However, some apps were associated with more well-being (e.g., Camera, News, Snapchat) and others with less (e.g., Facebook, Reddit, Tinder, Twitter). (151 words)

Keywords: digital technology, smartphone, social media, well-being, depression, loneliness, self-esteem

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“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

The smartphone has spread faster than any technology in human history (DeGusta, 2012). With its rise, narratives about the 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, books, shows, podcasts, memes, and more that provide “ten arguments for deleting your social media accounts” and pose questions about whether “smartphones destroyed a generation” (Arnold et al., 2019; Brooker & Wright, 2018; Dmodepl, 2019; Lanier, 2018; Moby, 2016; Twenge, 2017a). Ironically, anxiety about smartphones and social media has gone viral on these very devices and platforms. Yet researchers across multiple fields are still debating whether digital technology use is harmful or beneficial to well-being.

In annual surveys from 1991 to 2016, Twenge and colleagues (2017, 2018) examined several large-scale datasets ($N=506,820$ –1.1 million) and found that U.S. adolescents (aka Gen Z) 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 smartphone and social media use. A key finding from that paper examined correlations between happiness and self-reported time spent on various types of activities. Specifically, nonscreen activities (e.g., exercising, socializing) were positively correlated with happiness ($r=.02$ – $.16$). However, screen activities (e.g., texting, gaming) were negatively

correlated with happiness ($r_s = -.11$ – $.00$). The researchers concluded that Gen Z individuals who spent more time on screen activities and less time on nonscreen activities had lower well-being—in other words, digital technology use may interfere with happiness.

However, Orben and Przybylski (2019a) argued that worries about digital technology use may be unwarranted. These researchers analyzed three large-scale datasets (total $N=355,358$) and found 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. In two additional large-scale datasets (total $N=17,247$), Orben and Przybylski (2019b) 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 well-being, depression, or self-esteem.

Other researchers have found that greater depression predicts greater screen time (Zink et al., 2019) or that the two influence each other reciprocally (Houghton et al., 2018) or not at all (George et al., 2018). Most of the mixed and inconclusive correlational work yields small associations between screen time and psychosocial well-being (e.g., self-esteem and loneliness) and relies heavily on retrospective and self-reported measures of digital technology use (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; Scharrow, 2016). Collecting objective indicators of screen time from smartphone devices is a promising approach to address this measurement issue.

As such, researchers have begun to examine objective indicators of smartphone time using a variety of methods, such as mobile network provider data, smartphone tracker apps, and Apple's Screen Time function (Andrews et al., 2015; Boase & Ling, 2013; Sewall et al., 2020, 2021). Notably, this work has shown that, on an average day, users spend 2.5 to 5 hours and make over 100 app switches 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). Furthermore, light users tend to overestimate their actual smartphone 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; Twenge & Farley, 2021; Verduyn et al., 2017; David et al., 2018). Thus, some types of screen time may be better for psychosocial well-being than others (e.g., using Facebook passively vs. actively, gaming vs. social media 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

Our study sought to explore whether objectively measured smartphone time is associated with lower well-being, and whether some activities are more strongly associated than others. To this aim, we recruited Gen Z individuals to complete a survey of well-being and

related psychosocial outcomes (e.g., life satisfaction, loneliness), while also collecting Screen Time screenshots from their iPhones. Our analyses were preregistered as exploratory as we did not have predetermined hypotheses. Specifically, we explored three research questions: How accurate is self-reported smartphone and social media time relative to objective indicators? Are nonscreen activities associated with greater well-being than screen activities? And, are some specific smartphone apps more strongly associated with well-being than others? Preregistration, data, materials, and R code are available for this study at [redacted pending peer review and publication].

Method

Participants

We obtained approval from the Institutional Review Board at the University of California, Riverside, and recruited participants from the psychology department's online research participation system. Participants were offered course credit as compensation. Eligibility criteria included the following: 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.

This study used data collected in the lab during a single time point, which was obtained as part of a larger preregistered experimental study with two time points (Walsh, 2021), yielding a total sample of 414 participants. We aimed to collect a sample of at least $N \geq 400$ because the experimental study involved 4 conditions, and we wanted at least 100–125 participants per condition in line with previous open science recommendations (Vazire, 2014).

A sensitivity power analysis using Gpower (Faul et al., 2007), assuming two-tailed $\alpha = 0.05$ and 80% power, revealed a minimum effect size of $r = .14$.

Among the 414 participants ($M_{age} = 19.4$, $SD = 2.2$; 75.1% female), almost all (97.8%) belonged to Gen Z (also referred to as iGen), which was the first generation to grow up with smartphones (Turner, 2015; Twenge, 2017b). Participants' ethnic backgrounds were Asian (40.8%), Hispanic (33.1%), White (11.1%), Black (4.1%), other (5.1%), and more than one (5.8%). The majority were not in a relationship (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 \$60,001 and \$100,000; 21.3% earned over \$100,000; and 13% did not know their household income.

Procedure

To limit demand effects, we recruited participants for a so-called "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 this study were collected in-person in our lab from February 19, 2019 to February 24, 2020. All data collection was completed just 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 Walsh (2021).

Measures

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

In addition to the below measures, we collected several other dependent variables (DVs) as part of the larger experimental study (Walsh, 2021); specifically: brief happiness and satisfaction, mindful attention, need satisfaction, stress, and health. However, in the interests of parsimony and reducing the number of statistical tests in this study, we focused on the three key components of subjective well-being (positive emotions, negative emotions, and life satisfaction), as well as some important related variables to assess psychosocial constructs (depression, loneliness, and self-esteem).

Positive and Negative Emotions

To assess hedonic well-being, we 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 [ω s]) were .89 for positive affect and .77 for negative affect.

Life Satisfaction

To gauge a relatively more stable, cognitive type of well-being, we 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 $\omega = .85$.

Depression

We 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 $\omega = .87$.

Loneliness

Participants also completed a 6-item loneliness scale (e.g., “A lot of times I feel lonely”; 1 = *disagree*; 5 = *agree*) from Monitoring the Future, a large longitudinal survey of American adolescents (Johnston et al., 2017). The reliability for loneliness was $\omega = .62$.

Self-Esteem

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

Nonscreen Activities

We also asked participants to report on their nonscreen activities (i.e., “daily habits”) 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, we asked them, “As accurately as possible, please estimate the total amount of time you spend using your smartphone on average per day.” We 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, varying the duration from 3 to 13 days, depending on the participant. Thus, we used Screen Time’s “Weekly Total” estimate to create a daily average objective smartphone time composite.

We 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. We 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, our 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, 79% of social media site visits come from mobile devices (Tankovska, 2021), so this composite still provides a useful assessment of objective social media time.

Other Smartphone User Characteristics

Using Screen Time screenshots, we were also able to collect 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 we collected Screen Time data on 194 apps, we only ran correlations for the 36 most frequently 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 [e.g., Mail, Reminders], 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 applicable and has been done in previous studies (Boase & Ling, 2013; Sewall et al., 2020). However, we calculated summary statistics (e.g., *M*, *SD*, *Mdn*) of the raw (untransformed) variables (in minutes).

We also created several composites for specific analyses. First, we computed a nonscreen frequency composite that accounted for how frequently participants reported exercising, being outdoors, relaxing, attending religious services, and volunteering overall. We also created a nonscreen time composite that accounted for combined self-reported time spent reading, working, studying, and socially interacting with others. We also computed a standardized subjective well-being composite (Positive Emotions – Negative Emotions + Life Satisfaction) to examine how smartphone 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 outcome, nonscreen activities, and screen time variables, presented in raw (untransformed) format for ease of interpretation.

Self-Report vs. Objective Smartphone Time

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

Participants' average self-reported smartphone time ($M = 323.09$, $SD = 155.15$) and objective smartphone time ($M = 321.53$, $SD = 106.66$) (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 revealed 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 of the discrepancy scores revealed that people misestimated their daily smartphone time by an average of 91.52 minutes ($SD = 95.17$). Overall, half of the participants (52.9%) 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 ($M = 113.07, SD = 62.13$) (in minutes) were less similar (a difference of 117.89 minutes). These variables were also positively correlated ($r = .25, p < .001$). However, a paired-sample t -test revealed a significant difference between the self-reported 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. People misestimated their average daily social media time by an average of 129.18 minutes ($SD = 98.94$). Overall, most participants (69.8%) misestimated their objective social media time by an hour per day or more.

Screen vs. Nonscreen Activities and Well-Being

Are nonscreen activities linked to higher well-being than screen activities? Table 2 and Figure 4 show correlations for both screen and nonscreen activities with the standardized subjective well-being composite. Table 2 also displays correlations for the separate measures that comprise it (positive affect, negative affect, and life satisfaction). Several nonscreen

activities were positively associated with well-being, including relaxing ($r = .24, p < .001$), being 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 nonscreen activities were not meaningfully linked with well-being, such as reading ($r = .02, p = .739$), working ($r = -.05, p = .304$), and studying ($r = -.04, p = .4$). Nonscreen activities assessed for frequency with 5-point Likert scales (e.g., exercising, relaxing) were generally more strongly linked with well-being than nonscreen activities assessed via self-reported time (e.g., reading, studying). The nonscreen frequency composite was significantly associated with higher subjective well-being ($r = .31, p < .001$), but our nonscreen time composite was not ($r = .02, p = .618$).

Some objectively assessed screen activities were positively correlated with well-being, such as gaming apps ($r = .23, p = .071$) and Apple's "News" app ($r = .12, p = .02$). Notably, the gaming apps effect size was larger ($r = .23$) than for other screen activities, but likely did not reach significance because a relatively smaller number of participants frequently used apps in this category ($n = 64$). Other screen activities, however, were negatively correlated with well-being, especially app groups that included social media-like apps, such as social networking apps ($r = -.21, p < .001$) and dating apps ($r = -.17, p = .001$). Apple's "other" apps category ($r = -.26, p = .033$) was also negatively correlated with well-being, but we were unable to determine which specific apps were included in this category. Correlations for average daily pickups ($r = -.02$) and notifications ($r = -.05$) were close to zero ($ps > .2$). Notably, the self-reported correlations were similar in magnitude to those involving objective indicators. Overall, total

daily objective smartphone time was significantly related to lower well-being ($r = -.16$, $p = .001$).

Notably, a comparison of the nonscreen frequency composite and objective screen time correlations ($r_s = .31$ vs. $-.16$) revealed a significant difference between the two ($Z = 6.91$, $p < .001$). Similarly, the nonscreen time and objective screen time correlations ($r_s = .02$ vs. $-.16$) were also significantly different ($Z = 2.61$, $p = .009$). Thus, our data suggest that self-reported nonscreen activities are linked to higher well-being than objectively measured screen time.

We also examined correlations involving other aspects of psychosocial well-being, such as depression, loneliness, and self-esteem (see Table 2). Spending more time outdoors, exercising, and relaxing (nonscreen 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 ($r = .08$, $p = .088$). Combined nonscreen time was not significantly linked to depression, loneliness, or self-esteem. The r_s were relatively close to zero, and all p_s were greater than $.12$.

A few objectively assessed screen activities were associated with lower loneliness (e.g., pickups, notifications) and higher self-esteem (e.g., creativity apps), while several were consistently associated with poorer loneliness, depression, and self-esteem (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 $.14$) than did 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 ($r = -.08, p = .086$).

Specific Apps and Well-Being

Are some specific smartphone apps associated with higher psychosocial well-being than others? To address this question, we examined correlations for the most used iPhone apps (e.g., News, Facebook, Calculator, Photos). As Table 2 and Figure 4 show, some apps may be “better” for well-being than others.

Our results revealed that 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 subjective well-being ($r = .10, p = .041$) and lower depression ($r = -.12, p = .019$). The “Find My Friends” app was linked to lower depression ($r = -.11, p = .026$) and loneliness ($r = -.12, p = .014$). Apple’s News app was significantly associated with greater well-being ($r = .12, p = .02$) and marginally with self-esteem ($r = .09, p = .074$). The Phone app was associated with greater self-esteem ($r = .12, p = .018$) and lower depression ($r = -.12, p = .015$). Finally, counter to correlations found for other social media, Snapchat was linked to higher well-being ($r = .10, p = .036$) and self-esteem ($r = .10, p = .049$), as well as less loneliness ($r = -.11, p = .021$) and marginally less depression ($r = -.09, p = .065$).

Other apps were negatively associated with psychosocial well-being, suggesting that the more these apps were used, the worse off participants were. The “Blackboard” app (which undergraduate students use to access coursework and grades) was associated with marginally lower well-being ($r = -.09, p = .063$) and higher loneliness ($r = .09, p = .082$).

Facebook was marginally associated with less well-being ($r = -.09, p = .077$), more depression ($r = .14, p = .006$), and lower self-esteem ($r = -.15, p = .002$). Apple's "Mail" app was linked to marginally less well-being ($r = -.10, p = .051$) and more loneliness ($r = .09, p = .075$). Reddit was associated with higher depression ($r = .10, p = .039$) and lower self-esteem ($r = -.13, p = .007$). Apple's "Safari" Internet browsing app was linked to less well-being ($r = -.12, p = .012$) and marginally greater loneliness ($r = .09, p = .075$). Tinder was associated with lower well-being ($r = -.14, p = .004$) and self-esteem ($r = -.14, p = .004$) and higher depression ($r = .16, p = .001$). Finally, Twitter was linked to significantly less well-being ($r = -.12, p = .012$) and more loneliness ($r = .11, p = .025$), as well as marginally higher depression ($r = .08, p = .097$) and lower self-esteem ($r = -.09, p = .071$).

Additionally, several apps were not significantly correlated with psychosocial well-being and revealed r s close to zero. Examples include the Clock app (r s = $-.06$ to $.02, p$ s $> .1$), Dictionary app (r s = $-.03$ to $.02, p$ 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 = $-.03$ to $.06, p$ s $> .1$) and WhatsApp (r s = $-.03$ to $.08, p$ s $> .1$).

Discussion

On an average day, Gen Z individuals used their smartphones 5 hours and 21 minutes, picked up their phones 135 times, and received 187 notifications. Replicating previous work, most of our participants were relatively inaccurate in estimating how much time they spent on their smartphones and social media apps. Although self-reported and "actual" screen time were highly correlated, 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 participants reported time spent on all devices, and the objective indicator only picked up iPhone time. 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, 2021).

Overall, combined self-reported nonscreen activities assessed for frequency (daily vs. never) were associated with higher well-being ($r=.31$), but nonscreen time variables (reported in minutes) were not ($r=.02$). However, the more participants objectively interacted with their smartphones, the less happy they were ($r=-.16$). This constitutes a “small” effect size ($rs=.1-.3$; Cohen, 1992). However, small effects can aggregate over time to meaningfully impact outcomes (Funder & Ozer, 2019). Overall, our subjective nonscreen frequency and time composites were both associated with greater well-being than objectively measured screen time.

Finally, our analyses suggest that some apps may support psychosocial well-being more than others. Specifically, as illustrated in Figure 4, the more time participants spent on News, Camera, and Snapchat—apps that appear to involve interactions with others or the wider world—the better off they were. The more time participants spent on Facebook, Reddit, Tinder and Twitter—notably, all social media-like apps—the worse off they were. Notably, these analyses only consider time spent on specific apps, and previous research suggests how people use an app (e.g., using Facebook passively vs. actively) may alter its effects (Verduyn et al., 2015).

It is worth noting that we found little evidence to support previous research that has suggested that subjective reports may overinflate correlations between smartphone time and

mental health (Sewall et al., 2020; Shaw et al., 2020). Our study also demonstrates that specific apps, even from the same category (e.g., Snapchat vs. Twitter, both social media) are differentially linked to well-being. Still, future experimental work is needed to determine the types of use (when, how, by whom) for each app that might positively or negatively impact psychosocial well-being. Overall, our nuanced 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 & Leita, 2020; Twenge & Farley, 2021).

Limitations and Future Directions

Although our study was able to assess objective time spent on screen activities (via iPhone Screen Time screenshots), we still relied on retrospective self-reports of nonscreen activities, which people frequently estimate inaccurately (Grondin, 2010). Future studies with more objective indicators of nonscreen activities—for example, using objective sensor data from smartphones to assess time spent sleeping, exercising, and socializing (Wang et al., 2014)—may provide an even clearer picture of the differential well-being effects of screen vs. nonscreen time.

Additionally, our results represent merely a snapshot of specific individuals (American Gen Z undergraduate students) using a specific device (iPhone) with specific apps at a specific time and place. Future studies could expand these findings to other populations (e.g., Millennials), nations, devices (Android), apps (e.g., reading) and timeframes (post-COVID-19).

Further, although our sample size was adequate ($N=414$), the previous correlational research that has relied on self-report has deployed considerably larger sample sizes. 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 not easily scalable. If future researchers deploy a big data, many labs approach, combined with the use of a smartphone sensing app (e.g., Aware), such work may substantially push the field forward (Klein et al., 2014; Nishiyama, 2021).

Finally, it bears repeating that the analyses presented here are correlational, and therefore cannot indicate the direction of causality. For example, the negative correlations reported between subjective well-being and smartphone/social media time (both $r_s = -.16$) could be explained in a few different ways: (a) more smartphone use may impair well-being, (b) people with low well-being may reach for their smartphones more, or (c) a third variable (e.g., loneliness) could be driving both higher smartphone use and lower well-being. Experimental work is necessary to illuminate the causal direction between smartphone time and well-being.

Conclusion

In little more than a decade, the smartphone has become a ubiquitous and essential tool for over 3.6 billion souls (O'Dea 2021), and most people report being happier with this tool than without it (Crabtree et al., 2018). Does spending more time on one's smartphone matter to well-being and does it matter how that time is measured? Although most of our Gen Z participants were unable to accurately recall their smartphone time, we found that screen activities—whether assessed subjectively or objectively—were associated with lower well-being than nonscreen activities. However, not surprisingly, we found that not all smartphone time

was created equal, with some apps associated with more happiness and others associated with less.

However, the more our participants reported or were observed using their smartphones and social media apps, the less happy they were (r s ranging from $-.14$ to $-.16$). These effect sizes are not large, but they are generally larger than what has been reported in previous work relying on self-report. Indeed, these results suggest that smartphone time may be about as harmful to well-being as volunteering is helpful to well-being ($r = .15$). Although further work should better establish the direction of causality, this study demonstrates that people who objectively spend more time on their smartphones are more likely to be unhappy.

Author Contributions

L. C. Walsh, J. M. Twenge, and S. Lyubomirsky developed the study concept and design. Study execution and data collection were performed by L. C. Walsh, K. Okabe-Miyamoto, and A. Regan. L. C. Walsh performed the data analysis, interpretation, and manuscript write-up under the supervision of S. Lyubomirsky. All authors provided critical revisions and approved the final version of the manuscript for submission.

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Table 1*Summary Statistics*

Variable	<i>n</i>	<i>M</i>	<i>SD</i>	<i>Mdn</i>	Min	Max
Outcomes:						
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
Nonscreen Activities:						
<i>Frequency variables (1-5 scale):</i>						
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
Combined Nonscreen Frequency	414	2.01	0.54	2.00	1.00	5.00
<i>Time variables (in mins):</i>						
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
Combined Nonscreen Time	414	590.99	313.51	510.00	120.00	2220.00
Screen Time Activities:						
Self-Report Smartphone Time	414	323.09	155.15	300.00	60.00	1200.00
Objective Smartphone Time	409	321.53	106.66	315.00	70.00	779.00
Self-Report Social Media Time	414	230.96	113.43	220.00	5.00	630.00
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	<i>n</i>	<i>M</i>	<i>SD</i>	<i>Mdn</i>	Min	Max
<i>Screen Time Activities (continued):</i>						
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, nonscreen and screen time variables are presented in raw (not log-transformed) form (in minutes).

Table 2*Zero-Order Pearson Correlations*

	SWB	Pos Aff	Neg Aff	Life Sat	Depress	Lonely	Self-Est
<i>Nonscreen Activities:</i>							
<i>Frequency variables:</i>							
Exercising	0.18***	0.18***	-0.18***	0.09 [†]	-0.09 [†]	-0.18***	0.14**
Outdoors	0.19***	0.19***	-0.12*	0.16**	-0.13**	-0.14**	0.18***
Relaxation	0.24***	0.23***	-0.15**	0.21***	-0.16***	-0.16***	0.19***
Religious Services	0.10*	0.08 [†]	-0.05	0.12*	-0.07	-0.15**	0.10*
Volunteering	0.15**	0.14**	-0.04	0.17***	-0.12*	-0.03	0.15**
Nonscreen Frequency	0.31***	0.31***	-0.21***	0.25***	-0.21***	-0.23***	0.26***
<i>Time variables:</i>							
Reading	0.02	0.04	0.04	0.03	-0.05	0.02	0.07
Sleeping	0.06	0.09 [†]	-0.06	0.00	0.02	0.00	0.05
Working	-0.05	-0.03	0.07	-0.02	0.01	0.04	0.06
Studying	-0.04	-0.06	0.06	0.02	-0.03	0.07	-0.03
Social Interaction	0.12*	0.19***	-0.03	0.09 [†]	-0.06	-0.16**	0.08 [†]
Nonscreen Time	0.02	0.05	0.06	0.07	-0.07	-0.05	0.08
<i>Screen Activities:</i>							
SR Smartphone Time	-0.14**	-0.06	0.19***	-0.10 [†]	0.14**	0.12*	-0.10*
Obj Smartphone Time	-0.16**	-0.12*	0.21***	-0.06	0.11*	0.10 [†]	-0.08 [†]
SR Social Media Time	-0.17***	-0.08 [†]	0.21***	-0.13**	0.19***	0.16***	-0.10*
Obj Social Media Time	-0.16**	-0.11*	0.21***	-0.07	0.08	0.11*	-0.11*
Dating Apps	-0.17***	-0.10*	0.13*	-0.19***	0.19***	0.12*	-0.13**
Creativity Apps	0.01	-0.02	-0.08	-0.05	-0.09	-0.03	0.17 [†]
Education Apps	0.07	-0.18	-0.11	0.36	-0.35	0.07	0.35
Entertainment Apps	-0.01	-0.03	0.01	0.02	-0.06	0.02	0.03
Gaming Apps	0.23 [†]	0.26*	-0.16	0.14	-0.08	-0.18	0.06
Other Apps	-0.26*	-0.23 [†]	0.29*	-0.16	0.31*	0.22 [†]	-0.33*
Productivity Apps	-0.05	-0.08	0.00	-0.03	-0.02	0.07	0.01
Reading & Reference Apps	-0.12	-0.16 [†]	0.06	-0.07	0.06	0.12	-0.07
Social Networking Apps	-0.21***	-0.17***	0.27***	-0.10*	0.13**	0.11*	-0.12*
Pickups	-0.02	0.03	0.10 [†]	0.00	-0.04	-0.09 [†]	0.02
Notifications	-0.05	0.03	0.14**	-0.02	0.00	-0.11*	-0.04

Table 2 (Continued)

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

Note. Screen and nonscreen time activity variables that were right-skewed and kurtotic were log-transformed. SWB = Standardized subjective well-being composite (PA – NA + LS); Pos Aff = Positive affect/emotions; Neg Aff = Negative affect/emotions; Life Sat = Life satisfaction; Depress = Depression, Lonely = Loneliness, Self-Est = Self-esteem; SR = Self-report; Obj = Objective. Significant and marginal positive correlations are highlighted in blue. Significant and marginal negative correlations are highlighted in pink. [†] $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

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*Self-Report vs. Objective Time Means*

Note. Self-report vs. objective smartphone and social media time means presented in raw (not log-transformed) form (in minutes).

Figure 3*Self-Report vs. Objective Discrepancy Score Histograms*

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

Figure 4*Subjective Well-Being Correlations for Nonscreen and Screen Activities*

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