PNAS Nexus, 2025, **4**, pgaf017
https://doi.org/10.1093/pnasnexus/pgaf017
Advance access publication 18 February 2025
Research Report

Blocking mobile internet on smartphones improves sustained attention, mental health, and subjective well-being

Noah Castelo[a,*], Kostadin Kushlev[b], Adrian F. Ward[c], Michael Esterman[d,e] and Peter B. Reiner[f]

[a]Department of Marketing, Business Economics, and Law, University of Alberta, Edmonton, AB, Canada T6G 2R6
[b]Department of Psychology, Georgetown University, Washington, DC 20057, USA
[c]Department of Marketing, University of Texas at Austin, Austin, TX 78705, USA
[d]National Center for PTSD, VA Boston Healthcare System, Boston, MA 02130, USA
[e]Department of Psychiatry, Boston University Chobanian and Avedisian School of Medicine, Boston, MA 02118, USA
[f]Department of Psychiatry, University of British Columbia, Vancouver, BC, Canada V6T 0A6
*To whom correspondence should be addressed: Email: ncastelo@ualberta.ca.
Edited By David Rand

Abstract

Smartphones enable people to access the online world from anywhere at any time. Despite the benefits of this technology, there is growing concern that smartphone use could adversely impact cognitive functioning and mental health. Correlational and anecdotal evidence suggests that these concerns may be well-founded, but causal evidence remains scarce. We conducted a month-long randomized controlled trial to investigate how removing constant access to the internet through smartphones might impact psychological functioning. We used a mobile phone application to block all mobile internet access from participants' smartphones for 2 weeks and objectively track compliance. This intervention specifically targeted the feature that makes smartphones "smart" (mobile internet) while allowing participants to maintain mobile connection (through texts and calls) and nonmobile access to the internet (e.g. through desktop computers). The intervention improved mental health, subjective well-being, and objectively measured ability to sustain attention; 91% of participants improved on at least one of these outcomes. Mediation analyses suggest that these improvements can be partially explained by the intervention's impact on how people spent their time; when people did not have access to mobile internet, they spent more time socializing in person, exercising, and being in nature. These results provide causal evidence that blocking mobile internet can improve important psychological outcomes, and suggest that maintaining the status quo of constant connection to the internet may be detrimental to time use, cognitive functioning, and well-being.

Significance Statement

Concern about how smartphones affect users is widespread: half of American smartphone users—and 80% of those under age 30—worry that they use their device too much, and correlational research suggests that smartphone use is negatively related to mental health and cognitive functioning. However, few large-scale experiments have tested for causal effects. We report such an experiment, finding that blocking mobile internet for 2 weeks reduces smartphone use and improves subjective well-being (SWB) (including life satisfaction and positive affect), mental health (more than antidepressants), and sustained attention (as much as being 10 years younger). Despite the many benefits mobile internet offers, reducing the constant connection to the digital world can have large positive effects.

Introduction

Smartphones have changed the daily habits of billions of people by offering access to the internet from anywhere at any time. These portals to the online world—to information on virtually every topic, endless varieties of entertainment, and constantly updating social media feeds—have become pervasive: 90% of American adults own a smartphone (1), and the average user spends 4.6 h per day on their device (2). At the same time, there is increasing public concern about how this technology might negatively affect people: half of American smartphone users—and more than four out of five users under age 30—worry that they use their device too much (3), while pundits worry that smartphones "hijack our minds" (4) and have "destroyed a generation" (5). Consistent with these concerns, recent correlational research has found that people who use their smartphones more have poorer SWB (6), mental health (7), and attentional abilities (8).

We conducted a preregistered randomized controlled trial testing whether blocking internet access on people's smartphones

Competing Interest: The authors declare no competing interests.
Received: September 4, 2024. **Accepted:** January 3, 2025

causally affected these outcomes. Our research design isolates the feature that makes smartphones "smart"—the ability to access mobile internet—and brings experimental evidence to bear on a question of critical importance in our increasingly connected world: If we were not constantly connected to the internet, would our cognitive and emotional well-being improve?

It is theoretically plausible that smartphone (over)use could causally impact psychological functioning. Humans evolved in a world where information, entertainment, and social contact were relatively hard to come by; as a result, we may struggle to control our thoughts and behaviors when these stimuli are constantly at our fingertips (9). For example, smartphones could impair attention by repeatedly interrupting ongoing tasks and encouraging media multitasking (10, 11) or by consuming users' cognitive resources when they attempt to resist these distractions (11). Smartphones could harm mental health and subjective well-being (SWB) by displacing or interfering with healthier activities, such as in-person socializing (12, 13).

Recent experiments provide preliminary evidence in support of these hypotheses. Lab experiments focused on cognitive functioning have shown that hearing smartphone notifications impairs performance on attention-demanding tasks (14) and that simply having one's smartphone present and visible can impair working memory (12) and sustained attention (15). Although these mere presence effects do not always replicate (16), meta-analyses conclude that they are small but significant (17, 18).

Beyond the lab, field experiments suggest that reducing smartphone notifications (10) and receiving smartphone notifications in batches, rather than continuously throughout the day (19), can improve self-reported attentional functioning. And in a field experiment focused on mental health, participants who were asked to limit their smartphone use for 1 week reported decreased symptoms of anxiety and depression (20). These and other studies have explored both the acute effects of smartphone-related distraction and short-term effects of modifying smartphone use on mental health. What is missing from the empirical record is a longer-term experiment that changes the nature of the smartphone itself and objectively measures participant compliance and cognitive performance.

We conducted a preregistered randomized controlled trial testing whether blocking internet access on people's smartphones affected participants' SWB, mental health, and attentional functioning. This intervention effectively turns a smartphone into a "dumb phone" by severing the constant connection to the online world while still permitting mobile communication via text messages and phone calls, as well as access to the internet from other devices such as tablets or laptops. Participants ($n = 467$) agreed to install a smartphone application (*Freedom*) that blocked all mobile internet access (including Wi-Fi and mobile data) from their phones for 2 weeks. In contrast to prior research (20), we objectively assessed compliance by using the app to track whether or not the block was indeed active throughout the intervention. We preregistered three key outcomes. First, we measured SWB using the standard tripartite model that consists of self-reported positive affect, negative affect, and life satisfaction (21). Second, we assessed overall mental health by measuring a range of mental health outcomes, such as symptoms of anxiety and depression, using diagnostic tools developed by the American Psychiatric Association (22). Finally, we examined attentional functioning using both self-reported attentional awareness (23) and objectively measured sustained attention. Sustained attention was measured using the gradual onset continuous performance task (gradCPT), a well-validated continuous performance task that characterizes the ability to maintain focused attention over time (24, 25). All measures were taken three times: at baseline (T1), 2 weeks later (T2), and another 2 weeks later (T3).

Participants were randomly assigned to one of two groups: those in the Intervention group blocked mobile internet access for the first 2 weeks only (T1–T2), while those in the Delayed Intervention group acted as a control for the first 2 weeks and then blocked mobile internet access for the second 2 weeks (T2–T3). This cross-over design let us test whether any effects persist post intervention and increased power by administering the intervention to all participants, albeit at different times. We intentionally chose a waitlist control, as our primary goal is to examine the effect of the status quo (constant access to mobile internet). The preregistration for this experiment is available at https://osf.io/tfdm6?view_only=919c2f5b0e494f7c872d9432611b083b.

Results

Compliance and attrition

Complying with the intervention was evidently difficult for participants: of the 467 who committed to blocking mobile internet for 2 weeks, 266 set up the app required to do so and 119 (25.5% of those who committed) met our preregistered definition of "compliant" (having the block active for at least 10 of the 14 intervention days, as recorded by the Freedom app). We focus our analyses on intention-to-treat (ITT) effects, without excluding any participants based on compliance, while also reporting treatment-on-treated (TOT) effects as secondary analyses.

Three hundred and twenty-seven participants completed both the T1 and T2 self-report surveys (70%), and 313 completed all three surveys (67%). Retention from T1 to T3 was statistically equivalent in the Intervention condition (69.8%) and the Delayed Intervention condition (64.0%, $\chi^2(1) = 1.54$, $P = 0.214$). In other words, the rate of attrition was equivalent across the two conditions. See CONSORT diagram in "Materials and methods" for details. Compared with participants lost to attrition, participants who completed all three time points had significantly better mental health and had better sustained attention at baseline. However, we found no differences in terms of age, gender, or education. Furthermore, we found no evidence for differential attrition by condition for a range of baseline variables including but not limited to: mental health, SWB, sustained attention, attention deficit hyperactivity disorder (ADHD) symptoms, mindfulness, fear of missing out (FoMO), age, gender, education, motivation and capability to reduce phone use, and belief that one is using their phone more than ideal (for detailed attrition analyses, see SI Appendix).

As preregistered, our primary analyses are based on 3×2 ANOVAs with Time (T1, T2, and T3) as a within-subjects factor and Condition (Intervention and Delayed Intervention) as a between-subjects factor. Accordingly, these analyses are based on "complete cases" only—that is, participants who provided data at all three time points. This approach maximizes internal validity in our cross-over design. Alternative analyses using all available data are consistent with our preregistered findings and are also reported in SI Appendix.

Effects on screen time

We first examined how the intervention impacted smartphone use. We asked participants to upload screenshots of their iPhone's screen time page showing their average daily screen time in the past week. Prior to blocking mobile internet, our participants' screen time was very similar to the screen time of the average American smartphone user (2). The intervention significantly reduced smartphone use. Average screen time decreased in the Intervention group from 314 min at T1 to 161 min at T2 (Cohen's $d_z = 2.22$, $P < 0.001$) and rebounded to 265 at T3 ($d_z = 1.02$, $P < 0.001$ compared with T1). In the Delayed Intervention group, daily screen time decreased slightly from 336 min at T1 to 322 min at T2 ($d_z = 0.32$, $P = 0.011$) and dropped to 190 at T3 ($d_z = 2.39$, $P < 0.001$).

Effects on psychological functioning

Figure 1 illustrates the effects of blocking mobile internet on our preregistered outcomes: how SWB, mental health, and attention changed over the course of the experiment. While attention was assessed with two measures, we chose the objective measure of sustained attention, the gradCPT, as our primary measure; results for self-reported attentional awareness are reported in "Materials and methods." As preregistered, we analyzed each outcome using a series of 3 (Time) × 2 (Condition) mixed ANOVAs tracking each dimension of psychological functioning across the duration of the experiment. After 2 weeks of blocking mobile internet (T1–T2), the Intervention group displayed significant improvements from baseline in SWB (an index including life satisfaction and positive and negative affect; $d_z = 0.46$, $P < 0.001$), mental health (a reverse-scored index including symptoms of depression, anxiety, anger, personality function, and social anxiety; $d_z = 0.57$, $P < 0.001$), and objectively measured sustained attention ability (defined as task accuracy, or d-prime score, on the gradCPT; $d_z = 0.24$, $P = 0.008$). See "Materials and methods" for details on each measure. Participants in the Delayed Intervention group, who retained complete access to mobile internet during this period, showed no differences on these measures between T1 and T2.

The effects of blocking mobile internet replicated in the Delayed Intervention group. After the second 2 weeks (T2–T3), during which the Intervention group could access mobile internet but the Delayed Intervention group could not, we observed significant improvements in the Delayed Intervention group on SWB ($d_z = 0.36$, $P = 0.009$), mental health ($d_z = 0.52$, $P < 0.001$), and sustained attention ($d_z = 0.28$, $P = 0.003$) of similar magnitude. Furthermore, in the Intervention group, SWB and mental health remained significantly higher at T3 than they were at T1. These persistent benefits may be attributable to the fact that screen time in the Intervention group remained lower at T3 than at T1, despite the fact that we did not require participants in this group to continue blocking mobile internet after T2.

To increase power and the precision of effect size estimates, we pooled data from both groups into combined "pre intervention" (all T1 data for the Intervention and Delayed Intervention groups) and "post intervention" observations (matching T2 data for the Intervention group and matching T3 data for the Delayed Intervention group). The ITT pre–post intervention effects were $d_z = 0.45$ ($P < 0.001$) for SWB, $d_z = 0.56$ ($P < 0.001$) for mental health and $d_z = 0.23$ ($P < 0.001$) for sustained attention.

To put these effects into context, the change in objectively measured sustained attention ability is about the same magnitude as 10 years of age-related decline (27) and about a quarter of the difference between healthy adults and those with ADHD, all estimated using gradCPT (28). The observed effect of the intervention on depression symptoms ($d_z = 0.56$) was larger than the meta-analytic effect of antidepressants (29) and similar to that of cognitive behavioral therapy (30). While these comparisons are thought-provoking, it is important to note that the nature of our sample and of our intervention is quite different from those studied in clinical psychology contexts.

In addition to these ITT analyses, we also estimated the TOT effects in analyses excluding participants who did not comply with the intervention according to our preregistered criteria. The pre–postintervention TOT effects were $d_z = 0.50$ ($P < 0.001$) for SWB, $d_z = 0.68$ ($P < 0.001$) for mental health, and $d_z = 0.26$ ($P = 0.009$) for sustained attention. These results suggest that the positive effects of the intervention were larger for participants who complied by leaving the mobile internet block in place for at least 10 days.

Experience sampling

In order to gain more fine-grained insight into how the mobile internet block affected well-being over time, we also preregistered and collected experience sampling data via short text messages (SMS) sent to participants four times per week, asking how they were feeling at that moment (from 1—bad to 10—good). For these analyses, we used multilevel models with all available data because these models are more robust than ANOVAs to missing data.

We found that participants in the Intervention condition had higher mood on average ($M = 6.62$, $SE = 0.13$) than participants in the Delayed Intervention condition ($M = 6.02$, $SE = 0.13$) during the initial 2-week phase of the study ($b = 0.59$, $P = 0.001$, $d = 0.33$; see Table S1, Model S1). We also found that participants in the Intervention group felt progressively better over the first 2 weeks as indicated by a positive slope across the eight consecutive measurements between T1 and T2, $b = 0.05$, $P = 0.045$. Participants in the Delayed Intervention did not show significant improvements in mood over the first 2 weeks, $b = -0.02$, $P = 0.501$. Over the second 2 weeks, we observed a progressively better mood within the Delayed Intervention group, $b = 0.08$, $P < 0.001$, and no change in mood in the Intervention participants, $b = -0.02$, $P = 0.423$. These experience sampling results suggest that the intervention becomes increasingly beneficial as time progresses and that these benefits persist over time. Additional analyses are available in "Materials and methods" and SI Appendix.

Investigating mechanisms

What mechanisms might explain the effects we observed? We preregistered the following possible mediators: time use, social connectedness, self-control, and sleep. We anticipated that blocking mobile internet access would free up substantial amounts of time that participants could spend on activities known to promote SWB, mental health, and cognitive functioning, including socializing in person, exercising, spending time in nature, and pursuing hobbies (31–34). Thus, changes in time use could mediate the effects of the intervention on these primary outcomes.

A second, related possibility is that the time freed up by the intervention could facilitate the development and maintenance of offline social relationships, such that participants might feel more socially connected while blocking mobile internet. Social connectedness might thus mediate the effect of the intervention on mental health and SWB in particular, since these outcomes are strongly linked to social relationships (33).

We also examined a third possibility: that the intervention could improve self-control, which is linked to well-being (35), by removing a major source of distraction from participants' lives. Finally, we investigated whether people would get more sleep when they did not have access to mobile internet, which could in turn improve psychological functioning (36).

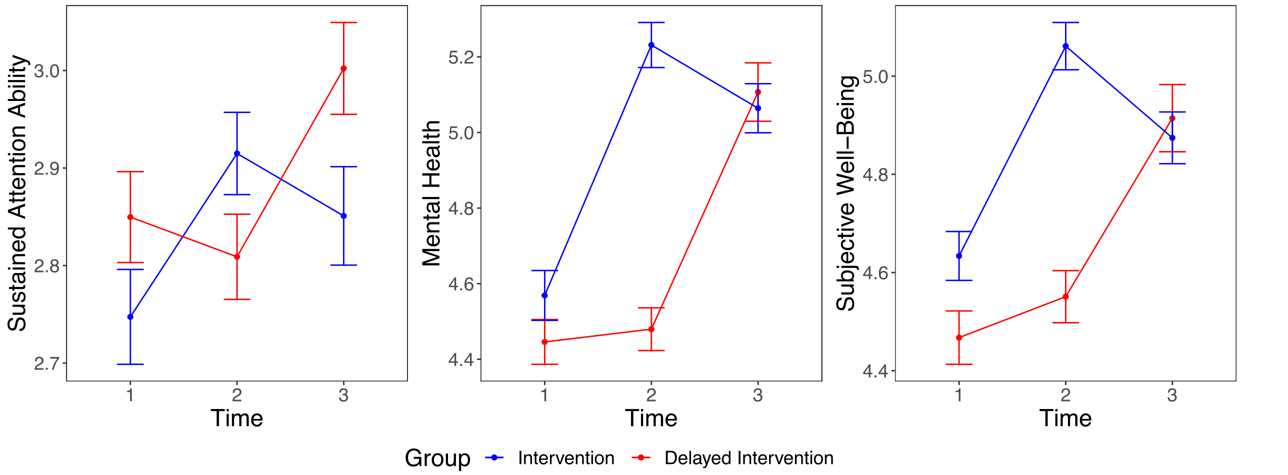

Fig. 1. Attention, mental health, and SWB improve after 2 weeks of blocking mobile internet. In the Intervention group, participants blocked mobile internet access from T1 to T2. In the Delayed Intervention group, participants blocked mobile internet access from T2 to T3. Error bars depict adjusted within-subjects SEs (26).

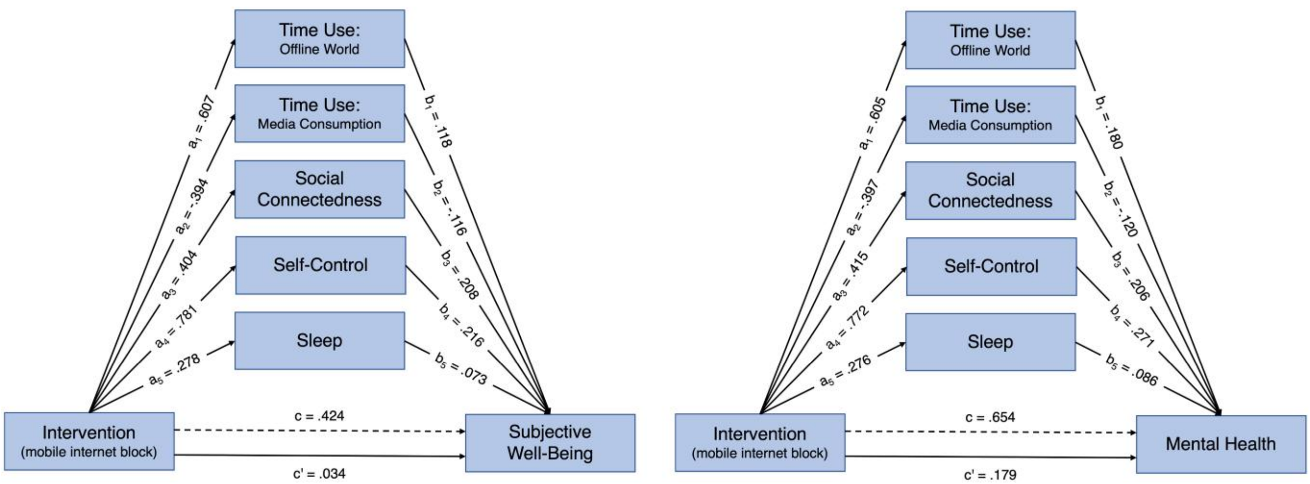

Fig. 2. Mechanisms linking blocked mobile internet access to SWB and mental health. Blocking mobile internet increased time spent in the offline world, decreased media consumption (across any device), improved social connectedness and self-control, and increased nightly hours of sleep. Each of these effects, in turn, improved SWB and mental health.

We explored impacts on time use by asking participants how much time they spent on each of 10 activities over the past week. As detailed in SI Appendix, an exploratory factor analysis revealed that these activities loaded on three factors, which we call "time in the offline world" (socializing in person, exercising, being in nature, pursuing a hobby, and reading a book), "digital communication" (communicating via text message, voice, or video calls on any device), and "media consumption" (reading the news, watching TV or movies, and watching YouTube on any device). Note that the specific composition of the time use factors was not preregistered, but emerged from a post hoc factor analysis. We measured social connectedness (37) and self-control (38) using self-report scales and measured sleep by asking people how many hours they slept per night, on average, during the past week. Each of these potential mechanisms was measured at T1, T2, and T3. To increase power, we pooled the data from both intervention conditions into combined "pre intervention" observations collected at baseline (T1) and "post intervention" observations collected immediately after the intervention for each group (T2 data for the Intervention group and T3 data for the Delayed Intervention group).

We found evidence that the intervention affected all four potential mechanisms: how people spent their time, social connectedness, self-control, and sleep. Within-subjects comparisons indicated that blocking mobile internet increased time spent in the offline world ($d_z = 0.70$, $P < 0.001$) and decreased time spent consuming media ($d_z = 0.41$, $P < 0.001$). The intervention did not affect time spent on digital communication through talk and text, which were not blocked by our intervention ($d_z = 0.08$, $P = 0.163$). Blocking mobile internet increased social connectedness ($d_z = 0.29$, $P < 0.001$), feelings of self-control ($d_z = 0.66$, $P < 0.001$), and sleep ($d_z = 0.14$, $P = 0.016$). Based on these results, we tested for mediation of our main effects by five factors: Time spent in the "offline world," time spent consuming media, social connection, self-control, and sleep.

We tested for mediation using the MEMORE macro for within-subjects mediation analyses (39). As with the potential mediators, we pooled data on our key outcome measures into combined "pre intervention" and "post intervention" observations. As in our primary analyses, we included data from "complete case" participants who provided data at all three time points. Each analysis used bias-corrected bootstrapping with 10,000 samples.

As shown in Fig. 2, the effects of the intervention on SWB and mental health were mediated by increased time spent in the offline world, decreased time spent consuming media, increased social connectedness, improved feelings of self-control, and increased sleep. We note that mediation analyses cannot provide definitive causal evidence for a mediator's role in shaping the outcome variables or vice versa. However, these results are consistent with the idea that changes in daily time use and experiences help explain the link between blocking mobile internet and improvements in psychological functioning, especially for SWB and mental health. None of these factors mediated the effect of the intervention on sustained attention.

Who benefits (most)?

Most—but not all—of our participants benefited from blocking mobile internet access—defined as the percentage of participants who had higher scores postintervention than preintervention. Across both conditions, 70.5% of participants reported better mental health postintervention than preintervention; this figure was 73.3% for SWB and 58.5% for objectively measured sustained attention. Overall, 90.7% of participants experienced an improvement in at least one of these three outcomes. From T1 to T2, more participants in the Intervention group improved compared with those in the Delayed Intervention group (SWB: 75 vs. 47%, $\chi^2 = 17.6$, $P < 0.001$; mental health: 68 vs. 52%, $\chi^2 = 13.0$, $P < 0.001$; sustained attention: 59 vs. 46%, $\chi^2 = 3.5$, $P = 0.062$).

Given this variation, what factors predicted whether and how much participants benefited? We preregistered two potential moderators of the effects on psychological functioning: FoMO, or the "pervasive apprehension that others might be having rewarding experiences from which one is absent" (40), which we expected might moderate effects on SWB and mental health; and ADHD symptoms, which we expected might moderate the effects on attention. We measured individual differences in FoMO and ADHD at baseline, before any participants experienced the intervention. We increased statistical power by pooling psychological functioning data from both intervention conditions into "preintervention" and "postintervention" observations.

We found that the effects of blocking mobile internet on SWB and mental health were moderated by individual differences in FoMO. Participants who felt more FoMO at baseline experienced larger improvements in SWB and mental health during the intervention, perhaps because mobile internet itself exacerbates FoMO by frequently showing people what they are missing out on (i.e. the activities their friends are posting about on social media). We did not observe any moderation of the effect on sustained attention.

Discussion

Our results provide evidence that blocking mobile internet from smartphones for 2 weeks can produce significant improvements for SWB, mental health, and the objectively measured ability to sustain attention. Even those who did not fully comply with the intervention experienced significant, though more modest, improvements. These findings suggest that constant connection to the online world comes at a cost, since psychological functioning improves when this connection is reduced.

Many open questions remain for future research. Our intervention blocked all mobile internet access, which likely has both benefits and costs for well-being. More targeted blocks may therefore be even more effective. For example, blocking Facebook is known to improve SWB, although the effect is only 20% as large as the effect documented in the current research (41); how would blocking all social media (but not all mobile internet) compare? What about blocking mobile internet for only certain strategically optimized times of day, or certain days of the week? Such interventions may also be easier for people to adhere to in their daily lives, potentially further boosting any positive effects. Indeed, the relatively low compliance observed with our intervention suggests that less restrictive approaches may be beneficial. Nevertheless, the fact that we still observed significant ITT effects (i.e. including noncompliant participants) suggests that fully blocking mobile internet is not necessary to produce benefits. Rather, simply reducing mobile internet use may be sufficient.

Our sample consisted mostly of individuals motivated to reduce their smartphone use: at the outset of the experiment, we asked how motivated participants were to reduce their smartphone use on a 1 (not at all) to 7 (very much) scale and 83% of our participants chose 5 or higher. Seventy-nine percent also felt highly capable of reducing their smartphone use. Whether our effects would be seen with a less-motivated sample remains to be seen. Nevertheless, given that half of Americans and 80% of those under the age of 30 think they use their smartphone too much (3), our sample is similar to a large segment of the general population. Of the wide range of demographic and baseline measures, we found little evidence that people who completed all three waves were different from those who signed up for the study. People who completed all three time points did, however, have significantly better mental health and higher sustained attention at baseline than those who did not (see SI Appendix for details). Thus, the generalizability of our findings may be limited to people who are relatively better at sustaining attention and are not experiencing relatively worse mental health symptoms.

Expectancy effects, such as placebo and demand effects, could have contributed to our findings. Indeed, participants were aware that they were signing up for a study about how smartphones impact well-being. Participants may have guessed that the intervention was intended to improve their well-being and responded accordingly even if they did not really feel better. This is a limitation of our design. However, we took steps to reduce this concern, by, for example, including an objective measure of attention that is not self-reported and thus less likely to be affected by demand effects, as well as employing experience sampling measures (via SMS messages). Nevertheless, future research could reduce these concerns further by comparing our intervention to a more active control condition that participants believe is intended to improve their well-being. Future research may also mitigate expectancy effects by using informant reports of well-being and mental health. Further, assessment of a wider range of psychological symptoms and cognitive functions could help address this issue by revealing greater specificity of the effects.

Future research could explore the mechanisms of our effects more deeply. We found that a large portion of the effects of the intervention on SWB and mental health could be explained by the mediators of time use, social connection, self-control, and sleep. However, none of them explained a significant portion of the intervention's effects on sustained attention. These divergent results suggest that constant access to the online world may affect different dimensions of psychological functioning through different pathways. For example, it could be that reducing smartphone use has a more direct effect on attention, whereby reducing a constant opportunity for distraction allows people to practice focusing on one activity or stimulus at a time, and increases the relative reward of focusing attention on activities other than one's phone.

It is also worth considering whether reducing the use of other internet-connected devices could have similar effects. While other devices, such as laptops or tablets, can also displace activities and distract users, smartphones are uniquely portable and therefore pervasive throughout daily life (42). For example, ~95% of smartphone owners report having used their phones during their most recent social activity—far exceeding the percentage who did so with any other digital device (43).

Technology often progresses much faster than our ability to understand its consequences. This is true not only of emerging technologies like AI, but also relatively mature technologies like smartphones. Our research is the first to test for causal effects in an experiment that uses an intervention to reduce smartphone use and objectively track compliance. These results provide causal evidence that blocking mobile internet can improve important psychological outcomes, and suggest that maintaining the status quo of constant connection to the internet may be detrimental to time use, cognitive functioning, and well-being. Balancing the practical benefits that smartphones offer (44) against these significant negative consequences is an important task for smartphone users. Our results suggest that, for many people, spending less time with their device can help achieve this balance.

Materials and methods

This study was approved by the Institutional Review Board at the University of British Columbia. All participants gave informed consent. Materials, data, syntax, and preregistration details are available at https://osf.io/uxcwm/? view_only=919c2f5b0e494f7c872d9432611b083b. Additional methodological and sampling details and full analyses are provided in SI Appendix.

We recruited American and Canadian participants from Prolific.co, an online labor pool. Only iPhone users were eligible to participate due to compatibility with the Freedom app that we used to block mobile internet. The average age was 32 years; 63% were female; 20% had only a high school diploma; 11% had attended community college; 37% had an undergraduate degree; 8% had a master's degree; and 3% had a doctorate. Fifteen percent of participants identify as Asian, 9% as Black, 62% as White, and 12% as Other. Twenty-nine percent were students, 42% were employed full-time, and 16% were employed part-time.

All participants were paid $5 USD for the baseline survey. Canadian participants were paid $50 Canadian dollars for the second survey and $45 for the third, while American participants were sent a $40 USD Amazon.com gift card for the second survey and a $35 USD Amazon.com gift card for the third. All participants were paid the same amounts at the same times regardless of the condition they were in. Thus, incentives cannot explain the effects of condition. Participants were explicitly informed that their payment did not depend on compliance; at T2 and T3, participants were told that they were eligible to "receive compensation even if you did not manage to keep the Internet blocked from your phone for the entire 2 weeks."

Our main survey, which we administered three times, consisted of self-report measures of SWB, mental health, attentional awareness, and our preregistered mediators and moderators; the survey also linked to an online version of the gradCPT, a task-based measure of sustained attention (which can be taken through the following link—enter "test" when asked for ID: https://gradcpt.org/one-time-task/94DbNgVdqXHujDsESN3J). Items for each construct were averaged to form composite/index measures. We supplemented this main survey with brief SMS surveys measuring mood and time use, sent to participants every Monday, Wednesday, Friday, and Sunday during the 4 weeks of the experiment.

The mental health measures were created by the American Psychiatric Association (22) and included brief measures of depression, anxiety, anger, social anxiety, and personality functioning. Contrary to preregistration, we did not measure repetitive thoughts and behaviors. Items were taken from the corresponding subscales of the DSM-5 Level 1 cross-cutting symptom measure for adults. We also selected an additional item to measure social anxiety from the severity measure for social anxiety disorder. We combined these into a single index of mental health ($\alpha = 0.90$). SWB was measured using the tripartite model (45), which consists of life satisfaction, measured using the Satisfaction with Life Scale (21), and positive and negative affect, measured using the Scale of Positive and Negative Experience (46). These measures were averaged to create a SWB index ($\alpha = 0.82$). Attentional awareness (a self-reported measure of attentional functioning) was measured using the six-item Attentional Lapses subscale of the Mindful Attention Awareness Scale ($\alpha = 0.93$) (45), which assesses the tendency "run on automatic" and have difficulty focusing on the present moment.

We also preregistered several potential mediators. We measured social connectedness with the validated three-item Relatedness Scale (47), $\alpha = 0.93$, and self-control with an abbreviated six-item version of the self-control scale (38), $\alpha = 0.82$. We explored time use by asking participants whether they had spent more or less time than they normally do on a range of online and offline activities (from 1—a lot less to 5—a lot more). We assessed sleep by asking people how many hours they had slept per night, on average, during the past week.

As a potential moderator of the intervention's effect on SWB and mental health, we measured participants' baseline FoMO, with an abbreviated six-item version of the 10-item FoMO Scale (40), $\alpha = 0.83$. As a potential moderator of the effect on attention, we measured self-reported attention deficit and hyperactivity disorder symptoms at baseline using a validated six-item version of the World Health Organization Adult ADHD Self-Report Scale, $\alpha = 0.81$ (48).

Immediately following the surveys, participants were redirected to a 5 min online version of the gradCPT task, which we used to objectively measure sustained attention. The gradCPT (24, 27) is a well-validated and widely used go/no-go continuous performance task (27, 49) in which participants are asked to react by pressing a button on the keyboard (space bar) when cities are shown (90% of trials), but not when mountains are shown (10% of trials). Using standard signal detection analyses, errors (commission, or presses to mountains; omission, nonresponses to cities) are used to calculate d-prime, a measure of discrimination ability and the key measure of sustained attention provided by gradCPT. Higher d-prime values indicate greater accuracy in selecting between response inhibition and response initiation.

We received 504 complete responses to the baseline survey, with 253 randomly assigned to the Intervention group and 251 to the Delayed Intervention group. After removing duplicate email addresses, phone numbers, and Prolific IDs, we retained 467 unique participants (242 in Intervention and 225 in Delayed Intervention; see CONSORT diagram in Fig. 3 for details of how the sample size changed over the course of the experiment due to attrition and invalid responses).

Participants who were assigned to the Intervention group were given a code to download the premium version of the Freedom app

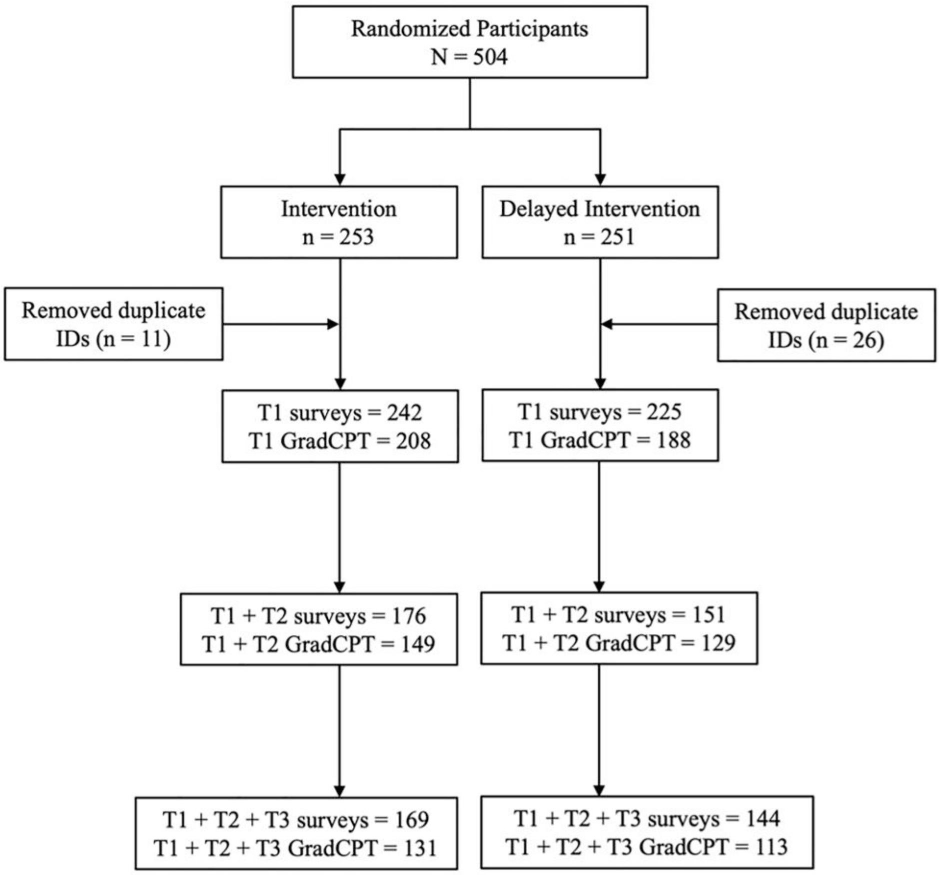

Fig. 3. CONSORT diagram.

and detailed instructions for how to install it and set up a complete mobile internet block that would last for 2 weeks; those assigned to the Delayed Intervention group were informed that their mobile internet block would begin 2 weeks later. Surveys 2 and 3 were only available for 48 h after we sent them to participants, in order to decrease the likelihood that the intervention's effects might have "worn off" before we could measure them.

The number of complete gradCPT responses at each time point was slightly lower, due partly to attrition (participants completed the surveys prior to being redirected to the gradCPT task) and due partly to invalid gradCPT responses—participants with prolonged inactivity on the task (>10 s with no response, or "tune outs") were excluded due to poor compliance/low effort (50; 38 attempts were excluded on this criterion 3.6% of all tests). Retention from T1 to T3 was statistically equivalent in the Intervention condition (63.0%) and the Delayed Intervention condition (60.1%, $\chi^2(1) = 0.34$, $P = 0.558$). See Fig. 3 for details.

In addition to our main surveys, we used text messages (SMS) to briefly assess mood we also ("How do you feel right now on a scale from 1 [bad] to 10 [good]?"). Participants received four text messages per week on Mondays, Wednesdays, Fridays, and Saturdays. Thus, we created a variable, Time, that indicated the survey number in order from 1 to 8 for each of the two study phases (phase 1: first 2 weeks; phase 2: second 2 weeks). See SI Appendix for details.

Compliance

We sent Freedom upgrade codes to the 467 participants who completed survey 1; these codes allowed participants to download a free copy of the premium Freedom app that can block all mobile internet and use a "Locked Mode" that makes it impossible to disable the block from within the app. Redeeming this code to sign up for an account on the Freedom app was therefore required to begin blocking mobile internet. Of the 467 codes, 272 were redeemed; ∼41.7% of participants therefore did not sign up for the app used to block mobile internet. Of these 272, 266 set up the initial mobile internet block, and 249 completed all three surveys. These 249 participants represent ∼79.5% of the 313 participants who completed all three surveys. Of these 249, 119 were deemed "compliant" based on our preregistered criteria of disabling the internet block fewer than five times during the intervention period. These 119 represent ∼25.5% of the participants who completed survey 1 and agreed to keep mobile internet blocked for 2 weeks, or 47.8% of those who downloaded and set up the Freedom app.

Main analyses

Our primary analyses are 2 × 3 ANOVAs. These analyses were reported in the main text; additional details are provided here. We calculate Cohen's d effect sizes for repeated measure designs by dividing the mean difference in outcome measures by the SD of that difference (50).

We computed ANOVAs with Time (three within-subjects levels) and Condition (two between-subjects levels) to predict the SWB index, the mental health index, attentional awareness, and sustained attention. For SWB, we measured life satisfaction using 1–7 scales and affect with 1–5 scales; we therefore multiplied the affect measures by 1.4 before combining them with life satisfaction to form a SWB index with the same measurement scales.

ANOVA revealed an effect of Time, $F(2,576) = 22.13$, $P < 0.001$, Condition, $F(1,302) = 3.52$, $P = 0.062$, and their interaction, $F(2,576) = 12.94$, $P < 0.001$. In the Intervention condition, SWB increased from T1 ($M = 4.65$, $SE = 0.09$) to T2 ($M = 5.05$, $SE = 0.09$, $t(166) = 5.98$, $P < 0.001$, $d_z = 0.46$) and decreased from T2 to T3 ($M = 4.89$, $SE = 0.09$, $t(166) = -2.28$, $P = 0.023$, $d_z = .-18$). In the Delayed Intervention condition, SWB did not change from T1 ($M = 4.45$, $SE = 0.10$) to T2 ($M = 4.54$, $SE = 0.11$, $t(136) = 1.24$, $P = 0.216$), but did improve from T2 to T3 ($M = 4.93$, $SE = 0.10$, $t(136) = 4.31$, $P < 0.001$, $d_z = 0.37$).

For mental health, which was measured on seven-point scales from 1—never to 7—all the Time, this analysis revealed effects of Time, $F(2,582) = 40.80$, $P < 0.001$, Condition, $F(1,306) = 3.39$, $P = 0.067$, and their interaction, $F(2,582) = 19.29$, $P < 0.001$. In the Intervention condition, mental health symptoms improved from T1 ($M = 4.58$, $SE = 0.12$) to T2 ($M = 5.22$, $SE = 0.10$, $t(164) = 7.31$, $P < 0.001$, $d_z = 0.57$) and did not significantly change from T2 to T3 ($M = 5.08$, $SE = 0.11$, $t(164) = 1.63$, $P = 0.105$). In the Delayed Intervention condition, mental health symptoms did not change from T1 ($M = 4.45$, $SE = 0.13$) to T2 ($M = 4.49$, $SE = 0.13$, $t(142) = 0.63$, $P = 0.532$), but improved from T2 to T3 ($M = 5.11$, $SE = 0.13$, $t(142) = 6.23$, $P < 0.001$, $d_z = 0.52$).

For objectively measured sustained attention (task accuracy/d-prime), ANOVA revealed effects of Time, $F(2,472) = 3.73$, $P = 0.026$, no effect of Condition, $F(1,242) = 0.32$, $P = 0.572$, and a significant interaction, $F(2,472) = 4.24$, $P = 0.016$. In the Intervention condition, accuracy improved from T1 ($M = 2.75$, $SE = 0.07$) to T2 ($M = 2.91$, $SE = 0.07$, $t(130) = 2.71$, $P = 0.008$, $d_z = 0.24$), and remained at a similar level from T2 to T3 ($M = 2.85$, $SE = 0.07$, $t(130) = 0.99$, $P = 0.325$). In the Delayed Intervention condition, accuracy did not change from T1 ($M = 2.85$, $SE = 0.06$) to T2 ($M = 2.81$, $SE = 0.07$, $t(112) = 0.65$, $P = 0.519$), but did improve from T2 to T3 ($M = 3.00$, $SE = 0.08$, $t(112) = 3.03$, $P = 0.003$, $d_z = 0.28$).

For the self-report measure of attentional awareness, which was measured using 1–6 scales with higher scores indicating higher incidence of attention lapses, the analysis revealed significant effects of Time, $F(2,606) = 103.55$, $P < 0.001$, Condition, $F(1,303) = 4.31$, $P = 0.039$, and their interaction, $F(2,606) = 24.09$, $P < 0.001$. In the Intervention condition, self-reported attention lapses decreased from T1 ($M = 3.50$, $SE = 0.09$) to T2 ($M = 2.68$, $SE = 0.07$, $t(163) = -10.07$, $P < 0.001$, $d_z = -0.79$) and remained at a similar level from T2 to T3 ($M = 2.79$, $SE = 0.08$, $t(163) = 1.51$, $P = 0.132$). In the Delayed Intervention condition, self-reported attention lapses also decreased from T1 ($M = 3.55$, $SE = 0.09$) to T2 ($M = 3.33$, $SE = 0.09$, $t(140) = -3.56$, $P < 0.001$, $d_z = -0.30$) and again from T2 to T3 ($M = 2.75$, $SE = 0.09$, $t(140) = -6.85$, $P < 0.001$, $d_z = -0.58$).

Mediation analysis

As preregistered, we tested for mediation of the effects of the mobile internet restriction on SWB, mental health, attentional awareness, and sustained attention by social connectedness, self-control, time use, and sleep. For these analyses, we increased statistical power by pooling data from both intervention conditions into combined "preintervention" observations collected at baseline (T1 for both conditions) and "postintervention" observations collected immediately after the intervention for each group (T2 data for the Intervention condition and T3 data for the Delayed Intervention condition).

We measured the potential mediator of time use using self-reports of time spent on ten different activities during the past week, relative to what is typical. These activities represent a wide diversity of activities that may have been differentially affected by the intervention; for example, the intervention may have increased time spent reading books but decreased time spent watching YouTube. In order to account for this possibility, we investigated the factor structure of these activities prior to conducting our mediation analyses. A factor analysis with Varimax rotation revealed a three-factor solution accounting for 54.22% of the variance in postintervention time use. Factor loadings are shown in Table S4 in SI Appendix.

We interpret the resulting factors as representing time spent in the "offline world," time spent on digital communication, and time spent consuming media. Note that the specific composition of the time use factors was not preregistered, but emerged from a post hoc factor analysis. In order to assess the suitability of each factor as a potential mediator, we created separate pre- and postintervention time use composite measures for each factor by averaging the ratings for all items in each factor at each time point. We then conducted a series of mixed ANOVAs with pre- vs. postintervention scores for a specified mediator as a repeated measures factor, condition (Intervention vs. Delayed Intervention) as a between-subjects factor, and a pre/post × condition interaction term to account for potential differences in the effect of the intervention across the two intervention waves. For these analyses, our focus is on the pre- vs. postintervention scores on the mediators, which indicate whether the intervention was associated with significant changes in these potential mechanisms. These analyses revealed that the intervention increased time spent in the "offline world" ($M_{pre} = 2.75$, $SD = 0.63$; $M_{post} = 3.36$, $SD = 0.66$; $F(1,311) = 150.610$, $P < 0.001$, $d_z = 0.70$) and decreased time spent consuming media ($M_{pre} = 3.10$, $SD = 0.67$; $M_{post} = 2.70$, $SD = 0.79$; $F(1,311) = 53.138$, $P < 0.001$, $d_z = -0.42$). The intervention did not significantly impact time spent on digital communication ($M_{pre} = 2.89$, $SD = 0.69$; $M_{post} = 2.79$, $SD = 0.95$; $F(1,311) = 1.960$, $P = 0.163$, $d_z = -0.09$). Based on these results, we retained two high-level time use composites for use in our mediation analyses: time spent in the offline world, and time spent consuming media.

Blocking mobile internet also increased social connectedness ($M_{pre} = 4.59$, $SD = 1.61$; $M_{post} = 4.99$, $SD = 1.50$; $F(1,310) = 27.517$, $P < 0.001$, $d_z = 0.29$), feelings of self-control ($M_{pre} = 4.00$, $SD = 1.18$; $M_{post} = 4.78$, $SD = 1.05$; $F(1,310) = 131.922$, $P < 0.001$, $d_z = 0.66$), and sleep ($M_{pre} = 7.10$, $SD = 2.75$; $M_{post} = 7.39$, $SD = 2.19$; $F(1,311) = 5.872$, $P = 0.016$, $d_z = 0.15$).

We conducted separate mediation analyses for each dependent measure. All mediation analyses were conducted using the MEMORE macro to apply the calculations for within-subjects mediation (39). These calculations assess whether the pre/post changes in a dependent variable are mediated by pre/post changes in a specified mediator or mediators. Our models tested for parallel mediation by time spent in the offline world, time spent consuming media, social connectedness, self-control, and sleep. Each analysis used bias-corrected bootstrapping with 10,000 samples.

For SWB, the total effect of the intervention ($c = 0.424$, 95% CI [0.31, 0.53]) was mediated by indirect effects of increased time spent in the offline world ($a_1b_1 = 0.072$, 95% CI [0.00, 0.15]), decreased time spent consuming media ($a_2b_2 = 0.046$, 95% CI [0.01, 0.10]), heightened feelings of social connectedness ($a_3b_3 = 0.084$, 95% CI [0.05, 0.14]), improved self-control ($a_4b_4 = 0.169$, 95% CI [0.10, 0.26]), and increased sleep ($a_5b_5 = 0.020$, 95% CI [0.00, 0.10]). After accounting for these indirect effects, the direct effect of the intervention on SWB was no longer significant ($c' = 0.034$, 95% CI [−0.09, 0.16]).

For mental health, the total effect of the intervention ($c = 0.654$, 95% CI [0.52, 0.79]) was mediated by indirect effects of increased time spent in the offline world ($a_1b_1 = 0.109$, 95% CI [0.02, 0.21]), decreased time spent consuming media ($a_2b_2 = 0.047$, 95% CI [0.00, 0.12]), heightened feelings of social connectedness ($a_3b_3 = 0.085$, 95% CI [0.04, 0.15]), improved self-control ($a_4b_4 = 0.209$, 95% CI [0.13, 0.31]), and increased sleep ($a_5b_5 = 0.035$, 95% CI [0.00, 0.11]). After accounting for these indirect effects, the direct effect of the intervention on mental health was reduced but remained significant ($c' = 0.179$, 95% CI [0.03, 0.33]).

For self-reported attentional awareness, the total effect of the intervention ($c = -0.812$, 95% CI [−0.93, −0.69]) was mediated by indirect effects of increased time spent in the offline world ($a_1b_1 = -0.142$, 95% CI [−0.22, −0.07]), heightened feelings of social connectedness ($a_3b_3 = -0.032$, 95% CI [−0.08, 0.00]), and improved self-control ($a_4b_4 = -0.284$, 95% CI [−0.39, −0.19]). The effect of the intervention on attentional awareness was not significantly mediated by decreased time spent consuming media ($a_2b_2 = -0.029$, 95% CI [−0.08, 0.01]) or increased sleep ($a_5b_5 = -0.003$, 95% CI [−0.06, 0.02]). After accounting for these indirect effects, the direct effect of the intervention on attentional awareness was no longer significant ($c' = 0.034$, 95% CI [−0.09, 0.16]). See Fig. S1 in SI Appendix for estimated effects of all causal paths in this analysis.

For sustained attention, the total effect of the intervention on gradCPT performance ($c = 0.159$, 95% CI [0.07, 0.25]) was not significantly mediated by any of the factors included in our analysis.

Moderation analysis

As preregistered, we tested for four possible moderation effects: whether changes in SWB were moderated by baseline levels of FoMO, whether changes in mental health were moderated by baseline FoMo, whether changes in attentional awareness were moderated by baseline levels of ADHD, and whether changes in sustained attention were moderated by baseline ADHD. For these analyses, we increased statistical power by pooling data from both intervention conditions into combined "preintervention" observations of psychological functioning, collected at baseline (T1), and "postintervention" observations, collected immediately after the intervention for each group (T2 data for the Intervention condition and T3 data for the Delayed Intervention condition). FoMo and ADHD were only measured at baseline. We tested each potential moderation in a separate mixed ANOVA with condition (Intervention and Delayed Intervention) as a between-subjects factor, pre- vs. postintervention scores on the relevant outcome measure as a within-subjects factor, and the potential moderator as a continuous factor. In these analyses, a significant two-way interaction between pre- vs. postintervention scores and the specified moderator indicates significant moderation—i.e. that the difference in pre- vs. postintervention scores on the outcome measure varies as a function of baseline scores on the specified moderator.

Our analyses revealed that individual differences in baseline FoMO significantly moderated the effect of the mobile internet block on SWB ($F(1,304) = 8.330$, $P = 0.004$) and mental health ($F(1,304) = 12.434$, $P < 0.001$). Follow-up floodlight analyses revealed that higher levels of baseline FoMO were associated with larger positive effects of the intervention on both outcomes; there were no Johnson–Neyman points in the data, indicating that the intervention significantly affected both outcomes for participants across the entire FoMO spectrum.

Our analyses also revealed that individual differences in baseline ADHD significantly moderated the effect of the mobile internet block on attentional awareness ($F(1,305) = 22.006$, $P < 0.001$), such that higher levels of baseline ADHD were associated with larger positive effects of the intervention. The floodlight analysis revealed a Johnson–Neyman point at 1.01 on the ADHD scale, indicating that the intervention significantly affected SWB for all participants at or above this level of the ADHD scale; this range includes 97.73% of the sample. Baseline ADHD did not significantly moderate the effect of the intervention on sustained attention ($F(1,254) = 1.020$, $P = 0.314$).

To examine whether the moderation effects above could be explained by differences in compliance, we examined the relationship between the moderators as measured at baseline and whether or not participants complied. In separate logistic regressions, FoMO (odds ratio = 1.06, $P = 0.636$) and ADHD symptoms (odds ratio = 0.91, $P = 0.516$) did not predict compliance.

Screen time analysis

We asked participants to upload a screenshot of their iPhone's Screen Time page which shows the average number of minutes that participants spent on the iPhone per day in the past week. Not all participants were able to do this: 294 participants uploaded at T1, 211 at T2, and 185 at T3. As in the other analyses, we report means using only data from participants who completed all three surveys (or, in this case, who uploaded three screenshots).

In the Intervention group, the average screen time decreased from 314 min at T1 to 161 min at T2, $t(91) = 21.26$, $d = 2.22$, $P < 0.001$, rebounding to 265 at T3, $t(91) = 9.83$ $d = 1.02$, $P < 0.001$ compared with T1. In the Delayed Intervention group, it decreased slightly from 336 min at T1 to 322 min at T2, $t(65) = 2.62$, $d = 0.32$, $P = 0.011$, dropping to 190 at T3, $t(65) = 19.41$, $d = 2.39$, $P < 0.001$ compared with T1.

Experience sampling analyses

We used text messages (SMS) to briefly assess mood and behavior during the study. Participants received four text messages per week on Mondays, Wednesdays, Fridays, and Saturdays. Thus, we created a variable, Time, that indicated the survey number in order from 1 to 8 for each of the two study phases (phase 1: first 2 weeks; phase 2: second 2 weeks). Since we are using multilevel models to analyze the data separately for phase 1 and phase 2, we used all available data for each phase. Since there was no cutoff time for answering the surveys, some participants answered the surveys on the following day (e.g. Tuesday). These responses were grouped under the same time point as those answered on the previous day. However, whenever a participant answered the survey twice on the same day, we removed the second response on that date; in total, 32 (0.7%) responses were removed this way. Overall, for these analyses, we had 4,024 data points across 349 participants (Delayed Intervention: $n = 168$; Intervention: $n = 181$). Of those, 2,004 (Delayed Intervention: $n = 923$; Intervention: $n = 1{,}081$) were reported during phase 1 and 2,020 (Delayed Intervention: $n = 941$; Intervention: $n = 1{,}079$) were reported during phase 2.

First, as preregistered, we used multilevel modeling to examine whether the mood of participants in the Intervention condition improved over the first 2 weeks of the study (phase 1) compared with the mood of participants in the Delayed Intervention condition. For all models, we used restricted maximum likelihood estimation and the Satterthwaite methods for the degrees of freedom. We found a nonsignificant trend for the Condition × Time interaction, $b = 0.07$, $t(256) = 1.87$, $P = 0.063$ (Table S1, Model S4, see SI Appendix). Simple effect analyses indicated that mood significantly improved over time in the Intervention condition, $b = 0.05$, $t(280) = 2.01$, $P = 0.045$, but there was no change over time in the Delayed Intervention condition, $b = -0.02$, $t(287) = -0.67$, $P = 0.501$. The main effect of condition was significant, $b = 0.59$, $t(381) = 3.26$, $P = 0.001$, $d = 0.33$ (Table S1, Model S1), indicating that Intervention participants had higher mood on average ($M = 6.62$, SE = 0.13) than Delayed Intervention participants ($M = 6.02$, SE = 0.13) over the initial 2-week phase of the study. Cohen's d effect sizes were approximated based on Wald's t tests and Satterthwaite degrees of freedom, $d = 2^*t/\text{sqrt(df)}$.

Next, we ran the same multilevel model for the second 2 weeks of the study (phase 2)—after participants in the Intervention condition had completed the Intervention phase and participants in the Delayed Intervention condition started the Intervention phase. We found a significant Time*Condition interaction, $b = -0.09$, $t(225) = -3.23$, $P = 0.001$. Simple effects analyses indicated a significant improvement in mood within Delayed Intervention participants (i.e. those currently undergoing Intervention), $b = 0.08$, $t(235) = 3.65$, $P < 0.001$, and no change in mood in the Intervention participants, $b = -0.02$, $t(230) = -0.80$, $P = 0.423$. The main effect of condition was significant, $b = 0.46$, $t(345) = 2.46$, $P = 0.015$, $d = 0.26$, indicating that Intervention participants had higher mood ($M = 6.76$, SE = 0.13) than Delayed Intervention participants ($M = 6.30$, SE = 0.14) on average over phase 2 of the study. Together, this pattern of findings suggests that the effects of restricting phone internet on mood materialize over time, but also that they persist even after the end of restriction.

Finally, we examined whether there were any differences in the Delayed Intervention participants before and after they restricted their mobile internet. The models were similar, but in this case, condition was also a Level 1 (within-subjects) predictor (0—normal use, 1—restricted use). Accordingly, we included the random effect of condition as well as its correlation with the random intercept and random effect of time. We found a significant Condition × Time interaction, $b = 0.07$, $t(1601) = 2.29$, $P = 0.022$. Simple effects analyses indicated that while the mood of Delayed Intervention participants improved when phone internet was restricted during phase 2, $b = 0.05$, $t(291) = 2.56$, $P = 0.011$, their mood remained unchanged when they used their phones as normal during phase 1, $b = -0.02$, $t(556) = -0.75$ $P = 0.456$. The main effect of the pre–post comparison on mood was, however, not significant, $b = 0.10$, $t(1{,}724) = 1.32$, $P = 0.186$, $d = 0.06$ (normal use: $M = 6.04$, SE = 0.14; restricted use: $M = 6.14$, SE = 0.14).

Attrition checks

Here, we check for differences between participants who completed only a preintervention survey and participants who completed all three surveys. At T1, participants who went on to complete all three surveys had slightly better mental health ($M = 4.51$) than those who only completed the first survey, $M = 4.17$, $t(466) = 2.21$, $P = 0.028$. SWB was equal across the two groups, $M = 4.56$ vs. 4.53, $t(466) = 0.23$, $P = 0.817$. Sustained attention performance (d-prime) was better among those who completed three surveys ($M = 2.79$) than among those who completed only one ($M = 2.53$, $t(395) = 3.34$, $P < 0.001$). Since our primary analyses include only participants who completed all three surveys, these differences do not affect our interpretation of our primary results, but they do affect the generalizability of the findings. Furthermore, participants' attrition status (attrited vs. not attrited) did not interact with condition (Intervention vs. Delayed Intervention) to predict any of our three primary outcomes at T1 (mental health, SWB, or sustained attention), suggesting that the attrition pattern did not vary by condition. Further attrition checks, including evidence for lack of differential attrition between conditions, are reported in SI Appendix.

Supplementary Material

Supplementary material is available at *PNAS Nexus* online.

Funding

Funding was provided by the Silicon Valley Community Foundation to P.B.R. (grant # GR027378).

Author Contributions

N.C. was involved in conceptualization, formal analysis, supervision, visualization, methodology, writing—original draft, project administration, and writing—review and editing. K.K. was involved in conceptualization, formal analysis, methodology, writing—original draft, and writing—review and editing. A.F.W. was involved in conceptualization, formal analysis, visualization, methodology, writing—original draft, and writing—review and editing. M.E. was involved in conceptualization, software, formal analysis, methodology, writing—original draft, project administration, and writing—review and editing. P.B.R. was involved in conceptualization, resources, funding acquisition, investigation, methodology, and writing—review and editing.

Data Availability

Materials, data, syntax, and preregistration details are available at https://osf.io/uxcwm/?view_only=919c2f5b0e494f7c872d9432611b083b.

References

1 Pew Research Center. *Mobile fact sheet*. Pew Research Center; 2024. [accessed 2024 Aug 20]. https://www.pewresearch.org/internet/fact-sheet/mobile/.

2 Harmony Healthcare. *Phone screen time addiction - new survey data & statistics*. Healthcare Data Management Software & Services | Harmony Healthcare IT; 2024. [accessed 2024 Aug 20]. https://www.harmonyhit.com/phone-screen-time-statistics/.

3 Saad L. *Americans have close but Wary bond with their smartphone*. Gallup.com; 2022. [accessed 2022 Jul 14]. https://news.gallup.com/poll/393785/americans-close-wary-bond-smartphone.aspx.

4 Carr N. 2017. How smartphones hijack our minds. *Wall Street J*. https://www.wsj.com/articles/how-smartphones-hijack-our-minds-1507307811.

5 Twenge JM. 2017. Have smartphones destroyed a generation? *Atlantic*. https://www.theatlantic.com/magazine/archive/2017/09/has-the-smartphone-destroyed-ageneration/534198/.

6 Horwood S, Anglim J. 2019. Problematic smartphone usage and subjective and psychological well-being. *Comput Human Behav*. 97:44–50.

7 Vahedi Z, Saiphoo A. 2018. The association between smartphone use, stress, and anxiety: a meta-analytic review. *Stress Health*. 34: 347–358.

8 Wilmer HH, Sherman LE, Chein JM. 2017. Smartphones and cognition: a review of research exploring the links between mobile technology habits and cognitive functioning. *Front Psychol*. 8:605.

9 Ward AF. 2013. Supernormal: how the internet is changing our memories and our minds. *Psychol Inq*. 24:341–348.

10 Kushlev K, Proulx J, Dunn EW. 2016. "Silence Your Phones": smartphone notifications increase inattention and hyperactivity symptoms. Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems; San Jose, CA, USA. p. 1011–1020.

11 Ophir E, Nass C, Wagner AD. 2009. Cognitive control in media multitaskers. *Proc Natl Acad Sci U S A*. 106:15583–15587.
12 Ward A, Duke K, Gneezy A, Bos M, Drain B. 2017. The mere presence of smartphones reduces cognitive capacity. *J Assoc Consum Res*. 2:140–154.
13 Sbarra DA, Briskin JL, Slatcher RB. 2019. Smartphones and close relationships: the case for an evolutionary mismatch. *Perspect Psychol Sci*. 14:596–618.
14 Stothart C, Mitchum A, Yehnert C. 2015. The attentional cost of receiving a cell phone notification. *J Exp Psychol Hum Percept Perform*. 41:893–897.
15 Jacquet T, Lepers R, Pageaux B, Poulin-Charronnat B. 2023. Acute smartphone use impairs vigilance and inhibition capacities. *Sci Rep*. 13:23046.
16 Ruiz Pardo AC, Minda JP. 2022. Reexamining the "brain drain" effect: a replication of ward et al. (2017). *Acta Psychol (Amst)*. 230: 103717.
17 Böttger T, Poschik M, Zierer K. 2023. Does the brain drain effect really exist? A meta-analysis. *Behav Sci (Basel)*. 13:751.
18 Parry DA. 2024. Does the mere presence of a smartphone impact cognitive performance? A meta-analysis of the "Brain Drain Effect". *Media Psychol*. 27:737–762.
19 Fitz N, *et al.* 2019. Batching smartphone notifications can improve well-being. *Comput Human Behav*. 101:84–94.
20 Brailovskaia J, *et al.* 2023. Finding the "sweet spot" of smartphone use: reduction or abstinence to increase well-being and healthy lifestyle?! An experimental intervention study. *J Exp Psychol Appl*. 29:149–161.
21 Diener E, Emmons RA, Larsen RJ, Griffin S. 1985. The satisfaction with life scale. *J Pers Assess*. 49:71–75.
22 American Psychiatric Association. *Online assessment measures*; 2013. [accessed 2021 Sep 14]. https://www.psychiatry.org/psychiatrists/practice/dsm/educational-resources/assessment-measures.
23 Brown KW, Ryan RM. 2003. The benefits of being present: mindfulness and its role in psychological well-being. *J Pers Soc Psychol*. 84:822–848.
24 Esterman M, Noonan SK, Rosenberg M, DeGutis J. 2013. In the zone or zoning out? Tracking behavioral and neural fluctuations during sustained attention. *Cereb Cortex*. 23:2712–2723.
25 Esterman M, Rothlein D. 2019. Models of sustained attention. *Curr Opin Psychol*. 29:174–180.
26 Morey RD. 2008. Confidence intervals from normalized data: a correction to Cousineau (2005). *Tutor Quant Methods Psychol*. 4: 61–64.
27 Fortenbaugh FC, *et al.* 2015. Sustained attention across the life span in a sample of 10,000: dissociating ability and strategy. *Psychol Sci*. 26:1497–1510.
28 Yamashita A, Rothlein D, Kucyi A, Valera EM, Esterman M. 2021. Brain state-based detection of attentional fluctuations and their modulation. *Neuroimage*. 236:118072.
29 Kirsch I, *et al.* 2008. Initial severity and antidepressant benefits: a meta-analysis of data submitted to the food and drug administration. *PLoS Med*. 5:e45.
30 Cuijpers P, *et al.* 2013. A meta-analysis of cognitive-behavioural therapy for adult depression, alone and in comparison with other treatments. *Can J Psychiatry*. 58:376–385.
31 Schertz KE, Berman MG. 2019. Understanding nature and its cognitive benefits. *Curr Dir Psychol Sci*. 28:496–502.
32 Brajša-Žganec A, Merkaš M, Šverko I. 2011. Quality of life and leisure activities: how do leisure activities contribute to subjective well-being? *Soc Indic Res*. 102:81–91.
33 House JS, Landis KR, Umberson D. 1988. Social relationships and health. *Science*. 241:540–545.
34 Warburton DER, Nicol CW, Bredin SSD. 2006. Health benefits of physical activity: the evidence. *CMAJ*. 174:801–809.
35 Hofmann W, Luhmann M, Fisher RR, Vohs KD, Baumeister RF. 2014. Yes, but are they happy? Effects of trait self-control on affective well-being and life satisfaction. *J Pers*. 82:265–277.
36 Scott AJ, Webb TL, Martyn-St James M, Rowse G, Weich S. 2021. Improving sleep quality leads to better mental health: a meta-analysis of randomised controlled trials. *Sleep Med Rev*. 60: 101556.
37 Sheldon KM, Gunz A. 2009. Psychological needs as basic motives, not just experiential requirements. *J Pers*. 77:1467–1492.
38 Tangney JP, Baumeister RF, Boone AL. 2004. High self-control predicts good adjustment, less pathology, better grades, and interpersonal success. *J Pers*. 72:271–324.
39 Montoya AK, Hayes AF. 2017. Two-condition within-participant statistical mediation analysis: a path-analytic framework. *Psychol Methods*. 22:6–27.
40 Przybylski AK, Murayama K, DeHaan CR, Gladwell V. 2013. Motivational, emotional, and behavioral correlates of fear of missing out. *Comput Human Behav*. 29:1841–1848.
41 Allcott H, Braghieri L, Eichmeyer S, Gentzkow M. 2020. The welfare effects of social media. *Am Econ Rev*. 110:629–676.
42 Kushlev K, Leitao MR. 2020. The effects of smartphones on well-being: theoretical integration and research agenda. *Curr Opin Psychol*. 36:77–82.
43 Smith A. *U.S. smartphone use in 2015*. Pew Research Center; 2015. [accessed 2024 Dec 13]. https://www.pewresearch.org/internet/2015/04/01/us-smartphone-use-in-2015/.
44 Rotondi V, Kashyap R, Pesando LM, Spinelli S, Billari FC. 2020. Leveraging mobile phones to attain sustainable development. *Proc Natl Acad Sci U S A*. 117:13413–13420.
45 Diener E. 1984. Subjective well-being. *Psychol Bull*. 95:542–575.
46 Diener E, *et al.* 2010. New well-being measures: short scales to assess flourishing and positive and negative feelings. *Soc Indic Res*. 97:143–156.
47 Sheldon KM, Elliot AJ, Kim Y, Kasser T. 2001. What is satisfying about satisfying events? Testing 10 candidate psychological needs. *J Pers Soc Psychol*. 80:325–339.
48 Kessler RC, *et al.* 2005. The World Health Organization adult ADHD self-report scale (ASRS): a short screening scale for use in the general population. *Psychol Med*. 35:245–256.
49 Madore KP, *et al.* 2020. Memory failure predicted by attention lapsing and media multitasking. *Nature*. 587:87–91.
50 Cumming G. 2014. The new statistics: why and how. *Psychol Sci*. 25:7–29.