Going Light: The Effects of Minimal Mobile Phone Adoption on Young Adults' Well-Being Depend on Motivation

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Abstract

Concerns about smartphone dependency have sparked interest in minimal mobile phones: devices supporting basic communication without social apps, web browsing, or games. These design choices are thought to improve well-being, but have not been tested empirically. We conducted a first-of-its-kind longitudinal experiment examining the effects of switching from smartphones to minimal mobile phones on young adults' psychological well-being over a week (n = 166). To account for individual variation in intrinsic motivation to try a minimal phone, we employed a quasi-experimental design comparing the outcomes of three groups: 1) high-interest volunteers who were asked to use minimal phones or participants that were randomly assigned to either 2) use minimal phones or 3) continue using their own smartphones. Results showed that switching to a minimal phone effectively reduced phone and social media use. However, only high-interest volunteers - those intrinsically motivated to participate - showed significant within-person changes in psychological well-being, reporting reduced stress, increased life satisfaction, and less FoMo. No effects on well-being were observed for those assigned to use the phone. Our results suggest that switching to a minimal mobile phone may support some motivated individuals in improving their sense of agency and well-being in an increasingly connected digital world.

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CCS Concepts

• **Human-centered computing → Empirical studies in collaborative and social computing**.

Keywords

mobile phone, digital disconnection, well-being, smartphone, agency, detox

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1 Introduction

Smartphones are an integral part of modern social life, enabling people to access information instantly, communicate with their peers at all times of the day, and navigate important elements of their personal and professional lives [66, 73]. Recent surveys have found that over 90% of adults and 85% of adolescents in the United States currently have their own smartphone – a number that has steadily increased over the last several years and continues to rise [18, 61].

However, there are concerns that smartphone use may be detrimental to psychological well-being - particularly among younger generations who grew up with constant smartphone use as the norm [35, 36, 75]. While mobile devices allow people to be constantly connected, the ability to be "always on and available" can have negative effects on their quality of life [29]. Many young users report feeling that their smartphone use disrupts their focus [43] and undermines their ability to be present for face-to-face interactions [3, 14]. Furthermore, research on compulsive and problematic smartphone use indicates that many people struggle with feeling dependent on their phones, such as using their devices when they do not mean to and feeling unable to reduce their screen-time, even when they believe it to be harmful [29, 31]. Accordingly, parents are worried about the effects of smartphone use on their children. A recent nationally representative poll found that 67% of American parents believed that "overuse of devices and screen-time" was harmful to their children's health, surpassing the number of parents who were concerned about the effects of school violence (49%) and smoking or vaping (48%) [1].

These negative experiences correspond with some research suggesting that smartphones are linked to the rise of mental health challenges among children and adolescents [7, 53]. In particular, scholars such as [24] have argued that increasing rates of depression, anxiety, and stress can be tied to the introduction of smartphones and social media into mainstream society. It is important to note that the question of whether smartphones indeed cause such strong negative effects continues to be the subject of rigorous empirical investigation and academic debate [52, 54]. However, experts generally agree that many people are concerned about the amount of time they personally spend on smartphones, and are seeking out more intentional forms of technology use that can help them have a greater sense of agency over their lives [33, 34, 39, 54].

To address this growing demand, researchers have developed digital disconnection strategies that support voluntary breaks from digital media, particularly smartphones [68]. Most take an individual-focused approach by offering users features that allow them to control notification frequency, set limits on app use, and manage when they can use their phones (e.g., in the morning, at bedtime). These are designed to support positive behavioral change by helping users align their smartphone habits with their personal goals [63]. More intensive disconnection options involve digital "detoxes" where individuals try to fully stop using their devices for a day, a week, or even months [71, 76]. However, one limitation of these strategies is that they require continuous self-control that can be challenging for individuals to sustain long-term [58]. Recognizing these challenges, researchers and designers are now exploring a different approach that may reduce the burden placed on users: reimagining the fundamental design of mobile devices themselves to minimize unwanted distractions and enhance user autonomy [33, 80].

One promising device-level intervention for digital disconnection is the *minimal mobile phone*, which provides users with basic communication abilities, such as calling and texting, while removing access to features such as social media, games, and internet browsers that are often perceived as distracting [2, 8]. Also known as "dumbphones," these phones include classic models from well-known mobile technology companies, such as the Nokia Flip and the Maxcom MM135L, as well as "designer" mobile phones developed by new, smaller companies, including the Light Phone and the Balance Phone (see 1) [69]. By supporting essential communication while reducing exposure to the potential harms associated with smartphone use, minimal mobile phones provide a middle ground between light-touch applications that encourage reductions in use (i.e., Apple ScreenTime limits) and intensive behavioral changes like disconnecting from smartphones entirely for a period of time. Despite their availability and increasing public interest [63, 69], little empirical research has tested the causal effects of using a minimal mobile phone on psychological well-being.

In this paper, we conduct an experimental evaluation of the effects of minimal mobile phone adoption on psychological well-being and quality of life. We recruited students to participate in a one-week, between-subjects experiment that involved switching from their regular smartphone to the Light Phone II, a minimal mobile phone that allows individuals to make phone calls, send text messages, navigate using GPS, and setting an alarm. The phone did not afford any use of social media, web browser applications, or games. This device-level intervention enabled us to investigate how design choices (i.e., the exclusion of specific features) impact people's psychological well-being over time.

Crucially, this study tackles the role that a young adult's motivation plays in shaping the effects of switching to the minimal phone on well-being outcomes. People naturally vary in the extent to which they are interested in adopting a new technology, whether that involves a relatively "light-weight" change, such as downloading an app, or more intensive behavioral changes, such as switching their primary mobile device [80]. Previous work suggests that people often vary in their motivations for pursuing digital disconnection [34], and that those who opt for a minimal mobile phone tend to be strongly motivated to find a "low-distraction digital handset" [69]. To account for this individual variation in intrinsic motivation to try a minimal phone, we employed a quasi-experimental design comparing the outcomes of three groups: 1) high-interest volunteers who were asked to use minimal phones or participants that were randomly assigned to either 2) use minimal phones or 3) continue using their own smartphones. Our results make important contributions to both the growing discourse on the effects of smartphones on society and designer-led efforts to improve our relationship with digital devices.

2 Related work

2.1 Smartphone use and psychological well-being

The relationship between smartphone use and psychological well-being has received widespread public and scholarly attention. To date, hundreds of empirical studies [11, 38, 45, 79] have investigated how particular elements of smartphone use relate to a wide variety of indicators of psychological well-being, including the quality and strength of their relationships (relational well-being), their satisfaction with their lives (eudaimonic well-being), their day-to-day mood (affective well-being), and their experience with symptoms of stress, depression, and anxiety (psychological distress) [30].

Several mechanisms have been proposed to explain why smartphone use influences well-being in different ways, under the displace-interfere-complement framework [36]. On one hand, smartphones are theorized to improve well-being when they complement individuals' experiences by providing otherwise unavailable opportunities and affordances [73]. Indeed, some studies find that people who spend more time on their smartphones and use it more frequently experience more positive emotions on a daily basis because it allows them to stay in touch with friends and family [42]. A large-scale study of British youth (n = 120,115) found that smartphone and social media use was not inherently harmful and, in moderate amounts, could even be beneficial for psychological well-being and bring advantages in a connected world [57]. These benefits appear to be particularly pronounced for individuals who are separated from established communities, such as among college students moving away from home [16] or adolescents isolated from their peers due to the COVID-19 pandemic [47].

On the other hand, smartphone use may be harmful when it displaces other activities such as face-to-face social interactions [35] or interferes with other important activities such as homework or sleep [45, 72]. For example, a meta-analysis of 83 empirical studies found that smartphone use can disrupt in-person social interactions, thereby undermining the quality of the interaction and potentially harming the relationship itself [51]. More broadly, many individuals can become sufficiently dependent on their smartphones that they experience stress and anxiety when they must go without it - an experience termed *nomophobia* that has been linked to increased psychological distress (for a review, see [62]).

It is also important to consider the effect of smartphones on psychological well-being over time [22]. Much of the existing literature has treated media use as having linear effects on psychological well-being, assuming that more use is associated with proportionally greater harms or benefits [46]. However, emerging research leveraging longitudinal studies or intensive ecological momentary analyses of individuals' real-time responses to media suggests that these relationships are often non-linear [59, 77]. For example, a two-wave panel study of Belgian adolescents revealed curvilinear associations between active Facebook use and loneliness [81], suggesting that moderate use related to lower loneliness, while heavy use was linked to increased loneliness. Leveraging even more granular data, a study by [9] following signals of individuals' smartphone use and well-being over the course of two years found that using increased smartphone use frequency was linked to nonlinear decreases, and increases, in well-being that varied depending on the person examined. Understanding the real effects of smartphone use - and minimal phone use - on individuals' psychological well-being therefore requires consideration of the shape of the trajectory of these potential media effects. In this study, we focused on investigating whether switching to minimal phones would affect participants' psychological well-being in linear or nonlinear ways.

2.2 Approaches to digital disconnection

Given widespread concerns about the potential harms of digital technologies, there has been a notable increase in interest in digital disconnection strategies to help people better manage their relationship to their digital devices [63]. People are increasingly searching for options that help them "unplug" or "detox" from their smartphones [58], citing motivations including desires to improve their well-being, reduce distractions, and feel more present in their day-to-day lives [48, 80]. Indeed, the App Store is now filled with numerous digital tools that aim to give individuals more control over their interactions with their devices, such as the Forest app or Detox [58].

Approaches to digital disconnection vary substantially in the duration of time they are applied for, the level of granularity at which they operate, and the extent to which they focus on teaching individuals to self-regulate their own use or remove distracting features [48]. The digital disconnection continuum framework offers a useful way to conceptualize these strategies by situating them along a spectrum of voluntary non-use [67]. On one end of the spectrum are light-touch interventions, such as apps that nudge users to pause before opening social media (e.g., one sec; [23]) or tools that track screen time and prompt self-monitoring. These aim to cultivate awareness and habit disruption without restricting access. Moving along the continuum, interventions may place more explicit constraints, such as time limits on specific apps or entire categories of content (e.g., entertainment), features now embedded in Apple's ScreenTime and Android's Digital Wellbeing dashboards. At the most intensive end are full digital detoxes, which involve complete abstinence from devices for a designated period, whether individually or as part of collective efforts like the National Day of Unplugging.

However, empirical evidence on the effectiveness of disconnection strategies remains decidedly mixed. In their review of 21 experimental studies investigating the effectiveness of digital detox interventions on psychological well-being and quality of life, [58] found that some efforts to promote digital disconnection were successful at improving individual outcomes but others produced null effects. A similar review focusing on digital well-being tools in the field of human-computer interaction designed to support individual agency over devices [63] also noted that some interventions were more effective at improving well-being than others, with many not resulting in anticipated changes. For example, an experimental study of 127 students asked to lock their smartphones in a cabinet for three days found that this full restriction in smartphone use did not improve their affective well-being [15]. In fact, relative to the control group that had access to their smartphones, students who restricted their smartphone use felt more fear of missing out instead of feeling more present with their peers.

This heterogeneity in individual responses to digital disconnection interventions can be understood through the differential susceptibility to media effects model [78], which argues that media effects are not uniform, but vary across individuals. Past research has highlighted how investigating the effects of smartphone use on well-being is inherently challenging because smartphone use is highly idiosyncratic: people use their smartphones for different amounts of time, with different, across different applications [9, 60]. Accordingly, digital disconnection interventions should have different effects on individuals depending on what aspect of smartphone use is being reduced or restricted [34, 80]. Closer examination of the existing literature suggests that more research has focused on the effects of asking individuals to restrict or abstain from using social media, than from their smartphones [58, 63], which appear to demonstrate greater effects on psychological well-being. For

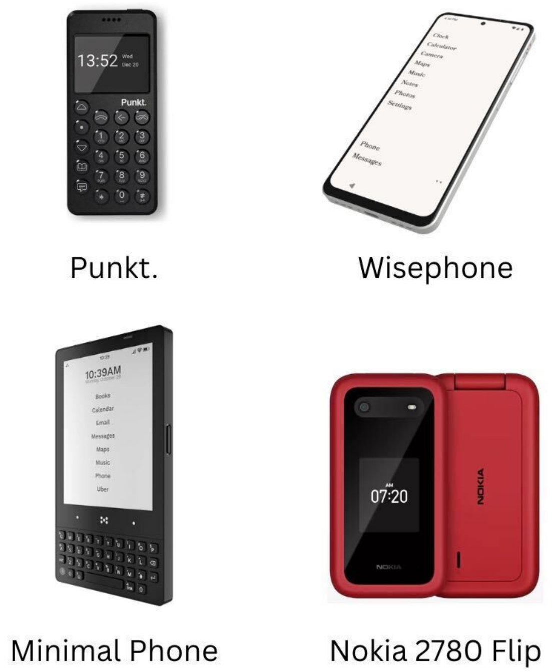

Figure 1: Examples of minimal mobile phones include "designer" phones custom-made to reduce distracting features, as well as conventional mobile phones that focus on providing calling and texting features.

instance, a large-scale randomized experiment on Facebook abstinence found that abstaining from the platform led to reduced online activity, increased offline social interactions, and improved subjective well-being [2]. Similarly, a one-week intervention aimed at social media disconnection showed slight improvements in mental health and perceived social support, as well as a decrease in fear of missing out [6].

2.3 Minimal mobile phones as a device-level intervention

Given that research shows digital disconnection affects different people in different ways, it can be challenging to draw useful causal conclusions about how these interventions should be designed or what people should do. One promising approach to better isolate these effects is conducting device-level interventions that systematically remove certain design features while preserving others. Rather than studying complete digital detoxes or wholesale smartphone abstinence, researchers can manipulate specific technological elements, such as disabling push notifications while maintaining calling and texting capabilities, or removing social media apps while preserving productivity tools. This targeted approach aligns with Roffarello and De Russis's (2024) call for more research on the differentiated effectiveness of disconnection strategies. In addition to allowing us to draw more precise causal inferences about which features drive problematic usage patterns, identifying the specific features that are linked to benefits and harms not only strengthens our theoretical understanding but also provides actionable guidance for technologists.

Minimal phones represent one such opportunity to specifically test the effects of removing certain features, while preserving others, on user outcomes. Their rising popularity matches growing public interest in approaches that make it easier for people to reduce their phone usage by default [63]. For instance, more people than ever are expressing interest in giving up their smartphones in exchange for minimal mobile phones [69]. Contrary to popular perceptions that youth are highly attached to their smartphones, this shift is driven by young adults: 28% of Gen Z expressed interest in switching to a minimal phone, while Boomers were the least likely.

Although changing devices involves a more radical shift than downloading an app or implementing a screen-time limit, it may also be easier for people to uphold their goals when certain affordances are restricted by design. In their review of digital disconnection interventions, [58] found that many people who opted for lighter-touch disconnection strategies, such as reminders and screen-time limits, often struggled to maintain these digital habits. Rather than persuading users to change their behavior within the context of a fully functional smartphone, these devices eliminate the option altogether by removing access to social media, web browsing, and app stores (see Figure 1). In their article, [70] highlighted that interventions that encourage technology non-use by design through structural constraints, rather than nudges or rewards, may be more effective because they do not require individuals to self-regulate.

Recent scholarship has framed these devices within broader movements, such as calm technology and slow design, which seek to align technological experiences with values like focus, presence, and intentionality [63, 74]. In contrast to the always-on, efficiency-driven logic of most digital tools, minimal phones are intended to promote autonomy and reduced cognitive load by minimizing technological demands on users' attention [69]. Qualitative and journalistic accounts highlight some promising outcomes, such as users reporting feelings of relaxation, focus, and control [44]. However, empirical evidence remains limited. Few studies have systematically evaluated the effects of these devices in controlled or longitudinal settings with larger sample sizes. Our study aims to address this important gap in the literature.

2.4 Individual differences in motivation to disconnect

One important dispositional factor that may shape the effects of digital disconnection interventions, like switching to a minimal phone, focuses on individual motivation. People vary in how much they are intrinsically interested in wanting to pursue options designed to support digital well-being, and their reasons why they may choose to disconnect. In a recent comprehensive review, [48] identified six primary motivations for disconnection, including: (1) perceived overuse of digital media, which can prompt individuals to reassess their habits; (2) a desire to improve social interactions, manage relationships, and control self-presentation; (3) the pursuit of enhanced psychological well-being, such as reducing stress, anxiety, or depressive symptoms; (4) the need to increase productivity and reduce digital distractions; (5) concerns over data privacy and surveillance; and (6) the wish to reclaim purposeful engagement and resist habitual media use.

Motivations to disconnect are multifaceted and dynamic. While some drivers, such as overuse or privacy concerns, may reflect longer-term patterns or values, others such as the desire to avoid distractions or be fully present are more context-dependent and situationally triggered. Importantly, expressed motivations (e.g., for well-being) and actual disconnection behaviors vary greatly across individuals as well as within individuals over time. Notably, disconnection does not always follow negative experiences with technology. Instead, disconnection can be triggered by important life transitions or lifestyle choices reflecting an individual's complex and ambivalent relationship with technology [49]. Therefore, some individuals might take their motivation to disconnect a step further by actively replacing, reducing, or removing technology at certain times [32]. For these highly motivated users, disconnection is often a deliberate, value-driven lifestyle choice. These individuals may therefore benefit to a greater extent from a minimal mobile phone that is intended to support such disconnection.

3 The Present Study

The purpose of this study was to investigate the effects of minimal mobile phone adoption on young adults' psychological well-being. To address these questions, we employed a quasi-experimental design comparing three groups: 1)high-interest volunteers who actively sought to participate in the minimal phone intervention, and 2) participants who were either randomly assigned to use minimal phones or 3) randomly assigned to continue using their regular smartphones. This approach allows us to test the causal effects of this device-level intervention on multiple dimensions of psychological well-being over time, while also examining how individual motivation shapes intervention outcomes.

The Light Phone II was "designed to be used as little as possible" by removing access to social media platforms, web browsers, games, and entertainment app. We therefore first predicted that these design constraints would reduce time spent on social media engagement by making them more difficult to access, and overall phone usage throughout the day. A summary of our hypotheses, research questions, and key findings can be found below.

H1: Participants who use the Light Phone will (a) spend less time on their phones and (b) less time on social media than those in the control condition.

Removing these features at the device-level should influence how much agency and control individuals feel they have over their phones. We predicted that without constant notifications, the temptation to play games, or the ability to scroll social media or check their email, participants should experience less feelings of dependency on their phones and more control over their phone use.

H2: Participants who use the Light Phone will experience will report (a) less dependency on their phones and (b) more perceived agency over their phones.

Past work on digital disconnection, such as the displace-interfere-complement framework, suggests that switching to a minimal phone should affect how people feel [14, 35]. The removal of distracting features should help people feel more present and attentive in their day-to-day lives. Therefore, we predicted using the Light Phone would improve participants' affective well-being.

H3: Participants who use the Light Phone will experience better affective well-being in terms of their (a) positive affect and (b) feelings of productivity, than those in the control condition.

However, the same literature emphasizes that smartphones can complement social interactions by allowing people to readily maintain communication across distance [16, 35, 47]. We therefore predicted that removing access to social media platforms and communication channels may would reduce participants' sense of social connection to others.

H3: Participants who use the Light Phone will experience will report lower levels of social connectedness, than those in the control condition.

Drawing from research linking smartphone use to increased psychological distress [25, 29], we predicted that reducing exposure to distracting smartphone features would improve psychological well-being. The constant connectivity, social comparison opportunities, and addictive design elements present in smartphones may contribute to stress and depressive symptoms, while their removal should promote greater psychological well-being and life satisfaction.

H4: Participants who use the Light Phone will experience will report (a) lower levels of depression, (b) lower levels of stress, and (c) higher levels of life satisfaction, than those in the control condition.

In addition to our hypotheses, we considered two additional exploratory research questions that guided our investigation of individual differences and temporal dynamics. We posed these as research questions rather than hypotheses given that little past work has explicitly examined these factors in the digital disconnection, and we therefore approached them from an exploratory angle. The differential susceptibility to media effects model suggests that interventions will not affect all individuals uniformly [78], and existing research indicates that people vary substantially in their motivations for pursuing digital disconnection [34, 80]. The inclusion of the high-interest group of volunteers tackles the motivational challenge that is inherent to many behavioral intervention studies [37, 41]: people are more likely to participate when they are intrinsically interested. We examined if those who voluntarily seek minimal phone alternatives would experience different outcomes than those randomly assigned to use these devices.

RQ1: Does individual motivation to disconnect moderate the effects of switching from smartphones to minimal phones on psychological well-being and perceived agency?

Emerging research suggests that technology-wellbeing relationships often exhibit curvilinear patterns rather than simple dose-response effects [9]. Across all outcomes, we were interested in understanding whether the effects of minimal phone adoption emerge immediately, develop gradually, or follow more complex trajectories is crucial.

RQ2: Do relationships between smartphone or minimal phone use conditions and well-being outcomes follow linear or non-linear trajectories?

Table 1: Summary of Hypotheses, Results, and Research Question Findings

	Hypothesis	Results	RQ1: Does user motivation matter?	RQ2: What are the trajectories of change over time?
H1a	Light Phone users will spend less overall time on their phones.	Supported	Stronger effects among high-interest Light Phone users	Linear growth model had better fit
H1b	Light Phone users will spend less time on social media.	Supported	Stronger effects among high-interest Light Phone users	Linear growth model had better fit
H2a	Light Phone users will report lower dependency.	Supported	Stronger effects among high-interest Light Phone users	Quadratic growth model had better fit
H2b	Light Phone users will report higher perceived agency/control.	Supported	–	–
H3a	Light Phone users will experience higher positive affect.	Not supported	–	–
H3b	Light Phone users will experience greater feelings of productivity.	Not supported	–	–
H3c	Light Phone users will report lower social connectedness.	Not supported	–	–
H4a	Light Phone users will report lower depression.	Not supported	–	–
H4b	Light Phone users will report lower stress.	Partially supported	Significant effects only among high-interest Light Phone users	Quadratic growth model had better fit
H4c	Light Phone users will report higher life satisfaction.	Partially supported	Significant effects only among high-interest Light Phone users	Linear growth model had better fit

Note. Table summarizes preregistered hypotheses, model results, and findings for two exploratory research questions. RQ1 examines whether effects differed by initial motivation to adopt the Light Phone (high-interest users). RQ2 indicates whether linear or nonlinear (quadratic) growth models provided the best fit for each outcome. Dashes indicate no significant moderation effects or model fit differences.

4 Method

4.1 Study design and procedure

We conducted a longitudinal, between-subjects experiment to investigate the effects of switching from a smartphone to a minimal mobile phone for one week on young adults' well-being. From April to November 2024, participants were recruited from an American university to complete a study on "Personal experiences with smartphones" that involved completing four surveys over the course of one week. All procedures were approved by the [Anonymized] Institutional Review Board.

As shown in Figure 2, prospective participants completed a screening questionnaire to determine their eligibility. They were required to be over 18, enrolled as a student, and to have a mobile phone with a physical SIM card that could be transferred to the minimal phone. Because choosing to give up one's smartphone and try a new mobile device involves substantial effort and is more intrinsically appealing to some people than others [34, 80], we recruited participants through two approaches. Paper flyers and emails were distributed to recruit people who were strongly interested in trying the minimal phone - termed the *high-interest* group because of their intrinsic motivation to pursue this experience. In addition, we recruited students from a social studies class to participate in an experiment where participants were *randomly assigned to either a treatment group* that were asked to use the minimal phone for one week or a *control group* that continued to use their smartphones as usual. This design enabled explicit comparisons between participants who were motivated to reduce smartphone use and those who engaged without prior interest, supporting a more nuanced understanding of who benefits from digital disconnection interventions [58, 67, 78].

Next, participants attended a brief, in-person information session. Students in the high-interest group and the treatment group received information about the minimal phone used in the study, including its features and its capabilities. The control group received information about smartphones. Upon consenting, participants set up their Light Phones with assistance from trained research assistants who helped transfer the SIM cards into the minimal phone, set up contact directories, and answer questions about the device. Participants were asked not to use their regular smartphone during the study period. They were required to submit a screenshot of their Apple iOS ScreenTime or Android Digital Well-being screentime at the end of the week to ensure compliance. Control group participants were instructed to continue using their smartphones as usual, and submit a screenshot of their screen-time. All participants completed the baseline survey (Time 1) and a series of three additional surveys over the course of the week (Time 2, Time 3, Time 4). Throughout the study, participants received reminders that they were allowed to exit the study and return to their original devices at any time.

At the end of the study period, participants in the high-interest group were allowed to keep their phones if they wished; treatment

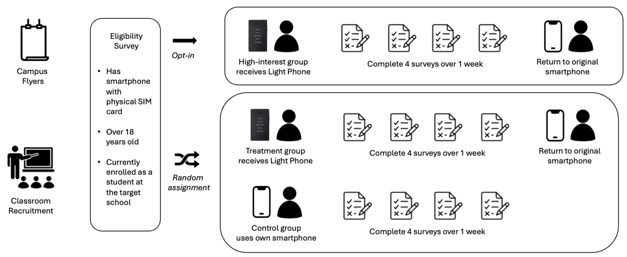

Figure 2: Participants were recruited through two approaches: 1) campus flyers that identified individuals who opted into using the Light Phone and 2) classroom recruitment that randomized participants into treatment or control groups.

group participants were asked to return to their regular smartphones; and control group participants were given the opportunity to try the minimal phone for one-week if they desired. The research assistants helped participants transition back to their own devices. All participants were compensated financially or with course research credits, depending on their choice at the conclusion of the study.

4.2 The Light Phone II

The minimal mobile device used in this study was the Light Phone II. This phone has been described as a designer dumbphone by previous human-computer interaction researchers [69] because it is a newly developed mobile device that has been specifically redesigned to meet the needs of users interested in improving their digital well-being.

As shown in Figure 3, the Light Phone has a black-and-white E-Ink display, physical navigation buttons, and a simplified operating system built on the Android Open Source Project that excludes most conventional smartphone capabilities. Unlike most smartphones, the Light Phone II does not support social media, email, web browsing, or any app store. Instead, it only includes calling, texting, alarms, a basic calendar, a calculator, a notes app, a simple MP3 music player, GPS navigation, and the ability to use the device as a WiFi hotspot. It has no camera, no background app multitasking, and no push notifications beyond calls and text messages. In terms of its hardware, it has Bluetooth, WiFi, a micro-USB charging port, and a headphone jack to allow users to listen to downloaded music.

4.3 Participants and attrition

We conducted an *a priori* power analysis to examine how many participants we would need to recruit to detect changes in well-being over time, between groups. Results indicated 150 participants (50 per group) were needed to complete four surveys to detect significant time × condition interaction effects with an expected small effect size of Cohen's $d = 0.073$ (median = 0.059; range = 0.039 – 0.146) across experimental conditions, with 80% power at $\alpha = 0.05$. This design supported both heterogeneous treatment effect (HTE) analyses comparing the high-interest and assigned treatment groups to the control group, and combined analyses

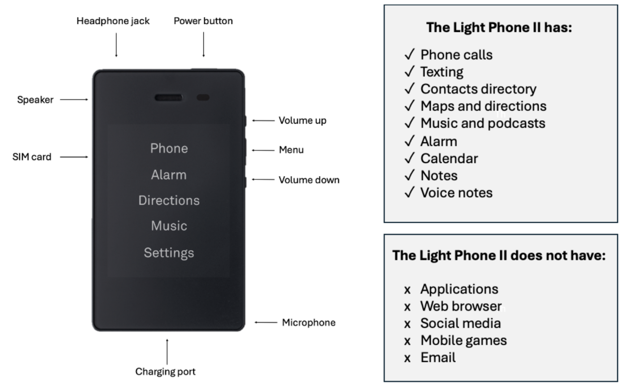

Figure 3: An illustration of the Light Phone II's key features. The Light Phone II does not support social media, email, web browsing, or any app store, but enables calling, texting, notes applications, and WiFi.

pooling Treatment and High-Interest groups into a single Light Phone condition versus Control.

A total of 209 participants enrolled in the initial study, of which 156 completed all four waves. For the high-interest group, 102 participants finished Time 1 and 97 finished Time 4. For the control group, 55 participants finished Time 1 and 42 finished Time 4. For the treatment group, 52 finished Time 1 and 15 finished Time 4. Of the final sample, there were 58 men (36.7%), 85 women (53.6%), 8 who were non-binary (5.1%), and 2 who preferred not to indicate their gender (1.3%). Our sample was relatively diverse, with 56 students who were white (34%) and 106 who were non-white (67.1%). The average age for our participants was 21 years old ($SD = 2.27$ years). The majority of participants' primary mobile phone was an iPhone ($n = 139$), with 7 having Androids, 1 having a Samsung, and 2 who had a different phone.

4.4 Measures

4.4.1 Psychological well-being. Psychological well-being was assessed along several different dimensions in line with past research highlighting how technology use can affect distinct mental health outcomes in different ways [40, 46, 78]. Participants were asked to indicate their feelings over the last two days. Please see the Supplement for all survey materials.

Affective well-being was assessed with a brief, adapted version of the Positive and Negative Affect Schedule (PANAS) with 10 items about how they felt in the moment [82]. Separate scores were calculated for positive affect (e.g., happy, proud) and feelings of productivity (e.g., capable, attentive). The measure demonstrated good reliability (Cronbach's $\alpha = .83$).

To measure **psychological distress**, participants completed a 14-item version of the Depression, Anxiety, and Stress Scale [50]. Items were on a 4-point Likert scale (1 = not at all, 4 = almost always). Scores were calculated for depression ("I have felt downhearted and blue") and stress ("I have found it difficult to relax"). The scale had good internal reliability (Cronbach's $\alpha = .87$).

Life satisfaction was measured with the Satisfaction with Life Scale, a 5-item survey to assess individuals' global cognitive judgments of satisfaction with their lives [13]. Example items include "So far I have gotten the important things I want in life" and "If I could live my life over, I would change almost nothing." Items were on a 7-point Likert scale (1 = "strongly disagree", 7 = "strongly agree"). The scale had good reliability (Cronbach's α = .88).

4.4.2 Phone experiences. Next, we asked participants to share how they felt about their phone use. All Light Phone users were asked to complete these questions referring to their experience with the Light Phone, while control group participants completed these questions referring to their own smartphones.

Participants' **phone dependency** was measured using 7 items adapted from [12] designed to capture subjective experiences with smartphones. These questions asked participants to describe if they habitually checked their phones ("I mostly checked my phone without thinking", "I constantly monitored my phone to see what was happening online") and if their desire to use their phones disrupted other activities ("I had a hard time disengaging mentally from online content on my phone", "I felt distracted by my phone"). Items were asked on a 5-point Likert scale (1 = not at all, 5 = extremely). The measure demonstrated good reliability (Cronbach's α = .87).

Agency and valence mindsets refer to participants' core assumptions about the role that their phones played in their lives. These were assessed using a 12-item adapted form of the Social Media Mindsets Scale [40]. Agency mindsets refer to the extent participants felt they had control over their engagement with their phones ("I know how to manage my phone use") or not ("I end up using my phone even when I don't mean to"). Valence mindsets refer to participants' belief that their phone use was personally beneficial and meaningful ("Using my phone facilitates my learning and growth") or harmful ("Using my phone is a waste of time"). The measures demonstrated good reliability (Cronbach's α = .83).

4.4.3 Individual differences. Participants answered questions about their **demographics**, such as their age, gender, education level, and ethnicity. They were allowed to skip any questions they did not feel comfortable with. Measures of psychological individual differences were collected at baseline given our interest in understanding how different people respond to the minimal phone intervention [69]).

Participants' **personality** was assessed using the Ten-Item Personality Inventory (TIPI) [20], which captures openness to new experiences, conscientiousness, extroversion, agreeableness, and neuroticism. Items were scored on a 7-point Likert Scale (1 = disagree strongly, 7 = agree strongly). The scale had good internal reliability (Cronbach's α = .68).

4.5 Entropy balancing

To address potential baseline covariate imbalances between the groups (Control, Treatment, and High-Interest), we employed entropy balancing [26] using the *ebal* package [27]. This preprocessing procedure reweights the data to achieve exact balance on specified characteristics (moments) of covariate distributions. Unlike traditional matching methods that discard observations, entropy balancing retains all participants by assigning weights to those in the Treatment and High-Interest groups. In contrast, Control group participants receive a weight of 1. The method optimizes these weights to ensure that the weighted distributions of covariates in these groups match the characteristics of the Control group distribution precisely. In other words, the method ensures that the Treatment and High-Interest groups are comparable to the Control group on all specified characteristics.

We denote each participant's group assignment as G_i, which can take one of three values: Control (C), Treatment (T), or High-Interest (H). For each participant i, we observe a set of baseline characteristics denoted by $\mathbf{X}_i$. These characteristics include: age, personality traits measured by the Ten Item Personality Inventory, gender (indicators for Female, Male, Non-binary), ethnicity (indicator for White or Non-white), and education level (indicator for Associate's degree).

The entropy balancing procedure assigns a weight w_i to each participant in the Treatment and High-Interest groups. Weights are chosen to solve an optimization problem with two key components. First, the weights should make the characteristics of these groups match those of the Control group. Mathematically, this means that for each characteristic we want to balance (such as age or personality measures), the weighted average in either the Treatment or High-Interest group should equal the unweighted average in the Control group. Second, among all possible sets of weights that achieve this balance, we choose the set that deviates as little as possible from equal weighting of all participants. This minimizes the influence of any single participant while still achieving the desired balance.

Formally, for each pairwise comparison (Treatment vs. Control and High-Interest vs. Control), entropy balancing solves an optimization problem. The goal is to find weights that make the treatment groups look as similar as possible to the control group, while keeping the weights as close as possible to equal weighting (where every participant would have the same weight).

$$\min_{\mathbf{w}} \sum_{i|D=1} w_i \log\left(\frac{w_i}{q_i}\right)$$

subject to three key requirements:

$$\sum_{i|D=1} w_i c_r(\mathbf{X}_i) = m_r, \quad r = 1, \ldots, R$$

$$\sum_{i|D=1} w_i = 1$$

$$w_i \geq 0, \quad \forall i \text{ where } D = 1$$

The equations represent the following process: We assign a weight w_i to each participant in the Treatment or High-Interest groups (denoted by D=1). These weights start from a baseline of equal influence (q_i) and are then normalized by their mean to ensure proper scaling while maintaining the desired balance across key characteristics.

The first requirement establishes the weighted average of each characteristic (e.g., age or personality measures) in the treatment group must match the average of that characteristic in the control group. This matching process occurs across all characteristics included in the balancing procedure (represented by r = 1,...,R).

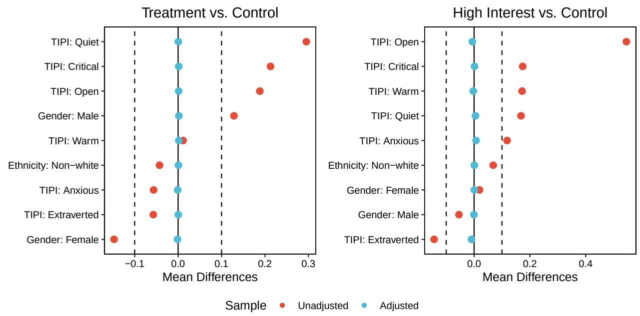

Figure 4: Covariate Balance Assessment via Love Plot Before and After Entropy Balancing. Standardized mean differences (SMDs) are shown for baseline covariates comparing Treatment vs. Control and High-Interest vs. Control groups. Vertical lines indicate the balance threshold (SMD = 0.1).

The second requirement specifies that the weights must sum to 1, following standard weighting conventions. The third requirement ensures all weights remain positive, as negative weights would not have a meaningful interpretation in this context.

The optimization equation (shown above) measures deviation of the final weights from equal weighting. Its mathematical form ensures large deviations in individual weights incur greater penalties, thereby promoting a more even distribution of influence across participants while maintaining the desired balance.

Data were prepared using the following steps. First, missing data values in any characteristic were filled in using the average value within each group to preserve group-specific distributions and avoid biasing covariate relationships [17]. Next, we enforced the region of common support by verifying that the ranges for the Treatment and High-Interest groups fell within those observed for the Control group to ensure adequate counterfactual units existed for all treated cases [10, 64]. To ensure numerical stability in the optimization procedure, we removed redundant or perfectly collinear characteristics so the constraint/design matrices were full rank [19, 26]. Finally, we standardized continuous variables, such as age, to mean zero and unit variance [28].

Using the *cobalt* package [21], we confirmed that after weighting, the absolute standardized mean differences (SMDs) were below 0.1 for all characteristics (see Figure 4), a commonly accepted threshold for good balance. For continuous variables, such as personality traits measured by TIPI, the variance ratios were close to 1.0, indicating similar spread of values between groups. The weighting procedure was particularly effective: the largest remaining imbalance after weighting was only 0.0017 for gender (male) in the Treatment versus Control comparison and -0.0095 for extraversion in the High-Interest versus Control comparison. These diagnostics indicate that the weighting successfully achieved comparable groups for our subsequent analyses.

These participant-specific weights were then merged into the longitudinal dataset to be incorporated in all subsequent statistical analyses, thereby adjusting for pre-treatment differences in the observed baseline characteristics.

4.6 Analytical approach

To analyze how switching to the Light Phone affected participants over time, we used multi-level growth models that capture both individual trajectories and group-level differences in change [22]. We conducted analyses using two complementary approaches: (1) combined analysis comparing the unified Light Phone intervention group against the control group, and (2) heterogeneous treatment effects (HTE) analysis comparing treatment and high-interest groups separately against the control group. For each outcome scale and analytical approach, we estimate and report both linear and quadratic growth models to fully characterize the temporal dynamics of the intervention. When a scale consists of multiple items, each item is treated as an observation, and thus the coefficients represent changes at the item-level measurement.

Before presenting the formal model specifications, we clarify the conceptual distinction between the two model types. *Linear growth models* assume outcomes change at a constant rate—a steady increase, steady decrease, or no change across time points. *Quadratic growth models* allow the rate of change itself to vary over time, capturing trajectories such as initial declines that level off, reverse, or accelerate; or initial improvements that fade, stabilize, or compound. We estimate both model types for each outcome for two reasons. First, it is an empirical question whether switching to a minimal phone produces immediate effects that persist, gradual effects that build, or initial changes that later stabilize or reverse. Second, understanding the shape of these trajectories—not just whether change occurs—is essential for informing how digital disconnection interventions should be designed and how long they should be sustained.

The linear growth model for item measurement Y_{it} (representing the response to an item within a scale) for person i at time t is specified as:

$$Y_{it} = \beta_{0i} + \beta_{1i}\text{Time}_{it} + \epsilon_{it}$$

where Time_{it} is coded as 0, 1, 2, 3 for T1 through T4, respectively. T1 was recorded *before* the intervention, while T2, T3, and T4 were recorded *during* the intervention. The key parameters of interest are the time coefficients, which capture how outcomes change during the intervention period. Specifically, β_{0i} represents a participant's baseline level at T1, while β_{1i} represents their rate of change per time point, indicating whether the measure changes during the intervention period.

To examine how these temporal patterns differ by condition, we specify the level-2 equations for the combined approach using a single binary indicator for people using the Light Phone:

$$\beta_{0i} = \gamma_{00} + \gamma_{01}\text{LightPhone}_i + u_{0i}$$
$$\beta_{1i} = \gamma_{10} + \gamma_{11}\text{LightPhone}_i + u_{1i}$$

Here, LightPhone_i is a binary indicator equal to 1 for participants in either the Treatment or High-Interest groups, and 0 for Control participants. The critical parameter γ_{11} reveals the overall effect of using the Light Phone on the rate of change, compared to control participants.

For the HTE approach, we use separate indicators for each intervention group:

$$\beta_{0i} = \gamma_{00} + \gamma_{01}\text{Treatment}_i + \gamma_{02}\text{HighInterest}_i + u_{0i}$$
$$\beta_{1i} = \gamma_{10} + \gamma_{11}\text{Treatment}_i + \gamma_{12}\text{HighInterest}_i + u_{1i}$$

Here, Treatment_i and HighInterest_i are binary indicators for group membership, with the Control group serving as the reference category. The critical parameters are γ_{11} and γ_{12}, which reveal whether each group had different patterns of change compared to the control condition.

Both combined and HTE models include random effects for both the intercept (u_{0i}) and linear time slope (u_{1i}), allowing each participant to have their own baseline level and rate of change.

To capture potential non-linear patterns - such as initial adaptation followed by stabilization or rebound effects - we also estimate quadratic growth models:

$$Y_{it} = \beta_{0i} + \beta_{1i}\text{Time}_{it} + \beta_{2i}\text{Time}_{it}^2 + \epsilon_{it}$$

with corresponding level-2 equations. For the combined approach quadratic model, we first specify:

$$\beta_{0i} = \gamma_{00} + \gamma_{01}\text{LightPhone}_i + u_{0i}$$
$$\beta_{1i} = \gamma_{10} + \gamma_{11}\text{LightPhone}_i + u_{1i}$$
$$\beta_{2i} = \gamma_{20} + \gamma_{21}\text{LightPhone}_i$$

For the HTE approach quadratic model, we specify:

$$\beta_{0i} = \gamma_{00} + \gamma_{01}\text{Treatment}_i + \gamma_{02}\text{HighInterest}_i + u_{0i}$$
$$\beta_{1i} = \gamma_{10} + \gamma_{11}\text{Treatment}_i + \gamma_{12}\text{HighInterest}_i + u_{1i}$$
$$\beta_{2i} = \gamma_{20} + \gamma_{21}\text{Treatment}_i + \gamma_{22}\text{HighInterest}_i$$

In both models, β_{1i} represents the initial trajectory at T1, while β_{2i} captures whether this change accelerates or decelerates over time. For the combined approach, the linear coefficient (γ_{11}) captures the initial effect of the LightPhone intervention, while the quadratic coefficient (γ_{21}) captures the acceleration or deceleration of that effect over time. For the HTE approach, the group interactions with these time components ($\gamma_{11}, \gamma_{12}, \gamma_{21}, \gamma_{22}$) reveal whether each intervention group shows distinct temporal patterns. Therefore, linear and quadratic coefficients of the same sign indicate that the intervention has a consistent directional effect over time, while opposite signs indicate that the intervention may "taper off" or eventually begin to revert over time.

All models were estimated using restricted maximum likelihood via the `nlme` package in R [55], incorporating the entropy balancing weights through inverse variance weighting. We conducted both weighted (using entropy balancing) and unweighted analyses for both HTE and combined approaches to assess robustness. We report both linear and quadratic specifications for all outcomes to fully characterize the temporal dynamics of each measure's trajectory. Full model details, including weighted and unweighted combined and HTE models can be found in the Supplemental Materials.

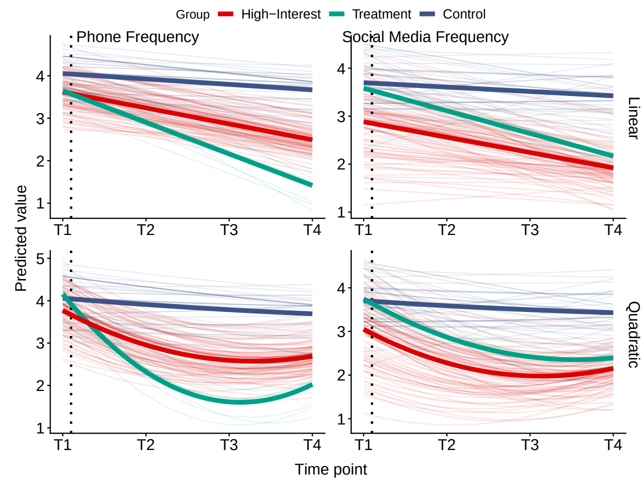

Figure 5: Changes in time spent on phones and time spent on social media over time. Red lines indicate high-interest participants who volunteered to try the Light Phone, green lines indicate treatment participants randomized to using the Light Phone, and blue lines indicate control participants randomized to using their own smartphones.

5 Results

5.1 Minimal phones reduced phone use and social media use

One of the core premises of device-level interventions is that switching from a smartphone to a device like the Light Phone should reduce the time that people spend on their phones and social media (H1). As seen in Figure 5, the results revealed that switching to the Light Phone effectively reduced the time people spent on their phones and on social networks.

Relative to the control group, participants who used the Light Phone demonstrated significant nonlinear decreases in phone use frequency, with steep initial declines ($\beta_{timexlightphone} = -1.12$, *SE* = .21, $p < .001$) followed by partial rebounds ($\beta_{time^2 lightphone}$ = .28, *SE* = .07, $p < .001$). Motivation influenced the trajectory of this reduction, as those assigned to using the Light Phone demonstrated sharper reductions in phone use ($\beta_{timextreatment}$= -2.23, *SE* = .31, $p < .001$; $\beta_{time^2 xtreatment}$ = .55, *SE* = .10, $p < .001$) than high-interest individuals who opted in ($\beta_{timexhigh-interest}$= -.88, *SE* = .21, $p < .001$; $\beta_{time^2 xhigh-interest}$ = .21, *SE* = .07, $p < .01$).

A similar pattern was observed for social media use. Using the Light Phone steeply reduced participants' social media use ($\beta_{timexlightphone} = -.96$, *SE* = .20, $p < .001$), followed by small rebounds ($\beta_{time^2 xlightphone}$ = .23, *SE* = .07, $p < .001$). The decline differed between groups. At baseline, high-interest participants used social media less than control participants ($\beta_{high-interestvs.control}$ = -.82, *SE* = .18, $p < .001$) and had less steep reductions ($\beta_{timexhigh-interest}$= -.88, *SE* = .21, $p < .001$; $\beta_{time^2 xhigh-interest}$ = .22, *SE* = .07, $p < .01$) than the treatment group ($\beta_{timextreatment}$ = -.97, *SE* = .30, $p < .01$; $\beta_{time^2 xtreatment}$ = .20, *SE* = .09, $p < .05$).

Table 2: Growth Models for Phone and Social Media Use

	Phone Use		Social Media Use	
	Lin	Quad	Lin	Quad
Fixed Effects				
Intercept	4.05***	4.06***	3.70***	3.70***
	(.13)	(.13)	(.15)	(.15)
Time	-.13+	-.16	-.09	-.13
	(.07)	(.18)	(.07)	(.18)
Time^2	—	.01	—	.01
		(.06)		(.06)
Treatment	-.41+	.10	-.11	.05
	(.24)	(.24)	(.25)	(.25)
High-Interest	-.43**	-.29+	-.82***	-.65***
	(.16)	(.16)	(.18)	(.19)
Time × Treatment	-.62***	-2.23***	-.38**	-.97**
	(.13)	(.31)	(.14)	(.30)
Time × High	-.25**	-.88***	-.23*	-.88***
	(.08)	(.21)	(.09)	(.21)
Time^2 × Treatment	—	.55***	—	.20*
		(.10)		(.09)
Time^2 × High	—	.21**	—	.22**
		(.07)		(.07)
Random Effects				
SD(Int)	.58	.64	.78	.82
SD(Slope)	.19	.23	.29	.31
Cor(Int, Slope)	-.53	-.55	-.69	-.70
Residual SD	.66	.58	.61	.55
Model Fit				
AIC	1367.10	1307.28	1365.86	1338.06
BIC	1408.28	1360.73	1407.06	1391.53
N	460	460	461	461

Note. Standard errors in parentheses. LightPhone = LightPhone treatment, High = High-Interest, Int = Intercept. Model comparisons indicated that linear growth models provided better fit than quadratic models for positive affect (ΔAIC = 10.74, χ^2 = 6.74, df = 2, p = .034). For productivity affect, quadratic model comparisons were not significant. $^+p < .10$, $^*p < .05$, $^{**}p < .01$, $^{***}p < .001$

5.2 Minimal phones reduced phone dependency and increased perceived agency

We tested H2 by examining if people experienced within-person changes in their feelings of smartphone dependency and their mindsets about their phone use after switching to the Light Phone, relative to the control participants continuing to use their own smartphones.

Reduced smartphone dependency. Model comparisons indicated nonlinear growth models fit the data better than linear models (*LRT* $\chi^2(2)$ = 58.6, p < .001). As shown in Table 2, the significant interaction term between time and condition indicated that using the Light Phone reduced people's feelings of dependency on their phones ($\beta_{timexlightphone}$ = -.25, SE = .07, p < .001). More specifically, we saw differences in the high-interest and treatment groups. The high-interest group showed a steep drop in smartphone dependency ($\beta_{timexhigh-interest}$ = -.98, SE = .14, p < .001) which rebound again ($\beta_{time^2xhigh-interest}$ = .24, SE = .04, p < .001). In contrast, the treatment group showed a significant increase in smartphone dependency ($\beta_{timextreatment}$ = .49, SE = .21, p < .05) which deceased over time ($\beta_{time^2xtreatment}$ = -.19, SE = .06, p < .01). These results indicated that while switching to the Light Phone reduced feelings of dependence for all users, it was more effective for highly motivated individuals.

Greater agency over phones. Non-linear models were a better fit to the data (*LRT* $\chi^2(2)$ = 42.75, p < .001). The results indicated that overall, people who switched to the Light Phone felt significantly more control over their phone use ($\beta_{timexlightphone}$ = .54, SE = .15, p < .001) that marginally diminished over time ($\beta_{time^2xlightphone}$ = -.08, SE = .05, p < .10). Closer examination indicated people in the high-interest group reported significantly greater improvements in agency relative to the control ($\beta_{timexhigh-interest}$ = .60, SE = .15, p < .001) and the treatment benefited slightly less ($\beta_{timextreatment}$ = -.02, SE = .07, p > .10; $\beta_{time^2xtreatment}$ = -.10, SE = .05, p < .05).

No change in valence of phones. Linear models were a better fit to the data (*LRT* $\chi^2(2)$ = 9.91, p < .01). Results indicated that people who switched to the Light Phone did not come to hold more positive or negative views about their phones ($\beta_{timexlightphone}$ = -.02, SE = .06, p > .01). Relative to the control participants, high-interest individuals who volunteered to try the Light Phone had more negative views about phones at baseline ($\beta_{high-interest vs.control}$ = -.47, SE = .10, p < .001). Although the high-interest participants did not change their perception of the valence of their phone use over time ($\beta_{timexhigh-interest}$ = .04, SE = .06, p > .10), the treatment participants assigned to using the Light Phone developed more negative beliefs about phone use ($\beta_{timextreatment}$ = -.26, SE = .10, p < .01).

Table 3: Growth Models for Phone Dependency and Mindset

	Phone Dependency		Perceived Agency		Valence of Phone Use	
	Lin	Quad	Lin	Quad	Lin	Quad
Fixed Effects						
Intercept	2.92***	2.93***	2.77***	2.72***	3.72***	3.71***
	(.12)	(.13)	(.12)	(.13)	(.08)	(.08)
Time	-.11+	-.18	.10	.32*	-.06	-.01
	(.06)	(.12)	(.07)	(.13)	(.05)	(.11)
Time^2	—	.02	—	-.08*	—	-.02
		(.04)		(.04)		(.03)
Treatment	-.14	-.30+	.14	.06	.06	.08
	(.17)	(.17)	(.18)	(.18)	(.14)	(.15)
High-Interest	-.24	-.07	-.04	-.12	-.47***	-.44***
	(.15)	(.16)	(.15)	(.15)	(.10)	(.10)
Time × Treat	-.06	.49*	.21+	.29	-.26**	-.34+
	(.11)	(.21)	(.13)	(.23)	(.10)	(.19)
Time × High	-.27***	-.98***	.31***	.60***	.04	-.06
	(.07)	(.14)	(.08)	(.15)	(.06)	(.13)
Time^2 × Treat	—	-.19**	—	-.02	—	.03
		(.06)		(.07)		(.06)
Time^2 × High	—	.24***	—	-.10*	—	.04
		(.04)		(.05)		(.04)
Random Effects						
SD(Int)	.75	.78	.73	.75	.41	.41
SD(Slope)	.26	.26	.28	.29	.21	.21
Cor(Int, Slope)	-.52	-.55	-.27	-.31	-.11	-.11
Residual SD	.98	.96	.87	.86	.85	.85
Model Fit						
AIC	11318	11206	7699	7665	9907	9928
BIC	11379	11285	7756	7740	9968	10006
N	3247	3247	2320	2320	3094	3094

Note. Standard errors in parentheses. Treat = Treatment, High = High-Interest, Int = Intercept. Model comparisons indicated that quadratic growth models provided better fit for phone dependency (ΔAIC = 111.91, χ^2 = 117.93, df = 3, p < .001) and perceived agency (ΔAIC = 34.17, χ^2 = 40.17, df = 3, p < .001), while the linear model provided better fit for valence of phone use (ΔAIC = 20.23, χ^2 = 14.23, df = 3, p = .003). $^+p < .10$, $^*p < .05$, $^{**}p < .01$, $^{***}p < .001$

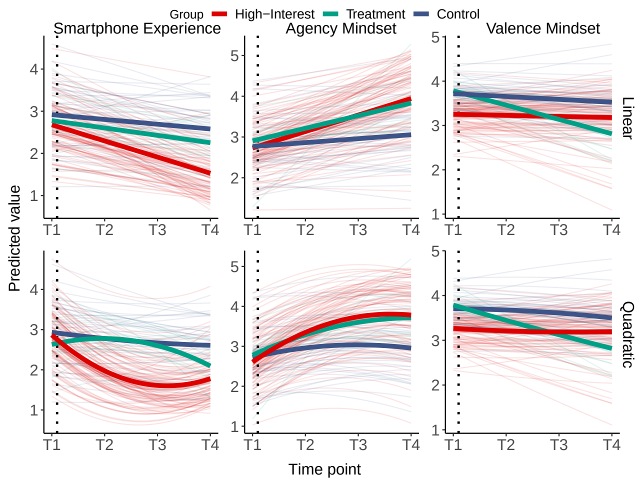

Figure 6: Predicted Trajectories of Smartphone Dependency and Mindsets by Group. The figure shows both linear (top row) and quadratic (bottom row) model predictions for smartphone dependency, perceived agency over phone use, and phone valence. Bold lines represent prototypical (group-level) trajectories for Control (red), Treatment (blue), and High-Interest (green) groups, while semi-transparent lines show individual participant trajectories. The y-axis shows predicted values on each scale, and the x-axis shows time points (T1-T4). The vertical dotted line at T1 marks the start of the intervention period, immediately following the pre-treatment baseline survey.

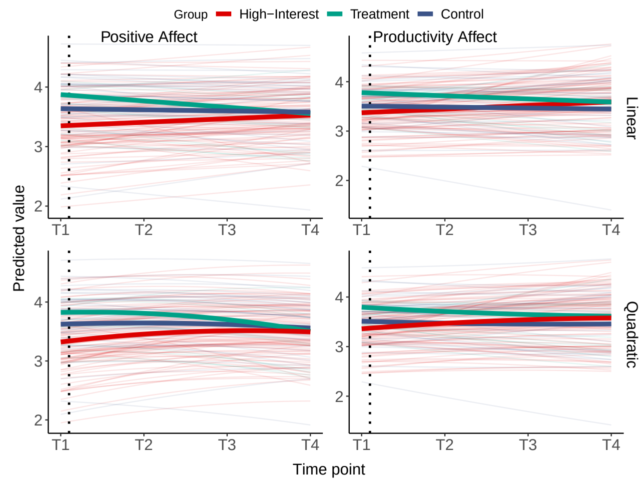

Figure 7: Predicted Trajectories of Affective Well-being by Group. The figure displays both linear (top row) and quadratic (bottom row) model predictions for feeling positive (left) and productive (right). Bold lines represent prototypical (group-level) trajectories for Control (red), Treatment (blue), and High-Interest (green) groups, while semi-transparent lines show individual participant trajectories. The y-axis shows predicted values on each mental health scale, and the x-axis shows time points (T1-T4). The vertical dotted line at T1 marks the start of the intervention period, immediately following the pre-treatment baseline survey.

5.3 Minimal phones only improve certain indicators of well-being, among motivated users

No significant change in affective well-being. We tested H3 by examining if people using minimal phones experienced within-person improvements in state affect relative to those in the control who continued to use their own smartphones. Separate models were estimated to examine changes in positive affect (i.e., "happy", "proud") and alertness (i.e., "alert", "attentive"). Comparisons indicated linear growth models fit the data better than non-linear models (*LRT* $\chi^2(2)$ = 6.74, $p < .05$).

As shown in Table 1, there was no significant interaction term between time and condition. Using the Light Phone did not affect how positive ($\beta_{timexlightphone}$ = .04, *SE* = .06, $p > .10$) and alert people felt ($\beta_{timexlightphone}$ = .07, *SE* = .05, $p > .10$). Although the high-interest participants were less positive than the control at baseline ($\beta_{high-interestvs.control}$ = -0.29, *SE* = .13, $p < .05$), neither the high-interest ($\beta_{timexhigh-interest}$ = .08, *SE* = .06, $p > .10$) nor treatment participants ($\beta_{timextreatment}$ = -.09, *SE* = .09, $p > .10$) demonstrated significant changes in positive affect, or alertness ($\beta_{timexhigh-interest}$ = .09, *SE* = .06, $p > .10$; $\beta_{timextreatment}$ = -.04, *SE* = .09, $p > .10$) over time.

No significant change in social connection. Using the same analytical approach as above, we tested H2 if switching to minimal phones would reduce how connected individuals felt to their peers and communities. Model comparisons indicated the linear model was a better fit than the quadratic (*LRT* $\chi^2(2)$ = .55, $p > .10$). Counter to our predictions, switching to the minimal phone did not negatively affect how close participants felt to their friends ($\beta_{timexlightphone}$ = -.02, *SE* = .04, $p > .10$). Although the treatment participants were more connected at baseline than the control group ($\beta_{treatmentvs.control}$ = .24, *SE* = .11, $p < .05$), using the Light Phone did not appear to significantly alter social experiences over time for either the high-interest ($\beta_{timexhigh-interest}$ = -.01, *SE* = .04, $p > .10$) or treatment groups ($\beta_{timextreatment}$ = -.06, *SE* = .06, $p > .10$). These results indicate that switching to the minimal phone did not undermine participants' ability to maintain meaningful social connections over the week.

No significant change in depression. Based on the linear model (LRT $\chi^2(2)$ = 3.24, p > .10), there were no significant differences in symptoms of depression between Light Phone users and control participants' over time ($\beta_{timexlightphone}$ = -.07, *SE* = .05, $p > .10$). No change in depression was observed for either the high-interest ($\beta_{timexhigh-interest}$ = -.09, *SE* = .06, $p > .10$) or the treatment group ($\beta_{timextreatment}$= -.01, *SE* = .08, $p > .10$).

Reductions in stress, only among high-interest individuals. The quadratic model was a better fit for characterizing changes in stress over time (*LRT* $\chi^2(2)$ = 16.82, $p < .01$). The significant interaction indicated that people who used the Light Phone felt substantially less stressed over time ($\beta_{timexlightphone}$ = -.24, *SE* = .11, $p < .05$) that marginally rebounded over time ($\beta_{time^2xlightphone}$ = .07, *SE* = .04, $p < .10$). More specifically, examination of group-level

Table 4: Growth Models for Affective Well-Being and Social Connection

	Positive Affect		Productivity		Social Connection	
	Lin	Quad	Lin	Quad	Lin	Quad
Fixed Effects						
Intercept	3.64***	3.62***	3.51***	3.51***	3.71***	3.67***
	(.11)	(.11)	(.09)	(.09)	(.08)	(.09)
Time	-.02	.04	-.02	-.05	.06+	.29***
	(.05)	(.13)	(.05)	(.11)	(.03)	(.08)
Time^2	—	-.02	—	.01	—	-.08**
		(.04)		(.03)		(.03)
Treatment	.24	.20	.27+	.28+	.24*	.22+
	(.18)	(.18)	(.14)	(.15)	(.11)	(.12)
High-Interest	-.29*	-.30*	-.13	-.15	-.04	-.00
	(.13)	(.14)	(.11)	(.11)	(.10)	(.11)
Time × Treat	-.09	-.01	-.04	-.05	-.06	-.20
	(.09)	(.22)	(.09)	(.19)	(.06)	(.14)
Time × High	.08	.13	.09+	.18	-.01	-.19*
	(.06)	(.16)	(.06)	(.13)	(.04)	(.10)
Time^2 × Treat	—	-.03	—	.00	—	.05
		(.07)		(.06)		(.04)
Time^2 × High	—	-.02	—	-.03	—	.07*
		(.05)		(.04)		(.03)
Random Effects						
SD(Int)	.60	.60	.51	.51	.52	.52
SD(Slope)	.15	.16	.17	.17	.12	.12
Cor(Int, Slope)	-.34	-.35	-.07	-.05	.02	.00
Residual SD	.84	.84	.76	.76	.70	.70
Model Fit						
AIC	5974	5991	6998	7018	10441	10452
BIC	6029	6063	7056	7093	10503	10533
N	1859	1859	2323	2323	3717	3717

Note. Standard errors in parentheses. Treat = Treatment, High = High-Interest, Int = Intercept. Model comparisons indicated that linear growth models provided better fit for positive affect (ΔAIC = 16.92, χ^2 = 10.92, df = 3, p = .012), productivity (ΔAIC = 20.04, χ^2 = 14.04, df = 3, p = .003), and social connection (ΔAIC = 11.01, χ^2 = 5.01, df = 3, p = .171). $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Table 5: Growth Models for Mental Health

	Depression		Stress		Life Satisfaction	
	Lin	Quad	Lin	Quad	Lin	Quad
Fixed Effects						
Intercept	1.95***	1.99***	2.19***	2.20***	5.19***	5.17***
	(.11)	(.11)	(.11)	(.11)	(.18)	(.18)
Time	-.01	-.17	-.05	-.11	-.11	-.01
	(.05)	(.13)	(.04)	(.10)	(.07)	(.16)
Time^2	—	.05	—	.02	—	-.04
		(.04)		(.03)		(.05)
Treatment	-.14	-.08	-.45**	-.37**	.63**	.78**
	(.18)	(.19)	(.14)	(.15)	(.23)	(.24)
High-Interest	.19	.19	.00	.06	.03	.08
	(.13)	(.14)	(.14)	(.14)	(.22)	(.23)
Time × Treat	-.01	-.11	.03	-.16	-.17	-.74**
	(.08)	(.22)	(.08)	(.17)	(.13)	(.28)
Time × High	-.09	-.07	-.08^{+}	-.30**	.17*	-.04
	(.06)	(.16)	(.05)	(.12)	(.08)	(.19)
Time^2 × Treat	—	.03	—	.06	—	.19*
		(.07)		(.05)		(.08)
Time^2 × High	—	-.01	—	.07*	—	.07
		(.05)		(.04)		(.06)
Random Effects						
SD(Int)	.61	.62	.69	.70	1.14	1.14
SD(Slope)	.14	.14	.17	.17	.26	.26
Cor(Int, Slope)	-.46	-.48	-.47	-.49	-.08	-.08
Residual SD	.60	.60	.61	.60	.86	.85
Model Fit						
AIC	2518	2531	4903	4897	4771	4783
BIC	2567	2594	4958	4969	4824	4851
N	930	930	1860	1860	1395	1395

Note. Standard errors in parentheses. Treat = Treatment, High = High-Interest, Int = Intercept. Model comparisons indicated that linear growth models provided better fit for depression (ΔAIC = 13.07, χ^2 = 7.07, df = 3, p = .070), stress (ΔAIC = 13.07, χ^2 = 7.07, df = 3, p = .070), and life satisfaction (ΔAIC = 11.38, χ^2 = 5.38, df = 3, p = .146). $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

differences revealed that these benefits were only obtained by high-interest individuals ($\beta_{timexhigh-interest}$ = -.30, SE = .12, p < .05), though there were slight rebounds at the end ($\beta_{time^2xhigh-interest}$ = .07, SE = .04, p < .05). In contrast, treatment participants assigned to using the Light Phone did not report feeling less stressed ($\beta_{timextreatment}$ = -.16, SE = .17, p > .10; $\beta_{time^2xtreatment}$ = .06, SE = .05, p > .10).

Improvements in life satisfaction, only among high-interest individuals. The linear model (*LRT* $\chi^2(2)$ = 4.54, p > .10) indicated that overall, there were no significant changes in life satisfaction among all participants using the Light Phone ($\beta_{timexlightphone}$= .11, SE = .08, p > .10). However, closer examination indicated that the high-interest participants felt more satisfied with their lives while using the Light Phone ($\beta_{timexhigh-interest}$ = .17, SE = .08, p < .05), there were no changes among treatment participants assigned to using the Light Phone ($\beta_{timextreatment}$ = -.17, SE = .13, p > .10). Together, these results highlight how individual motivation influences the effect of minimal phone adoption on certain well-being outcomes.

6 Discussion

Our research addresses growing calls for user-centered solutions that support people in mitigating the potential harms of smartphone dependency and returning agency to their lives [39, 80]. Strong public interest in strategies to improve people's relationship to technology should be matched by rigorous empirical tests of these strategies' efficacy [33, 53, 54]. Minimal mobile phones, like the Light Phone II, represent a unique opportunity to conduct a device-level intervention that reduce distractions by design, rather than relying on consistent user self-regulation, but their causal effects have not yet been evaluated. This study revealed that minimal phones may improve people's sense of agency over their technology use, but may provide limited well-being benefits concentrated among people who are highly motivated in committing to this change in their digital routine.

6.1 Minimal phones enhance agency over technology

First, we found that switching to minimal phones effectively reduced the time people spent on their phones, the time they spent on social media, and feeling dependent on their phones. In terms of participants' sense of agency over their device use, we observed a clear increase over time in their sense of control and autonomy. This growing sense of agency suggests that deliberate interventions aimed at reducing phone use can meaningfully enhance users' ability to regulate their digital habits. Notably, this finding stands in contrast to recent research on disabling push notifications, which showed no association with perceived control [12]. While much

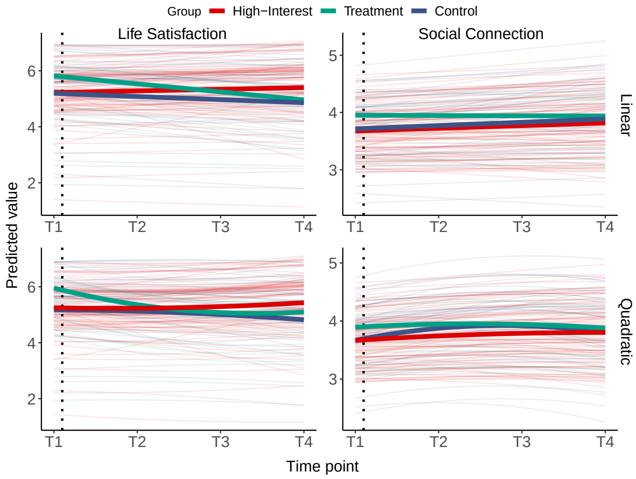

Figure 8: Predicted Trajectories of Life Satisfaction and Social Connection. The figure displays both linear (top row) and quadratic (bottom row) model predictions for life satisfaction and social connection. Bold lines represent prototypical (group-level) trajectories for Control (red), Treatment (blue), and High-Interest (green) groups, while semi-transparent lines show individual participant trajectories. The y-axis shows predicted values on each mental health scale, and the x-axis shows time points (T1-T4). The vertical dotted line at T1 marks the start of the intervention period, immediately following the pre-treatment baseline survey.

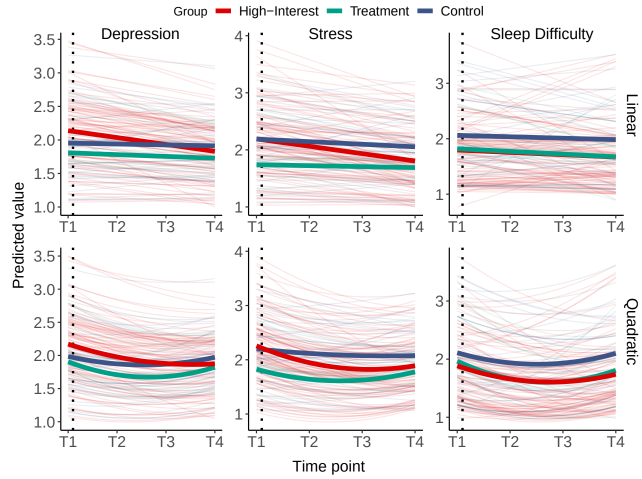

Figure 9: Predicted Trajectories of Mental Health Measures by Group. The figure displays both linear (top row) and quadratic (bottom row) model predictions for depression, stress, and sleep difficulty. Bold lines represent prototypical (group-level) trajectories for Control (red), Treatment (blue), and High-Interest (green) groups, while semi-transparent lines show individual participant trajectories. The y-axis shows predicted values on each mental health scale, and the x-axis shows time points (T1-T4). The vertical dotted line at T1 marks the start of the intervention period, immediately following the pre-treatment baseline survey.

of the literature on digital interventions has focused on design-level solutions such as screen time trackers or notification settings [8, 12, 71], our study provides empirical support for theorizing the device as a boundary object that affects sense of agency. By replacing smartphones with minimal mobile phones, participants were prompted to renegotiate their habitual digital behaviors, resulting in increased sense of agency.

These patterns align with models of mediated behavior change [4], which highlight the role of external tools in scaffolding intentional actions. Research emphasizes that smartphone habits are deeply ingrained, automatic behaviors that often occur outside of conscious awareness, making them resistant to intentional change. [5] highlight a key tension between habitual smartphone checking and goal-directed behavior, suggesting that frequent, cue-driven phone use can interfere with individuals' ability to stay aligned with their long-term goals and values. Because smartphones serve as ever-present gateways to social and informational rewards, they can hijack attentional resources and undermine reflective decision-making, particularly when self-control is low or environmental cues are strong [5]. This body of work underscores the importance of designing interventions that disrupt automaticity and reorient phone use toward more intentional, goal-congruent behavior. Thus, our study suggests rethinking switching from not just changes in design-features but also changing devices themselves as mechanisms of self-regulation. Our results indicate that modifying overall device use, rather than merely adjusting specific smartphone features, may have a more substantial effect on users' sense of agency. Such improvements in perceived agency over devices are not only important for fostering long-term behavioral change but also contribute to discussions around digital well-being and autonomy due to device-level interventions [39, 40].

6.2 Psychological well-being only improved among motivated individuals

Counter to past work theorizing that reducing smartphone use by switching to a minimal phone may broadly enhance psychological well-being [24], we did not find significant positive effects on affective well-being, social connection, or depression - suggesting that simply providing technological constraints may not be sufficient to improve psychological outcomes. Short-term changes in device use were not sufficient to influence general well-being [56]. This may be because our study was too short to detect longer-term accumulative changes as seen in [2] and [8], or because the reductions in smartphone and social media use were not strong enough to produce significant within-person changes.

Our results reinforce the notion that device-level digital disconnection interventions do not guarantee detectable improvements in psychological well-being. This has fundamental limitations for what we term the "device-deterministic paradigm" that dominates digital well-being interventions — the assumption that technological features directly and uniformly shape user well-being outcomes. This paradigm treats devices as having inherent effects that operate independently of user characteristics, contexts, or intentions. Our experimental evidence provides a critical corrective to this view. While the Light Phone eliminated social media, web browsing, and app stores for all participants, only those who were intrinsically motivated to change their technology use experienced significant improvements in psychological well-being—specifically increased sense of agency over their technology use (p = 0.010). Both the high-interest and randomly assigned treatment groups showed significant reductions in phone and social media usage frequency over time, but these behavioral changes translated to psychological benefits only for the motivated group. The randomly assigned treatment group experienced no improvements in psychological well-being measures and actually showed a significant decline in life satisfaction (p = 0.031). The core finding that motivation significantly moderates intervention effectiveness challenges the foundational assumption underlying most digital well-being tools: that removing or restricting access to potentially harmful features will uniformly improve user outcomes. Popular interventions like Apple's Screen Time, notification controls, and app usage limits all operate under device-deterministic logic, yet our experimental evidence demonstrates clear limits to this feature-centric approach.

This heterogeneity suggests that effective digital well-being design should account for user motivation as a primary factor, with systems that assess and respond to different motivation levels rather than applying uniform interventions. For users with low initial motivation, interventions should focus on building self-awareness through reflective prompts that help users connect their digital behaviors to their emotional states or gentle feedback that reveals discrepancies between stated values and actual behavior. For highly motivated users, systems should provide commitment tools such as user-defined restrictions that are difficult to override or social accountability features that help users honor their intentions. Based on our direct observations, motivated users benefit most when technology actively supports their existing goals rather than trying to create new ones, pointing toward "commitment-supporting" design that offers escalating levels of support including temporary app blocking with increasing friction to override, peer accountability systems, or "commitment contracts" where users define specific digital boundaries.

Broadly, our four-wave design revealed complex, non-linear patterns of change that highlight the critical need for temporal scaffolding in digital well-being design. Rather than showing simple linear improvements, motivated participants demonstrated quadratic patterns with initial changes followed by stabilization or fluctuation, while unmotivated participants showed minimal change across all timepoints. These non-linear trajectories suggest that digital habits follow complex adaptation patterns rather than straightforward improvement curves [60]. Systems should anticipate this natural complexity by providing adaptive support that responds to fluctuating user states—not just initial enthusiasm or final outcomes, but the varied pathways in between. This points toward "graceful failure" pathways that reframe temporary setbacks as normal parts of the change process rather than permanent failures, and dynamic interventions that can intensify or lighten support based on real-time user patterns. For example, if a user's technology agency initially increases but then plateaus, the system could offer renewed challenges or alternative approaches rather than assuming the intervention has failed.

6.3 Temporal Phases and Intervention Design

The quadratic growth patterns we observed suggest that digital disconnection interventions unfold across distinct temporal phases, with user motivation shaping how each phase is experienced.

During the *initiation phase* (early in the intervention), participants showed steep initial changes in phone and social media use. However, motivation moderated internal responses: high-interest participants experienced immediate reductions in phone dependency, while treatment participants actually reported *increased* dependency despite reducing their phone use even more sharply. This divergence suggests that initial responses reflect readiness for change rather than the effectiveness of the intervention. Intervention designers should not evaluate success based only on early outcomes, and unmotivated users may need additional support to manage initial discomfort.

The *adaptation phase* (later in the intervention) is where the quadratic patterns emerged most clearly. Phone use partially rebounded (β_{time^2} = .28); agency gains began to plateau; stress reductions showed slight reversal. Importantly, motivated users navigated this phase while maintaining psychological benefits, whereas unmotivated users showed no improvement in well-being even as their behavioral adaptation continued. For intervention design, these findings suggest that support should be back-loaded rather than front-loaded: users may need additional intervention touches and encouragement precisely when initial enthusiasm wanes, and adaptation challenges emerge.

Finally, our data point toward a *stabilization phase* that our one-week study may not fully capture. The rebound patterns suggest we observed adaptation in progress rather than stable endpoints. This finding has implications for intervention duration: one week may be sufficient for motivated users to establish new patterns, but unmotivated users, whose initial trajectories move in the opposite direction of the intended effects, may require longer exposure before benefits emerge. Researchers evaluating digital disconnection interventions should therefore carefully consider measurement timing, as assessments during initiation may overstate effects, while assessments during peak adaptation may understate eventual benefits.

6.4 Practical implications

Our findings have important implications for designers and practitioners to support everyday people's digital well-being. While interventions like adopting a minimal phone can have positive effects on some psychological outcomes, simply deploying them to the public does not appear to be sufficient to produce lasting changes in important indicators of mental health. Device-level interventions like minimal phones, or disconnection-based interventions such as screen-time restriction applications, may be most effective when they align with users' internal goals and motivations. Cultivating healthier relationships with technology is not only the product of smarter or more prosocial design but additionally consideration of individuals' personal desires to take steps to engage in meaningful behavioral change. The importance of user motivation revealed in our study suggests that designers should pair the implementation of features designed to support well-being with 1) efforts to target reach communities of intrinsically motivated individuals who may most benefit from such interventions, and 2) opportunities to increase user motivation to engage in long-term behavior change. Whether it is because they are feeling unsatisfied with their current digital lives or because they would like to take steps to improve their relationship with technology, some people are inherently more interested in and motivated to participate in interventions (i.e., adopt new technologies). Our study suggests that designers seeking to optimize the effects of their efforts may benefit from specifically engaging communities of individuals that are highly motivated. In addition, when working with broader or more general user populations, designers may consider integrating opportunities to increase individual motivation by providing space for users to reflect on their own digital media use, clarify personal intentions, and become motivated to have their behaviors align with their values. For example, applications that are designed to help individuals form more meaningful social connections may be strengthened by including a brief message or reflection activity that increases individual motivation by thinking about how this digital tool may be useful for their personal goals.

6.5 Methodological implications

Our findings have critical methodological implications for HCI research, most importantly that future studies must employ motivation-stratified sampling and analysis as standard practice, as averaging effects across motivated and unmotivated participants obscures genuine intervention benefits. Additionally, our focus on diverse psychological well-being constructs (social connection, life satisfaction, stress) rather than purely behavioral metrics proved essential for capturing real effects. Most importantly, our study's demonstration that identical interventions produce markedly different outcomes across user groups suggests that much of the mixed evidence in this field may result from unexamined heterogeneity. The field's reliance on small-n user studies may be insufficient for detecting these heterogeneous effects, as such studies lack the statistical power to identify meaningful subgroup differences. Large-scale randomized controlled trials with pre-specified subgroup analyses are essential for identifying not just whether interventions work on average, but for whom they work, under what conditions, and through what mechanisms. Only with adequate sample sizes can researchers reliably detect the small effect sizes that characterize real-world digital well-being interventions while simultaneously examining how effectiveness varies across user characteristics, contexts, and implementation approaches. This methodological shift toward large-scale, heterogeneity-focused RCTs would move the field beyond conflicting findings toward understanding when and how digital well-being interventions can be effective.

6.6 Limitations and future directions

The results of our study should be interpreted with respect to their limitations. First, we note that the study was conducted with college students attending a residential university in the United States - a social, physical, and cultural context that should influence how they responded to the adoption of the minimal mobile phone [65, 77]. Our findings suggest that this particular population may benefit from using minimal mobile devices that enable them to maintain their everyday communications while restricting access to features that could be distracting. However, it is essential to acknowledge that the results may vary for other young adults and individuals from different age groups. For instance, residential college students may be uniquely positioned to benefit from these devices because they have access to on-campus social communities that may protect them from any negative effects of reducing their smartphone use on relational maintenance [16, 80]. In comparison, young adults that commute or are not currently in school may respond differently to using a minimal mobile phone.

The quasi-experimental design, while innovative in addressing the role of individual motivation, may also introduces interpretive challenges. Although we accounted for baseline differences through entropy balancing methods, there may still be differences between high-interest volunteers and randomly assigned participants. Future research should examine whether individual motivation to participate in such a digital disconnection intervention may be manipulated through an experiment to more directly test the effect of motivation on user outcomes.

In addition, we note that the experimental period involved asking a cohort of students in the high-interest and treatment groups to switch over to using the minimal mobile phones at the same time. Being able to take part in this shared experience may have made it easier for students to disengage from their smartphones, reduce the friction involved in the transfer process, and mitigated any social costs involved with switching. Furthermore, participating in this new experience with others may have created new social ties that may have benefited students' sense of social connection with peers beyond their everyday friendships. Future work should investigate the effects of implementing a digital disconnection strategy on individuals who are asked to disengage on their own compared to groups of individuals who collectively participate in the same experience. Research on the welfare effects of social media [2] indicate that it may be easier for people to disconnect from ubiquitous social technologies, like smartphones, when they are doing so in conjunction with their peer networks. Indeed, scholars [25] have argued that the "social costs" of reducing reliance on smartphones should be mitigated when group-level interventions are applied, such as school-level phone bans. Understanding these dynamics is particularly important for efforts to determine the most effective ways to support diverse communities worldwide in developing healthier relationships with their digital devices.

Longitudinal studies with longer follow-up periods are needed to understand whether the initial benefits observed among motivated users persist over time and whether unmotivated users might eventually experience positive effects with extended use. Research should also explore the mechanisms underlying the differential effects of motivation, potentially through ecological momentary assessment or qualitative methods that capture day-to-day experiences of minimal phone users.

7 Conclusion

Our study provides the first rigorous field test of minimal mobile phones' effects on psychological well-being. Minimal phones like the Light Phone II effectively reduce time spent on their devices and help people feel a greater sense of agency. Device-level interventions like the Light Phone II can help people have healthier relationships with social technologies by reducing distractions by design, rather than relying on consistent user self-regulation. However, this study also indicates that this is not a panacea for mental health challenges: switching to minimal phones may not broadly improve psychological well-being for everyone. Instead, we see that individuals' intrinsic motivation to pursue this behavioral change plays an important role in determining whether people obtain psychological benefits from such a disconnection strategy. Efforts to enhance user agency over technology and improve well-being should therefore consider both the design of the intervention and individuals' inherent motivation to change.

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References

[1] [n. d.]. Overuse of devices and social media top parent concerns — mottpoll.org. https://mottpoll.org/reports/overuse-devices-and-social-media-top-parent-concerns. [Accessed 11-09-2025].

[2] Hunt Allcott, Matthew Gentzkow, Benjamin Wittenbrink, Juan Carlos Cisneros, Adriana Crespo-Tenorio, Drew Dimmery, Deen Freelon, Sandra González-Bailón, Andrew M Guess, Young Mie Kim, et al. 2025. *The Effect of Deactivating Facebook and Instagram on Users' Emotional State*. Technical Report. National Bureau of Economic Research.

[3] Sameer Ansari, Ahmad Azeem, Irum Khan, and Naved Iqbal. 2024. Association of Phubbing Behavior and Fear of Missing Out: A Systematic Review and Meta-Analysis. *Cyberpsychology, Behavior, and Social Networking* 27, 7 (2024), 467–481.

[4] Albert Bandura. 2003. Social cognitive theory for personal and social change by enabling media. In *Entertainment-education and social change*. Routledge, 97–118.

[5] Joseph B Bayer, Sonya Dal Cin, Scott W Campbell, and Elliot Panek. 2016. Consciousness and self-regulation in mobile communication. *Human Communication Research* 42, 1 (2016), 71–97.

[6] Lorna Brown and Daria J Kuss. 2020. Fear of missing out, mental wellbeing, and social connectedness: A seven-day social media abstinence trial. *International Journal of Environmental Research and Public Health* 17, 12 (2020), 4566.

[7] Valerio Capraro, Laura Globig, Zachary Rausch, Steve Rathje, Alexandra Wormley, Jay Olson, Robert Ross, Sinan Aşçı, Ayoub Bouguettaya, Kaitlyn Burnell, et al. 2025. A consensus statement on potential negative impacts of smartphone and social media use on adolescent mental health. (2025).

[8] Noah Castelo, Kostadin Kushlev, Adrian F Ward, Michael Esterman, and Peter B Reiner. 2025. Blocking mobile internet on smartphones improves sustained attention, mental health, and subjective well-being. *PNAS nexus* 4, 2 (2025), pgaf017.

[9] Merve Cerit, Angela Y Lee, Jeffrey Hancock, Adam Miner, Mu-Jung Cho, Daniel Muise, Anna-Angelina Garròn Torres, Nick Haber, Nilam Ram, Thomas N Robinson, et al. 2025. Person-Specific Analyses of Smartphone Use and Mental Health: Intensive Longitudinal Study. *JMIR Formative Research* 9, 1 (2025), e59875.

[10] Richard K Crump, V Joseph Hotz, Guido W Imbens, and Oscar A Mitnik. 2009. Dealing with limited overlap in estimation of average treatment effects. *Biometrika* 96, 1 (2009), 187–199.

[11] Meredith E. David, James A. Roberts, and Brett Christenson. 2017. Too Much of a Good Thing: Investigating the Association between Actual Smartphone Use and Individual Well-Being. *International Journal of Human–Computer Interaction* 34, 3 (Aug. 2017), 265–275. doi:10.1080/10447318.2017.1349250

[12] Cynthia A Dekker, Sindy R Sumter, and Susanne E Baumgartner. 2024. Unraveling the dynamics of perceived smartphone overuse and disconnection strategies: Longitudinal insights. *New Media & Society* (2024), 14614448241303113.

[13] ED Diener, Robert A Emmons, Randy J Larsen, and Sharon Griffin. 1985. The satisfaction with life scale. *Journal of personality assessment* 49, 1 (1985), 71–75.

[14] Ryan J Dwyer, Kostadin Kushlev, and Elizabeth W Dunn. 2018. Smartphone use undermines enjoyment of face-to-face social interactions. *Journal of Experimental Social Psychology* 78 (2018), 233–239.

[15] Tine A Eide, Sarah H Aarestad, Cecilie S Andreassen, Robert M Bilder, and Ståle Pallesen. 2018. Smartphone restriction and its effect on subjective withdrawal related scores. *Frontiers in psychology* 9 (2018), 1444.

[16] Nicole B Ellison, Charles Steinfield, and Cliff Lampe. 2007. The benefits of Facebook "friends:" Social capital and college students' use of online social network sites. *Journal of computer-mediated communication* 12, 4 (2007), 1143–1168.

[17] Craig K Enders. 2022. *Applied missing data analysis*. Guilford Publications.

[18] Risa Gelles-Watnick. 2024. Americans' use of mobile technology and home broadband. *Pew Research Center* (2024).

[19] Gene H Golub and Charles F Van Loan. 2013. *Matrix computations*. JHU press.

[20] Samuel D Gosling, Peter J Rentfrow, and William B Swann Jr. 2003. A very brief measure of the Big-Five personality domains. *Journal of Research in personality* 37, 6 (2003), 504–528.

[21] Noah Greifer and Maintainer Noah Greifer. 2020. Package 'cobalt'. *R package version* 4 (2020).

[22] Kevin J Grimm, Nilam Ram, and Ryne Estabrook. 2016. *Growth modeling: Structural equation and multilevel modeling approaches*. Guilford Publications.

[23] David J Grüning, Frederik Riedel, and Philipp Lorenz-Spreen. 2023. Directing smartphone use through the self-nudge app one sec. *Proceedings of the National Academy of Sciences* 120, 8 (2023), e2213114120.

[24] Jonathan Haidt. 2021. Facebook's Dangerous Experiment on Teen Girls. *The Atlantic* (November 2021). https://www.theatlantic.com/ideas/archive/2021/11/facebooks-dangerous-experiment-teen-girls/620767/ Online; accessed 3-September-2025.

[25] Jonathan Haidt. 2024. *The anxious generation: How the great rewiring of childhood is causing an epidemic of mental illness*. Penguin.

[26] Jens Hainmueller. 2012. Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political analysis* 20, 1 (2012), 25–46.

[27] Jens Hainmueller and Maintainer Jens Hainmueller. 2014. Package 'ebal'. (2014).

[28] Trevor Hastie. 2009. The elements of statistical learning: data mining, inference, and prediction.

[29] Maxi Heitmayer and Saadi Lahlou. 2021. Why are smartphones disruptive? An empirical study of smartphone use in real-life contexts. *Computers in Human Behavior* 116 (2021), 106637.

[30] Marlies Houben, Wim Van Den Noortgate, and Peter Kuppens. 2015. The relation between short-term emotion dynamics and psychological well-being: A meta-analysis. *Psychological bulletin* 141, 4 (2015), 901.

[31] Rania Islambouli, Sandy Ingram, and Denis Gillet. 2024. Understanding digital wellbeing through smartphone usage intentions and regrettable patterns. In *2024 IEEE 12th International Conference on Healthcare Informatics (ICHI)*. IEEE, 426–435.

[32] Faltin Karlsen. 2020. Digital detox camp: Values and motivations for engaging in digital disconnect. *AoIR selected papers of Internet research* (2020).

[33] JaeWon Kim, Lindsay Popowski, Anna Fang, Cassidy Pyle, Guo Freeman, Ryan M Kelly, Angela Y Lee, Fannie Liu, Angela DR Smith, Alexandra To, et al. 2024. Envisioning new futures of positive social technology: Beyond paradigms of fixing, protecting, and preventing. In *Companion Publication of the 2024 Conference on Computer-Supported Cooperative Work and Social Computing*. 701–704.

[34] Julius Klingelhoefer, Alicia Gilbert, and Adrian Meier. 2024. Momentary motivations for digital disconnection: An experience sampling study. *Journal of Computer-Mediated Communication* 29, 5 (2024), zmae013.

[35] Kostadin Kushlev, Ryan Dwyer, and Elizabeth W Dunn. 2019. The social price of constant connectivity: Smartphones impose subtle costs on well-being. *Current Directions in Psychological Science* 28, 4 (2019), 347–352.

[36] Kostadin Kushlev and Matthew R Leitao. 2020. The effects of smartphones on well-being: Theoretical integration and research agenda. *Current opinion in psychology* 36 (2020), 77–82.

[37] Alexander P Landry and Eran Halperin. 2023. Intergroup psychological interventions: The motivational challenge. *American Psychologist* (2023).

[38] Matthew A Lapierre, Pengfei Zhao, and Benjamin E Custer. 2019. Short-term longitudinal relationships between smartphone use/dependency and psychological well-being among late adolescents. *Journal of Adolescent Health* 65, 5 (2019), 607–612.

[39] Angela Y Lee, Nicole B Ellison, and Jeffrey T Hancock. 2023. To use or be used? The role of agency in social media use and well-being. *Frontiers in Computer Science* 5 (2023), 1123323.

[40] Angela Y Lee and Jeffrey T Hancock. 2024. Social media mindsets: A new approach to understanding social media use and psychological well-being. *Journal of Computer-Mediated Communication* 29, 1 (2024), zmad048.

[41] Angela Y Lee, Ryan C Moore, and Jeffrey T Hancock. 2025. Building resilience to misinformation in communities of color: results from two studies of tailored digital media literacy interventions. *new media & society* 27, 6 (2025), 3545–3576.

[42] Laura Marciano, Michelle Ostroumova, Peter Johannes Schulz, and Anne-Linda Camerini. 2022. Digital Media Use and Adolescents' Mental Health During the Covid-19 Pandemic: A Systematic Review and Meta-Analysis. *Frontiers in Public Health* 9 (Feb. 2022). doi:10.3389/fpubh.2021.793868

[43] Jeremy Marty-Dugas, Brandon CW Ralph, Jonathan M Oakman, and Daniel Smilek. 2018. The relation between smartphone use and everyday inattention. *Psychology of Consciousness: Theory, Research, and Practice* 5, 1 (2018), 46.

[44] Katherine Maurer, Mert Kimyaci, Katy Konyk, and Christine Wekerle. 2023. Building resilience through daily smartphone app use: results of a pilot study of the JoyPop app with social work students. *Frontiers in Digital Health* 5 (2023), 1265120.

[45] Adrian Meier. 2022. Studying problems, not problematic usage: Do mobile checking habits increase procrastination and decrease well-being? *Mobile Media & Communication* 10, 2 (2022), 272–293.

[46] Adrian Meier and Leonard Reinecke. 2021. Computer-mediated communication, social media, and mental health: A conceptual and empirical meta-review. *Communication Research* 48, 8 (2021), 1182–1209.

[47] Thomas E Metherell, Sakshi Ghai, Ethan M McCormick, Tamsin J Ford, and Amy Orben. 2022. Digital access constraints predict worse mental health among adolescents during COVID-19. *Scientific reports* 12, 1 (2022), 19088.

[48] Lise-Marie Nassen, Heidi Vandebosch, Karolien Poels, and Kathrin Karsay. 2023. Opt-out, abstain, unplug. A systematic review of the voluntary digital disconnection literature. *Telematics and Informatics* 81 (2023), 101980.

[49] Minh Hao Nguyen. 2023. "Maybe I should get rid of it for a while…": Examining motivations and challenges for social media disconnection. *The Communication Review* 26, 2 (2023), 125–150.

[50] Peter J Norton. 2007. Depression Anxiety and Stress Scales (DASS-21): Psychometric analysis across four racial groups. *Anxiety, stress, and coping* 20, 3 (2007), 253–265.

[51] Tania R Nunez and Theda Radtke. 2024. Is socially disruptive smartphone use detrimental to well-being? A systematic meta-analytic review on being phubbed. *Behaviour & Information Technology* 43, 7 (2024), 1283–1311.

[52] Candice Odgers. 2018. Smartphones are bad for some teens, not all. *Nature* 554, 7693 (2018), 432–434.

[53] Office of the Surgeon General et al. 2021. Protecting youth mental health: The US surgeon general's advisory [Internet]. (2021).

[54] Amy Orben and J Nathan Matias. 2025. Fixing the science of digital technology harms. *Science* 388, 6743 (2025), 152–155.

[55] José C Pinheiro and Douglas M Bates. 1995. lme and nlme: Mixed-effects Methods and Classes for S and S-plus. *URL: Http://Www. Citeseer. Ist. Psu. Edu/Article/Pinheiro95lme. Html* (1995).

[56] Andrew K Przybylski, Thuy-vy T Nguyen, Wilbert Law, and Netta Weinstein. 2021. Does taking a short break from social media have a positive effect on well-being? Evidence from three preregistered field experiments. *Journal of Technology in Behavioral Science* 6, 3 (2021), 507–514.

[57] Andrew K Przybylski and Netta Weinstein. 2017. A large-scale test of the goldilocks hypothesis: quantifying the relations between digital-screen use and the mental well-being of adolescents. *Psychological science* 28, 2 (2017), 204–215.

[58] Theda Radtke, Theresa Apel, Konstantin Schenkel, Jan Keller, and Eike von Lindern. 2022. Digital detox: An effective solution in the smartphone era? A systematic literature review. *Mobile Media & Communication* 10, 2 (2022), 190–215.

[59] Nilam Ram, Xiao Yang, Mu-Jung Cho, Miriam Brinberg, Fiona Muirhead, Byron Reeves, and Thomas N Robinson. 2020. Screenomics: A new approach for observing and studying individuals' digital lives. *Journal of adolescent research* 35, 1 (2020), 16–50.

[60] Byron Reeves, Nilam Ram, Thomas N Robinson, James J Cummings, C Lee Giles, Jennifer Pan, Agnese Chiatti, MJ Cho, Katie Roehrick, Xiao Yang, et al. 2021. Screenomics: A framework to capture and analyze personal life experiences and the ways that technology shapes them. *Human–Computer Interaction* 36, 2 (2021), 150–201.

[61] V Rideout, A Peebles, S Mann, and M B Robb. 2021. *Common Sense census: Media use by tweens and teens, 2021.* Common Sense, San Francisco, CA.

[62] Antonio-Manuel Rodríguez-García, Antonio-José Moreno-Guerrero, and Jesus Lopez Belmonte. 2020. Nomophobia: An individual's growing fear of being without a smartphone—a systematic literature review. *International journal of environmental research and public health* 17, 2 (2020), 580.

[63] Alberto Monge Roffarello and Luigi De Russis. 2023. Achieving digital wellbeing through digital self-control tools: A systematic review and meta-analysis. *ACM Transactions on Computer-Human Interaction* 30, 4 (2023), 1–66.

[64] Paul R Rosenbaum and Donald B Rubin. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* 70, 1 (1983), 41–55.

[65] Mahnaz Roshanaei, Sumer S Vaid, Andrea L Courtney, Serena J Soh, Jamil Zaki, and Gabriella M Harari. 2024. Meaningful peer social interactions and momentary well-being in context. *Social Psychological and Personality Science* 15, 8 (2024), 921–932.

[66] Morgan Q. Ross. 2025. Paper Presentation at the International Communication Association conference. In *What is Constant Connectivity? Clarifying the Mobile Affordances that Underlie Potential Communication.*

[67] Morgan Quinn Ross, Alicia Gilbert, Julius Klingelhoefer, Mora Matassi, Lise-Marie Nassen, Sara Van Bruyssel, Alice Verlinden, and Douglas A Parry. 2024. Mapping a pluralistic continuum of approaches to digital disconnection. *Media, Culture & Society* 46, 4 (2024), 851–862.

[68] Morgan Quinn Ross and Kostadin Kushlev. 2024. Antecedents and consequences of smartphone self-extension. *Psychology of Popular Media* (2024).

[69] Annabel Rothschild and Janne Lindqvist. 2024. Swapping 5G for 3G: Motivations, Experiences, and Implications of Contemporary Dumbphone Adoption. *Proc. ACM Hum.-Comput. Interact.* 8, CSCW1, Article 125 (April 2024), 40 pages. doi:10.1145/3637402

[70] Christine Satchell and Paul Dourish. 2009. Beyond the user: use and non-use in HCI. In *Proceedings of the 21st annual conference of the Australian computer-human interaction special interest group: Design: Open 24/7.* 9–16.

[71] Desirée Schmuck. 2020. Does digital detox work? Exploring the role of digital detox applications for problematic smartphone use and well-being of young adults using multigroup analysis. *Cyberpsychology, Behavior, and Social Networking* 23, 8 (2020), 526–532.

[72] Anna Schnauber-Stockmann, Adrian Meier, and Leonard Reinecke. 2018. Procrastination out of habit? The role of impulsive versus reflective media selection in procrastinatory media use. *Media Psychology* 21, 4 (2018), 640–668.

[73] Andrew Schrock. 2015. Communicative Affordances of Mobile Media: Portability, Availability, Locatability, and Multimediality. *International Journal of Communication* 9, 0 (2015), 1229–1246. https://ijoc.org/index.php/ijoc/article/view/3288

[74] Phoebe Sengers, Kirsten Boehner, Shay David, and Joseph'Jofish' Kaye. 2005. Reflective design. In *Proceedings of the 4th decennial conference on Critical computing: between sense and sensibility.* 49–58.

[75] Jean M Twenge. 2020. Increases in depression, self-harm, and suicide among US adolescents after 2012 and links to technology use: possible mechanisms. *Psychiatric Research and Clinical Practice* 2, 1 (2020), 19–25.

[76] Isaac Vaghefi and Ofir Turel. 2025. Digital Detox? A Mixed-Method Examination of Hedonic IT Abstinence Maintenance and its Effects on Productivity and Moderation of Use. *Communications of the Association for Information Systems* 56, 1 (2025), 18.

[77] Sumer S Vaid, Lara Kroencke, Mahnaz Roshanaei, Sanaz Talaifar, Jeffrey T Hancock, Mitja D Back, Samuel D Gosling, Nilam Ram, and Gabriella M Harari. 2024. Variation in social media sensitivity across people and contexts. *Scientific Reports* 14, 1 (2024), 6571.

[78] Patti M Valkenburg and Jochen Peter. 2013. The differential susceptibility to media effects model. *Journal of communication* 63, 2 (2013), 221–243.

[79] Alexander J.A.M. van Deursen, Colin L. Bolle, Sabrina M. Hegner, and Piet A.M. Kommers. 2015. Modeling habitual and addictive smartphone behavior. *Computers in Human Behavior* 45 (April 2015), 411–420. doi:10.1016/j.chb.2014.12.039

[80] Mariek MP Vanden Abeele, Heidi Vandebosch, Ernst HW Koster, Tom De Leyn, Kyle Van Gaeveren, David de Segovia Vicente, Sara Van Bruyssel, Tim van Timmeren, Lieven De Marez, Karolien Poels, et al. 2024. Why, how, when, and for whom does digital disconnection work? A process-based framework of digital disconnection. *Communication Theory* 34, 1 (2024), 3–17.

[81] Kexin Wang, Eline Frison, Steven Eggermont, and Laura Vandenbosch. 2018. Active public Facebook use and adolescents' feelings of loneliness: Evidence for a curvilinear relationship. *Journal of adolescence* 67 (2018), 35–44.

[82] David Watson, Lee Anna Clark, and Auke Tellegen. 1988. Development and validation of brief measures of positive and negative affect: the PANAS scales. *Journal of personality and social psychology* 54, 6 (1988), 1063.