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Accepted Manuscript

DOI: https://doi.org/10.1089/cyber.2022.0027

Citation: Zimmermann L, Sobolev M. Digital Strategies for Screen Time Reduction: A Randomized Field Experiment. Cyberpsychol Behav Soc Netw. 2023 Jan;26(1):42-49.

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Digital Strategies for Screen Time Reduction:

A Randomized Field Experiment

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Running title: Digital Strategies for Screen Time Reduction

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Keywords: Screen time, Smartphone, Digital nudge, Goal-setting, Time limits, Design friction

An earlier version of this article is available at https://psyarxiv.com/nmgdz/

Conflicts of Interest: None.

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Abstract

Many consumers nowadays wish to reduce their smartphone usage in the hope of improving productivity and wellbeing. We conducted a pre-registered field experiment (N=112) over a period of several weeks to test the effectiveness of two widely available digital strategies for screen time reduction. The effectiveness of a design friction intervention (i.e., activating grayscale mode) was compared to a goal-setting intervention (i.e., self-commitment to time limits) and a control condition (i.e., self-monitoring). The design friction intervention led to an immediate, significant reduction of objectively measured screen time compared to the control condition. Conversely, the goal-setting intervention led to a smaller and more gradual screen time reduction. In contrast to the popular belief that reducing screen time has broad benefits, we found no immediate causal effect of reducing usage on subjective well-being and academic performance.

Keywords:

Screen time, Smartphone, Digital nudge, Goal-setting, Time limits, Design friction

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Introduction

Mobile technology connects people in ways that were previously impossible, but recently, concerns about maladaptive smartphone usage have been rising.[1, 2] In fact, a significant proportion (39%) of individuals want to reduce their mobile usage.[3] Faced with the reckoning of mobile addiction, Apple released a time management application ('Screen Time') in 2018, creating one of the most accessible solutions to controlling mobile usage. Within the app, users can manipulate their smartphone's choice architecture[4] and digitally self-nudge[5] to reduce screen time.

We investigate whether digital strategies for reducing screen time are indeed 'empowering interventions enabling people to design their own decision environment'.[4, 5] Specifically, we test the effectiveness of two strategies—a design friction versus a goal-setting tool—compared to a self-tracking control condition for reducing objectively measured screen time in a field experiment over several weeks.

Goal-setting with time limits

Within the Screen Time app, time limits are a central feature. Users can commit to abstain from their phone at specific times or after reaching self-set time limits. These limits are not strictly enforced, and users can override them without consequences, thus requiring self-control. We consider this self-commitment feature a goal-setting strategy as it requires individuals to proactively plan and commit to clearly defined, measurable goals, and employ self-control. Self-commitment through explicit goal-setting has been highly effective in many domains.[6-12] To enhance digital self-control, time limit apps are extremely popular and have been shown to effectively reduce self-interruptions, stress and, smartphone usage.[13-15]

Design friction: Grayscale mode

Design frictions, as self-imposed inconveniences to the usage process, do not require active self-regulation but aim to alter the underlying reward structure by making the usage experience less convenient or gratifying.[16, 17] Design frictions, such as screen changes, slowdowns or vibrations, can disrupt automatic behavior and stimulate more mindful smartphone interaction.[17, 18]

We chose grayscale mode as a widely accessible design friction tool.[19] Color perception literature indicates that an absence of bright, saturated colors reduces gratification and salience of eye-catching stimuli.[20-24] We argue that grayscale mode steers individuals towards reducing usage by making the experience less rewarding without active goal-setting, thus it can be considered effortless self-control.[19, 25]

We argue that both strategies should lead to a usage reduction when compared to self-tracking.[a] We expected an immediate reduction for the design friction strategy since it makes the mobile experience less gratifying from the beginning.[17-19] The goal-setting strategy should lead to a gradual reduction as consumers may find it difficult to reduce usage initially when relying on self-control. Due to habit formation, successful goal achievement on day one should facilitate achievement thereafter.[26, 27] Thus, over time, it should become easier to achieve goals and reduce usage.

We also investigate the causal impact of reducing usage on wellbeing and grade point average (GPA). Several studies highlight negative links between smartphone usage and

[a] We did not expect a reduction in the control condition since self-monitoring alone via screen time apps is unlikely to change mobile usage.[25]

performance,[28-31] cognitive capacity,[32] distractibility,[33, 34] emotional health[35] and sleep.[36] Nevertheless, the magnitude and causality of such relationships is highly debated.[37-41] Thus, another goal of this study was to investigate whether reducing mobile usage benefits wellbeing and performance.

Methodology

Design

Our preregistered[b] field experiment included three conditions: (1) *Control condition*: self-tracking (n=39); (2) *Design friction condition:* grayscale mode (n=40); (3) *Goal-setting condition:* time limits (n=33). All material, including the instructions per condition, is available at Open Science Framework.[c]

In the *control* condition, participants were instructed to use Screen Time for self-tracking without additional suggestions. In the *design friction* condition, participants additionally switched their display to grayscale (i.e., black and white screen). In the *goal-setting* condition, participants set time limits by activating two app features: 1) 'Downtime' to schedule time away from the screen during which only calls, and certain apps were available; 2) 'App Limits' to set daily time limits for apps or categories (e.g., social networking).

Sample and procedure

The study was part of a university workshop for different postgraduate programs which introduced students to the science of attention in the workplace. It consisted of two lectures and a smartphone project between the lectures. The smartphone project contained our intervention

[b] https://aspredicted.org/blind.php?x=/474_JGJ
[c] osf.io/k9bdf

(timeline in Fig. 1). Participants received course credit for participation and completion of the project. Due to scheduling constraints, the time between the lectures and therefore the intervention duration ranged from 7-25 days (M=16.83, SD=5.23, Med=18 days). This duration did not impact the results.

FIGURE 1

Out of 395 workshop participants 353 consented to participate in the study. To reduce variance, we only included iPhone users (75%). We excluded participants who did not submit screen time data, who did not complete the T2 survey or failed an intervention check (i.e., they completed a different task than they were assigned).[d] Our final sample consisted of 112 participants (M_{age}=26 years; 77% female; see Fig. 2.).[e] Previous research indicates high effect size (Cohen's d between 0.4-0.5) for screen time interventions.[17] A power analysis with GPower using a more conservative effect size (0.3) suggested that the desired sample size for a one-way ANOVA with three groups ($\alpha = 0.05$) and .80 power was N=111.

FIGURE 2

[d] The results are directionally similar albeit not reaching statistical significance when including these participants.
[e] We assigned slightly more participants to the intervention conditions to be better able to detect treatment differences. Note that the uneven allocation to the intervention conditions was due to an initial coding error which we corrected as soon as we noticed. There were no differences in characteristics between conditions (e.g., demographics, mobile phone behavior, efficacy expectations etc.).

Measures

In the T1 survey participants estimated their daily screen time, unlocks and notifications, ability to reduce screen time (scale: 0–100% reduction) and previous use of screen time apps. While participants were unaware of the intervention, we elicited beliefs about the effectiveness of techniques for reducing usage (efficacy expectations, table 1). We elicited subjective wellbeing with four standardized items for life satisfaction, sleep, stress and happiness (wording in table 3).[42-44] Participants then completed a smartphone dependence scale.[32] Finally, participants answered demographic questions. There were no differences at baseline between conditions on key variables (e.g., smartphone dependence, ability to reduce screen time, usage estimates; table 1).

TABLE 1

To collect objective screen time rather than inaccurate estimates,[45-47] participants submitted screenshots of their average smartphone usage (‘last 7 days’) from the app, after every seven days which were coded manually. Daily average screen time constituted our main dependent variable.

After the intervention, participants completed the T2 survey. Participants in the design friction condition indicated the percentage they had activated grayscale and rated its effectiveness. Participants in the goal-setting condition reported which time limit features they had activated, how frequently they had broken their limits and rated the effectiveness of time limits.

All participants estimated their percentage of productive mobile time and enjoyment of social media. Participants indicated whether Screen Time had helped reduce mobile usage, and how committed they had felt towards lowering usage. Finally, participants answered the wellbeing questions again.

GPA for the academic year was obtained from the university after several months.

Results

The average daily screen time was 261.50 minutes (*SD*=91.34; table 2). Due to scheduling constraints, participants submitted a varying number of screenshots (*M*=2.33, *SD*=0.84). Ninety-five percent submitted screenshots for at least two weeks, 40% submitted screenshots for at least three weeks. The number of screenshots did not differ across conditions ($F(2, 109)=0.05$, $p=.953$). Participants in the intervention conditions showed similarly high compliance and effectiveness ratings (compliance measures, table 3).

TABLE 2

A one-way ANOVA comparing the average screen time indicated a significant difference ($F(2, 109)=3.30$, $p=.040$). Screen time in the design friction condition (*M*=233.19, *SD*=88.18) was lower than in the control condition (*M*=283.20, *SD*=97.25, $t(77)=2.39$, $p=.019$) and marginally lower than in the goal-setting condition (*M*=270.17, *SD*=81.10, $t(71)=-1.84$, $p=.068$). There was no difference between the goal-setting and control condition ($t(70)=0.61$, $p=.543$). On average, the design friction grayscale lowered screen time by approximately 50 minutes per day.

Screen time in the goal-setting condition was not significantly lower than in the control condition.

This result was exactly the opposite to participants' efficacy expectations ($F(2, 220)=18.87$, $p<.001$). Self-monitoring was believed to be most effective, and grayscale least effective for reducing usage, with time limits in between (table 1).

Next, we look at the reduction of mobile usage over time (Fig. 3). We regressed the average daily screen time on the condition (base: control), the number of submitted screenshots (week 1, week 2 etc.) and their interaction. Screen time in the design friction condition did not vary over time (β=-11.64, p=.152). But there was a significant interaction for the goal-setting condition. Participants with time limits significantly lowered their usage over time (β=-20.37, p=.019). This indicates that the design friction had an immediate and stable, while the goal-setting intervention had a gradual effect on screen time.

FIGURE 3

An exploratory process analysis revealed that participants in the design friction condition enjoyed social media during the intervention marginally less than in other conditions (β=-9.27, p=.053). Productive mobile time did not differ across conditions (table 3).

At baseline, there were no differences between conditions for life satisfaction, stress, sleep, and happiness. At T2, we also found no differences. Repeated-measure ANOVAs revealed no systematic pattern consistent with the notion that reducing mobile usage improves wellbeing (table 3).

GPA did not differ across conditions ($F(2, 106)=0.10$, $p=.905$), but average screen time was negatively associated with GPA ($b=-.0004$, $p=.024$), controlling for age and gender.

TABLE 3

Discussion

We show that two digital tools for reducing screen time, which are freely available on nearly any smartphone, are indeed empowering people to lower their mobile usage. The design friction tool grayscale mode led to an immediate, consistent usage reduction of 17.6%, potentially due to lower enjoyment of social media. Conversely, the goal-setting intervention employing time limits, gradually reduced mobile usage suggesting that participants became progressively better at achieving their time limits. We suspect these to be conservative estimates since compliance was not enforced or incentivized following a self-nudging approach.[5, 48] Similar to past research, self-monitoring did not change mobile usage.[17, 49]

Interestingly, participants' efficacy expectations showed the opposite. Participants incorrectly believed self-monitoring to be most effective and grayscale to be least effective. People typically prefer educative 'system 2' interventions that enhance agency over non-educative 'system 1' interventions, unless they are informed about the effectiveness of the latter.[49, 50] Therefore, our findings contribute to the development of evidence-based solutions for reducing screen time which rely less on anecdotal evidence and expectations.

Mobile technology influences how we interact, connect and share information.[51, 52] But there is lesser evidence that wellbeing is generally being harmed, and moderate usage may even

be advantageous.[53-56] We add experimental evidence to this literature questioning the narrative that mobile usage is generally harmful. Wellbeing effects might depend on how, when and why smartphones are used.[53] Passive scrolling or phone checking at night might be especially problematic.[29] Future research could investigate longitudinal data of different usage types and proximal wellbeing outcomes. Similar to previous research, screen time was negatively associated with GPA.[30, 49, 57] However, our digital strategies despite lowering usage, did not increase GPA.

Our research has several limitations. We did not strictly enforce or objectively measure to what extent participants implemented the tools. Additionally, we focused our analysis on a subset of allocated participants (those who followed the instructions) rather than using an intent-to-treat approach, which might limit our conclusions. Future research could investigate which individuals are responsive to different interventions, and to what extent they must be enforced or incentivized to be effective in a broader population.

This research offers practical insights for anyone interested in reducing smartphone usage. Considering the median consumer would require a compensation of $48 to abstain from Facebook for one month,[58] there exists demand for cost-effective, scalable solutions to reduce mobile usage. Our findings can encourage individuals in occupational[29, 59] or educational settings[60, 61] to use their smartphones less with design friction or goal-setting tools. It is reassuring that screen time can be reduced with simple digital interventions. It suggests that excessive smartphone usage is more a self-control problem than an addiction and can be overcome with sufficient willpower and the right strategy.

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Tables

Table 1

Sample characterization.

	Total sample	Control (Tracking)	Design friction (Grayscale)	Goal-setting (Time Limits)	Test-statistic
Sample size	112	39	40	33	
Demographics					
Age	25.58 (3.62)	26.61 (4.28)	24.97 (2.69)	25.09 (3.56)	$F(2, 108)=2.50$, $p=.08$
Female %	77.06	76.92	71.79	83.87	$Chi^2(2)=1.42$, $p=.49$
Mobile phone behavior at T1					
Prior use of tracking app (% yes)	54.05	51.28	56.41	54.55	$Chi^2(4)=3.29$, $p=.50$
Estimated screen time daily minutes	221.1 (102.86)	210.61 (85.74)	206.66 (98.29)	250.57 (122.00)	$F(2, 108)=1.98$, $p=.14$
Estimated number of daily notifications	106.78 (117.41)	97.68 (89.85)	105.82 (118.39)	118.39 (144.03)	$F(2, 107)=0.27$, $p=.76$
Estimated number of daily unlocks	69.11 (56.25)	63.02 (51.87)	70.94 (61.96)	74.15 (55.20)	$F(2, 108)=0.38$, $p=0.68$
How much could you reduce screen time (0 - 100%)	52.61 (18.75)	51.15 (21.35)	53.00 (17.05)	53.87 (17.82)	$F(2, 108)=0.20$, $p=0.82$
Smartphone dependence	3.97 (1.16)	4.1 (1.32)	4.01 (1.01)	3.79 (1.15)	$F(2, 108)=0.64$, $p=0.52$
Efficacy expectations 0=not at all effective, 100=very effective					
Looking at detailed information about individual mobile phone usage	45.21 (28.87)	43.38 (28.87)	43.56 (28.05)	49.33 (30.27)	$F(2, 108)=0.47$, $p=.62$
Setting time limits for different apps	40.88 (29.61)	39.82 (29.83)	39.82 (27.86)	43.39 (32.04)	$F(2, 108)=0.17$, $p=.84$
Turning mobile phone to grayscale mode (screen black & white)	26.70 (25.92)	29.07 (27.68)	23.25 (26.08)	27.96 (23.85)	$F(2, 108)=0.54$, $p=.58$

Table 2

Screenshot data.

	N	M	SD
Screenshot 1	112	267.36	98.24
Screenshot 2	95	254.84	95.96
Screenshot 3	45	246.46	90.65
Average screen time	112	261.50	91.34

Table 3

Results for T1 and T2 survey measures across conditions.

	T1 Baseline					T2 Post-Treatment				
	Total	Control	Design Friction	Goal-setting	Test-statistic	Total	Control	Design Friction	Goal-setting	Test-statistic
Life satisfaction: All things considered, how satisfied are you with your life as a whole these days? 0=completely dissatisfied, 100=completely satisfied	75.28 (15.60)	75.64 (13.56)	73.30 (19.61)	77.21 (12.36)	$F(2, 108)=0.57$, $p=.567$	78.25 (17.14)	80.15 (16.45)	78.65 (19.24)	75.51 (15.28)	$F(2, 109)=0.67$, $p=.515$
Stress: Stress means a situation in which a person feels tense, restless, nervous or anxious or is unable to sleep at night because his/her mind is troubled all the time. Do you feel this kind of stress these days? 0=not at all, 100=very much	46.64 (27.56)	46.20 (26.76)	46.94 (30.93)	46.81 (24.98)	$F(2, 108)=0.01$, $p=.992$	51.34 (24.84)	49.05 (22.58)	52.12 (27.34)	53.12 (24.76)	$F(2, 109)=0.27$, $p=.766$
Sleep: How well did you sleep last night? 0=bad night's sleep, 100=good night's sleep	68.86 (26.28)	70.28 (24.30)	67.84 (30.26)	68.39 (24.10)	$F(2, 108)=0.09$, $p=.914$	66.47 (26.38)	68.30 (25.54)	64.45 (27.78)	66.75 (26.26)	F(2, 109)=0.21, $p=.810$
Happiness: Taking all things together, would you say you are: 0=not at all happy, 1=not very happy, 2=rather happy, 3=very happy	2.40 (0.56)	2.43 (0.59)	2.41 (0.59)	2.36 (0.48)	$F(2, 108)=0.15$, $p=.862$	2.52 (0.55)	2.48 (0.60)	2.60 (0.49)	2.48 (0.56)	$F(2, 109)=0.54$, $p=.583$
General Wellbeing Index	0.02 (0.82)	0.06 (0.78)	-0.02 (0.97)	0.03 (0.70)	$F(2, 108)=0.11$, $p=.893$	0.06 (0.87)	0.11 (0.88)	0.11 (0.90)	-0.03 (0.83)	$F(2, 109)=0.32$, $p=.729$
Social media enjoyment 0=not at all, 100=very much	-	-	-	-	-	52.28 (24.30)	55.17 (26.47)	46.32 (26.45)	56.09 (17.15)	$F(2, 111)=1.92$, $p=.152$

Estimated percentage of productive mobile usage 0%=no productive time, 100%=only productive time	-	-	-	-	-	45.36 (18.36)	41.79 (16.84)	47.97 (20.53)	46.42 (17.15)	$F(2, 109)=1.20$, $p=.305$
Was the Screen Time app helpful to reduce usage? 0=definitely not, 100=definitely yes	-	-	-	-	-	49.26 (29.20)	39.61 (26.23)	51.10 (29.72)	58.45 (29.31)	$F(2, 109)=4.05$, $p=.020$
Feeling committed to reduce usage? 0=not at all, 100=very much	-	-	-	-	-	52.15 (28.06)	43.35 (25.82)	57.62 (29.70)	55.90 (26.79)	$F(2, 109)=3.08$, $p=.049$
Compliance measures										
What percentage of the time did you have grayscale mode activated? 0=not at all, 50=about half the time, 100=all the time								46.5 (32.79)		
How frequently did you break your own screen time rules and limits? 0=almost never, 50=about half the time, 100=almost every day									53.18 (29.70)	
Did activating grayscale mode / setting yourself goals and limits on your phone help you to reduce your screen time? 0=definitely not, 100=definitely yes								52.80 (36.62)	55.42 (26.81)	$F(1, 72)=0.12$, $p=.732$