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Abstract

Sustaining behavior change is challenging when consumption is habitual, as with smartphone use. Across two longitudinal field studies involving 5,686 observations of objectively measured smartphone use from 153 individuals, we explore how to reduce smartphone usage sustainably. Our intervention leverages positive alternatives (learning a new language or engaging in walking) to sustain smartphone usage reductions after an intervention with incentives has ended. We study whether consumers who are incentivized to curb smartphone use and adopt a positive activity demonstrate greater long-term success compared to those solely incentivized to reduce smartphone use. Across both studies, participants reduced smartphone use while incentives were in place, but these reductions were not sustained after incentives were removed. However, individuals achieving both targets (instead of one) had lower social media and smartphone use during the post-treatment period relative to their baseline, especially if a higher proportion of idle time was occupied by the positive alternative. In the first study, higher engagement in the alternative activity was associated with lower self-reported social media addiction, while larger reduction in social media use was linked to improvement in subjective well-being. However, well-being findings were mixed: the second study found no effect of screen time reduction on subjective well-being.

Keywords: smartphone, social media, habits, psychology of technology, behavior change, digital addiction, sustainable consumption, adherence

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Introduction

Over the past 20 years, smartphones and social media have transformed key aspects of our lives, from work to leisure. However, concerns about health, well-being, and social relationships have ignited policy-relevant debates. Some researchers argue that these technologies are harmful (Twenge and Campbell 2019), while others contend that they pose little to no risk (Coyne et al. 2020), or that existing evidence is too weak to warrant intervention (Orben and Przybylski 2019). Meanwhile, digital consumptions have drawn attention from government agencies worldwide out of concerns for users (Ofcom 2024; United States Senate Committee on the Judiciary 2024; French Government 2024; Australian Government 2024; SMART Act 2019). Concrete measures have been taken to protect younger consumers from potential negative effects on mental health, sleep quality, and school performance (Nagata et al. 2025; Hisler, Twenge, and Krizan 2020; Giunchiglia et al. 2018). Notably, 79 governments have imposed smartphone bans in schools, despite ongoing debate over their impact on student well-being and educational benefits (Global Education Monitoring Report 2025), with recent research evidence either supporting (Figlio and Özek 2025) or rejecting (Goodyear et al. 2025) these bans.

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Irrespective of the contentious nature, many consumers are interested in taking action themselves, for instance, by actively managing smartphone use through incentive-based interventions (Verplanken and Wood 2006). A significant share of young adults (approximately 58%) indicate they would prefer living in a world without TikTok and Instagram. Moreover, between 46% to 60% of users of these platforms say they would be willing to pay to have their own and others' social media accounts deactivated (Bursztyn et al. 2025). However, smartphone usage is notoriously difficult to change. Interventions often fail to produce long-term effects (Wood and Neal 2016) due to the habit-forming nature of many smartphone applications (Berthon, Pitt, and Campbell 2019; Alter 2017).

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While previous research has concentrated on reducing smartphone use in isolation, we draw on the idea that changing a habit requires a comprehensive approach as it is inextricably linked to other daily activities (Marlatt and George 1984; Witkietvitz and Kirouac 2016). When consumers reduce undesired smartphone use, especially if it occupies significant time, they are confronted with more 'idle time'. Building on previous research (Adriaanse et al. 2011; Kushlev and Leitao 2020; Laibson 2001), we argue that if this idle time is occupied by an alternate activity, the previous smartphone usage pattern is less likely to recur. Thus, engaging in an alternative activity, ideally a beneficial one, may help achieve lasting change.

This constitutes our main research question: How effective is an intervention that simultaneously reduces smartphone (or social media) usage while fostering a beneficial alternative, compared to one that focuses solely on reduction? This question aims to address issues raised by marketing and public policy scholars regarding maladaptive consumption and intervention strategies (Martin and Stewart 2024; Berthon, Pitt, and Campbell 2019).

Across two longitudinal studies—a quasi-experimental pilot and a randomized field study—we investigate whether monetarily incentivizing consumers to reduce smartphone (or social media) use while simultaneously engaging in a beneficial activity leads to more sustained behavior change than incentivizing usage reduction alone.

As alternative activities, we chose language learning (pilot) and walking (experimental study). Like smartphone use, both can be measured objectively with tracking apps. They have benefits for health, cognitive function, and well-being (e.g., Chekroud et al. 2018; Lee and Buchner 2008; Zimmermann and Chakravarti 2022) and are commonly reported activities that consumers would like to engage in more (Hoare et al. 2017; Young 2014).

Our results show that, while intervention assignment *did not* reduce social media nor smartphone usage in the post-treatment relative to baseline, individuals who consistently performed the positive alternative activity (i.e., language learning, walking) and reduced

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social media / smartphone usage during the intervention tended to maintain relatively lower usage, even after the intervention period ended. Tying two distinct behaviors to a single monetary incentive may offer a more cost-effective intervention than traditional incentive schemes that focus on a single behavior. However, our findings suggest that any potential benefits of this approach depend on participants successfully adhering to both targets during the intervention period. Although achieving two targets for one incentive may appear more challenging, participants who successfully adhered to both targets tended to show more persistent reductions in usage than those who adhered to only one target. These findings highlight adherence as a key challenge and an important direction for future research.

Our research contributes to the behavioral change literature by integrating two approaches: monetary incentives and the promotion of alternative activities to encourage behavior change. Unlike previous studies, which either used monetary incentives (Allcott et al. 2020; Allcott, Gentzkow, and Song 2022; Collis and Eggers 2022; Stanley, Correia, and Irons 2022) or focused on recommending alternative activities (Brailovskaia et al. 2022; Esmaeili and Ahmadi 2018; Reed, Fowkes, and Khela 2023), we combine both strategies (see Appendix A for a summary of previous interventions). We establish concrete, actionable targets for both reducing smartphone usage and increasing engagement in an alternative activity. These dual-targets are tied to a single incentive, fostering daily repetition—a key factor in habit formation (Somasundaram, Koch, and Lim 2023; Somasundaram, Zimmermann, and Pham 2025). Methodologically, we overcome a drawback of previous studies by measuring behaviors objectively with smartphone tracking applications.

By examining reductions in social media (pilot) and smartphone usage (experimental study), we add to the policy debate about potential negative impacts of excessive usage on well-being. Our findings are mixed. In the pilot study, we find correlational evidence suggesting that social media reductions are associated with improvements in well-being. In

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contrast, in the experimental study, where participants were randomly assigned to reduce general mobile screen time, we found no consistent causal effect on wellbeing. While the studies are not directly comparable, the difference in findings is consistent with literature showing that social media, in particular, can exacerbate problematic smartphone use (Lowe-Calverley and Pontes 2020).

Our findings have implications for policy and practice. For example, schools could explore programs that combine goals to reduce social media use with engagement in alternative activities like extracurriculars. However, we emphasize that such programs are likely to be most effective when participants consistently adhere to both goals (i.e., reducing social media use and increasing alternative activities) throughout the incentivized period. More broadly, our findings highlight adherence as a challenge for future interventions seeking to promote lasting reductions in smartphone and social media use. Grassroots movements, such as parent groups advocating for youth's social media restrictions, can adopt similar home-based strategies. Social media companies, increasingly under scrutiny, might want to explore ways of promoting productive alternative activities and healthier habits, improve public perception, and reduce regulatory pressure. In the next section, we outline the relevant literature and derive our hypotheses.

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Literature Review and Hypotheses Formulation

Monetary Incentives for Reducing Mobile Usage

Monetary incentives are often used to change behavior, yet the effectiveness in producing long-term change remains debated. In the digital consumption context, they have been used to reduce smartphone and social media usage, with some studies showing persistent effects beyond the incentive period (Allcott, Gentzkow, and Song 2022; Brailovskaia et al. 2022; Somasundaram, Zimmermann, and Pham 2025), while others find that usage quickly returns to baseline once incentives end (Collis and Eggers 2022; Stanley,

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Correia, and Irons 2022). Given mixed prior evidence, our pilot study first assesses whether monetary incentives generate lasting reductions in social media use. This preliminary test establishes a foundation and ensures conceptual completeness for testing the effects of dual- versus single-target achievement. Accordingly, we hypothesize:

H1: Participants have lower social media usage in the post-treatment period compared to their baseline period, following an intervention period with monetary incentives.

A common limitation of many habit formation interventions (e.g., Charness and Gneezy 2009; Volpp et al. 2009) is that, after a period of successful behavior change, consumers revert to previous consumption levels, showing the "triangular relapse pattern" (Wood and Neal 2016) . To address this, we draw on addiction research to argue for changing an undesired behavior sustainably by encouraging the pursuit of an alternative activity.

Combining Mobile Usage Reductions with Fostering an Alternative Activity

Viewing smartphone use through an addiction lens allows us to tap into methods proven effective for more tangible addictions, such as smoking. For example, combining nicotine replacement therapy with a substituting activity, such as physical exercise, can improve smoking cessation outcomes (Prapavessis et al. 2016). Drawing on this, we argue that when consumers deliberately fill time freed up by reducing smartphone use with a beneficial alternative, they establish this alternative as a part of their routine and reduce the likelihood of re-engagement with the smartphone. To test this, we allowed participants to choose daily whether to just reduce social media use alone, or to pursue a dual-target approach—reducing social media use while simultaneously engaging in a beneficial alternative activity (i.e., using a language learning app). We hypothesize:

H2: Participants with higher dual-target achievement will show greater reductions in post-treatment social media usage compared to those with higher single-target achievement or no target achievement.

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Possible Mechanisms

We argue that the alternative activity (language learning) serves to fill the time freed up by reducing social media use. To explore this time-replacement effect, we introduce the *target replacement ratio,* which reflects the extent to which time allocated to social media reduction is replaced by time allocated to language learning. The ratio is high when a person's language learning target represents a large share of their social media reduction target. For example, if a person's social media reduction target is two hours and their language learning target is 0.4 hours, their target replacement ratio is 20%.

We expect sustained behavior change to depend not only on how targets are structured but also on how successful participants are in achieving them (i.e., adherence). The target replacement ratio reflects how much the alternative activity target (language learning) offsets the social media reduction target, while dual-target achievement captures the extent to which participants meet both targets during the treatment period. Thus, when participants have a higher replacement ratio and achieve both targets, they should be more likely to sustain reduced social media use in the post-treatment period. Based on this, we hypothesize an interaction effect between the target replacement ratio and dual-target achievement:

H3: The effect of dual-target achievement on social media reduction (post-treatment vs. baseline) will be stronger among participants with higher target replacement ratio.

This mechanism is supported by psychological accounts related to cues and self-signaling, which explain why engaging in an alternative activity may be more effective than simply trying to reduce the undesired behavior. First, thinking about *not* executing a habitual behavior (a *negation* implementation intention) can ironically strengthen it. In contrast, focusing on an alternative activity (a *replacement* implementation intention) weakens the cue-response link of the undesired habit by associating the cue with a different response (Adriaanse et al. 2011). Laibson's (2001) cue theory of consumption suggests that an activity

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is triggered when its associated cue surpasses an activation 'threshold'. For habits, this threshold is low, so subtle internal cues, such as boredom, can trigger the habit. Introducing alternative activities raises this threshold by competing with the habit. In our context, an alternative activity such as language learning or walking can increase the activation threshold for social media or smartphone use, making habitual engagement less likely to recur.

Second, self-signaling processes may also explain why engaging in alternative activities supports lasting change. Dai and Fishbach (2014) show that when consumers abstain from a behavior while having a salient alternative, they infer they have developed new tastes. Participants who abstained from Facebook and used Twitter instead reported a reduced desire for Facebook, suggesting the alternative signaled a shift in preferences. In our context, the alternative activities are not direct substitutes for social media, thereby avoiding compensatory addictions or simple habit substitution (Dey et al. 2019; Melumad and Pham 2020). Instead, engaging in a beneficial, non-substitute activity may signal to consumers that their dependency on social media is lower. This shift in self-perception may make consumers more open to exploring alternative activities beyond the incentivized one and encourage them to view their time as a valuable resource, thereby supporting sustained behavior change. Consistent with this, Mead and Patrick (2016) show that a replacement activity can facilitate unspecific postponement (e.g., "I can have it some other time"), signaling low importance of the tempting activity and reducing both immediate and long-term craving.

H4: Participants with higher dual-target achievement during the treatment period experience greater reductions in social media addiction compared to their baseline.

A variety of alternative activities could be used as substitutes. To enhance the generalizability of our results, we use two distinct alternatives: language learning with a smartphone app (pilot study), and walking (experimental study). These activities differ in two key aspects. First, walking physically separates consumers from their smartphones, reducing

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exposure to cues, such as push notifications, that often trigger social media use. In contrast, language learning on the same device does not provide such physical separation. Second, language learning demands more cognitive effort and specific interest, whereas walking is more accessible and requires less effort, making it more appealing to a broader audience.

Smartphone and Social Media Usage as Maladaptive Habits

Smartphone usage is highly habitual (Oulasvirta et al. 2012). On average, consumers check their phones 47-58 times daily (Deloitte 2017; MacKay 2019) and spend approximately four hours per day on them (App Annie 2021). Many reach for their phones first thing in the morning and last at night (Toh et al. 2019), and social media behaviors are largely automatic (Anderson and Wood 2021). Given that social media accounts for roughly 44% of smartphone use (Kemp 2021), it is not surprising that many consumers struggle to reduce usage despite recognizing its downsides.

Excessive smartphone use becomes maladaptive (Berthon, Pitt, and Campbell 2019; Alter 2017; Wang, Lee, and Hua 2015) when users crave its rewarding or stress-soothing effects at the expense of meaningful activities (Melumad and Pham 2020, Turel and Bechara 2021; Zimmermann and Somasundaram 2024). Overuse has been linked to lower academic (Giunchiglia et al. 2018; Zimmermann 2021) and work performance (Chadi, Mechtel, and Mertins 2022; Liu, Ji, and Dust 2020), lower well-being (Volkmer and Lermer 2019) and disrupted sleep (Hisler, Twenge, and Krizan 2020; Levenson et al. 2017). A key mechanism is time displacement: diverting time away from healthier, goal-aligned activities (Kushlev and Leitao 2020). We argue that heavy smartphone use precludes opportunities for pursuing more beneficial alternatives simply by consuming large amounts of time. Hence, our last aim is to examine whether reducing smartphone and social media improves subjective well-being.

H5: Reducing smartphone or social media use during the intervention is associated with improvements in subjective well-being after the intervention.

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Pilot Study: Reducing Social Media Usage in Combination with Language Learning

In this pilot, we implemented a quasi-experimental, longitudinal intervention designed to reduce social media use while promoting language learning as alternative activity. After a seven-day baseline period, participants entered a 20-day treatment period, followed by a 13-day post-treatment period. At the start of the treatment period, we informed participants about two incentive structures: (1) earning €1 per day for reducing social media use by 30% from baseline use (*single-target*), or (2) earning €2 per day for reducing social media by 30% AND increasing language learning by 20 minutes[1] (*dual-target*). We chose Duolingo (https://www.duolingo.com/) as the language learning app for its cross-platform availability (Android and iOS) and built-in habit fostering features (Tsai 2016). Each day, participants could choose to pursue the single target, the dual target, or neither.[2]

We hypothesized that, after the intervention, participants would exhibit lower social media use compared to their baseline (H1) and that those with more days of dual-target achievement would maintain lower use than those with more single- or no target achievement (H2). We further argue that the alternative activity (language learning) helps fill time otherwise spent on social media. To quantify this, we introduce the target replacement ratio which increases as the language learning target becomes larger relative to the social media reduction target. Participants with both a higher target replacement ratio and greater dual-target achievement are expected to show more sustained usage reductions (H3). By engaging in the alternative activity, consumers may self-signal that they are less addicted to social media (H4), thus helping maintain reduced social media use. Finally, we expected reduced

[1] During the baseline, 24 participants did not use Duolingo. One participant used Duolingo for 30 minutes a day on average. To make the language learning target reasonable for all participants, we chose 20 minutes per day.
[2] The target types were incentivized differently (dual-target achievement with 2€/day, single-target achievement with 1€/day) to motivate higher participation in the dual-target scheme. If both target types had been incentivized equally, there would have been little motivation to achieve both targets.

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usage during the intervention to be associated with improvements in subjective well-being afterward (H5).

Methods

Study design and procedures

The study was pre-registered (1,588 observations, $N = 43$; 72% females, 28% males; $M_{\text{age}} = 21.6$, $SD_{\text{age}} = 1.79$) and approved by the Institutional Review Board at a large European university. All surveys and materials of the pilot and experimental study can be found on Open Science Framework (OSF).[3] We advertised the study about 'mobile phone usage' to students from different courses via email and during lectures. To avoid self-selection bias (attracting only those highly motivated to reduce social media), we did not reveal that the study aimed at reducing usage. We informed participants that they would receive a €15 Amazon voucher and were eligible for a lottery worth €150. In addition, they could earn an extra payment of up to €40. Rewards were distributed after data collection. Interested students could sign up through a registration survey after which they received more information about the six-week study timeline and completed informed consent.

At the start of the baseline period, participants received instructions to install or activate a screen time tracking app and the language learning app.[4] At the end of each of six weeks, participants were asked to open their Screen Time app and report their daily social media use over the past seven days in an online survey. To validate responses, participants submitted a screenshot of their screen time app and their language learning app usage for the previous seven days (see Web Appendix A, Figure W1 for examples). This allowed us to collect objective individual-level panel data on daily social media use over six weeks.

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[3] Pre-registration link: https://aspredicted.org/3phg-6hkn.pdf. OSF Materials link: https://doi.org/10.17605/OSF.IO/SXNVA
[4] For iPhone users, Apple's inbuilt iOS Screen Time app was used. For Android users, an equivalent app, which could be downloaded free of charge, was used. Duolingo for the respective platforms can be downloaded here.

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The duration of the baseline (seven days), treatment (twenty days) and post-treatment (thirteen days) period was decided based on constraints from the academic calendar to minimize attrition, as well as to be consistent with past habit formation studies (e.g., Loewenstein, Price, and Volpp 2016). Figure 1 shows the design and timeline.

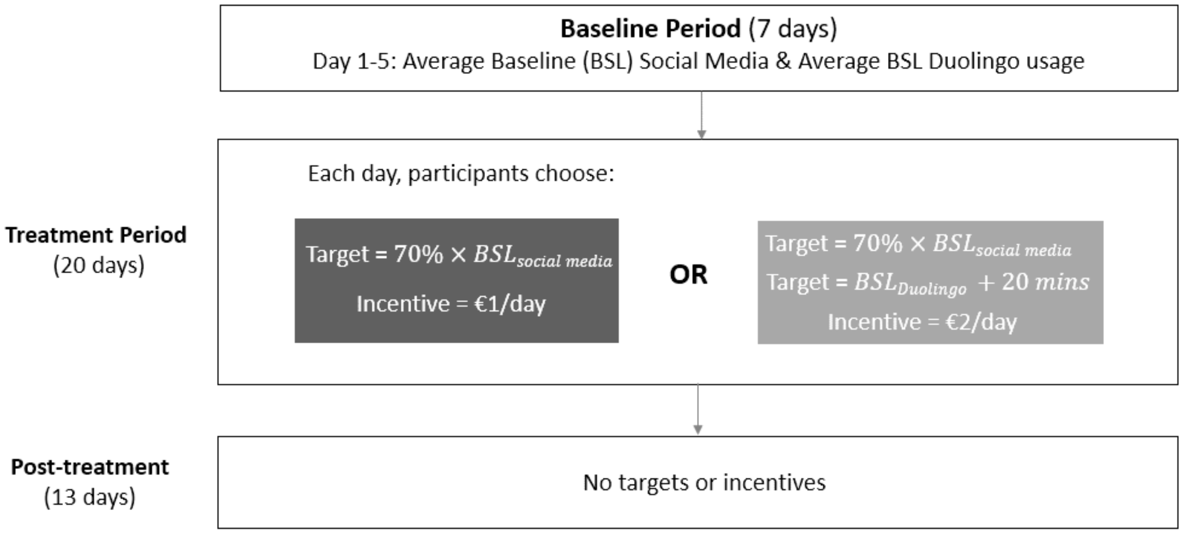

Figure 1. Design of the pilot study

During the baseline period, participants had no targets and used their phone as usual. At the start of the treatment period, participants were informed about their average baseline social media and language learning app usage and received a handout outlining the benefits of reducing social media and learning a new language (see OSF Materials, S1). They were informed they could earn €1 per day for meeting the single-target or €2 per day for meeting the dual-target. Each day during the treatment period, participants could choose whether to pursue the single-target or dual-target. This design captures variation in target achievement and associated changes in social media use, but it also introduces self-selection.

To ensure that participants understood the instructions and had time to prepare, we included a three-day gap between the baseline and treatment period. During this time, they completed a comprehension check to confirm understanding (i.e., baseline usage levels, target social media and language learning, incentive for daily single- or dual-target achievement).

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To strengthen the intervention, at the end of the first and second treatment week, we sent personalized text messages informing participants about the number of days they had achieved each target type (Web Appendix A, Figure W2). In the post-treatment, we removed the targets and incentives. Participants continued reporting their social media and language learning app use for thirteen days.

Surveys

Participants completed a baseline, pre-treatment, and post-treatment survey at the start of each period. In the baseline survey, we measured demographic and social media usage characteristics, along with willingness to reduce social media usage. On average, participants reported strong willingness to reduce usage ($M = 4.84$, $SD = 1.51$, 1 = not at all, 7 = very much; one-sample t-test vs. mid-point: $t(42) = 3.63$, $p < .001$). Additionally, 79% had previously attempted to reduce usage and found it difficult ($M = 4.65$, $SD = 1.43$, 7-point Likert scale; one-sample t-test vs. mid-point: $t(33) = 2.63$, $p = .013$).

We measured perceived social media addiction and well-being both during the baseline and post-treatment period (adapted from Allcott, Gentzkow, and Song 2022; OSF Materials, S2). The 6-item addiction scale ($\alpha = .75$) measures social media dependence over the previous three weeks (e.g., "*How often have you been worried about missing out on things online when not checking your phone?*"; 1 = Never, 5 = Always). The 7-item well-being scale ($\alpha = .84$) captures emotional and cognitive states over the previous three weeks (e.g., "*I was a happy person*", "*I was easily distracted*"; 1 = Strongly Disagree, 7 = Strongly Agree).

We also included questions about language proficiency. Participants were asked how many languages they spoke, whether they were currently learning a language, and if they used any mobile app to do so. Baseline survey measures and a correlation matrix are in Web Appendix A, Tables W1 and W2.

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Analyses and Results

The literature on randomized controlled trial methodologies identifies two analytical approaches: intent-to-treat and per-protocol analyses (Higgins et al., 2019; Tripepi et al. 2020; Molero-Calafell et al. 2024). Intent-to-treat analysis evaluates the effect of treatment assignment, addressing the question "*What is the effect of being assigned to a treatment condition?*". In contrast, per-protocol analysis examines the effect of adhering to the treatment, asking "*What is the effect of actually receiving the treatment?*" (i.e., achieving dual or single targets in our set-up). Our analyses examine the effect of the intervention (intent-to-treat) and the effect of the intervention contingent on adherence (per-protocol).

Intent-to-treat Effect on Social Media and Language Learning App Usage

Table 1 shows the average daily social media and language learning app use during the three periods. Baseline social media use was approx. three hours per day. On average, this was reduced by 54.7 minutes per day during the treatment and 11.6 minutes per day during the post-treatment period (see timeline graphs of average change in social media and language learning in Web Appendix A, Figure W3 and W4).

Table 1. Average Social Media and Language Learning App Usage Per Period (Standard Deviation in Brackets)

Period	Baseline	Treatment	Post-treatment	Repeated-measures ANOVA
Social media usage (hours)	3.08 (1.33)	2.05 (1.44)	2.85 (1.47)	$p < .001$
Language learning app usage (hours)	0.064 (0.16)	0.216 (0.29)	0.041 (0.15)	$p < .001$

To compare social media usage across periods, a repeated-measures ANOVA with period as within-subjects factor (levels: baseline, treatment, post-treatment) revealed a significant effect of period, $F(2, 84) = 43.71$, $p < .001$. Pairwise comparisons with Bonferroni correction showed usage decreased during the treatment period relative to baseline, $t(42) = -$

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7.32, $p < .001$, Cohen's $d = 1.12$, but did not differ significantly between post-treatment and baseline, $t(42) = -1.30$, $p = .199$, Cohen's $d = .20$. Thus, Hypothesis 1 was not supported.

To compare language learning time across periods, a repeated-measures ANOVA with period as within-subjects factor (levels: baseline, treatment, post-treatment) revealed a significant effect of period, $F(2, 84) = 27.26$, $p < .001$. Pairwise comparisons with Bonferroni correction showed increased language learning app usage during the treatment period relative to baseline, $t(42) = 4.72$, $p < .001$, Cohen's $d = 0.72$, but did not differ significantly between post-treatment and baseline, $t(42) = -1.36$, $p = .182$, Cohen's $d = .21$.

Robustness checks using panel regressions with robust standard errors yielded consistent results for both social media and language learning app usage (Web Appendix A, Table W3 and W4). Next, we explore the effect of single vs. dual-target achievement.

Per-Protocol Effect of Intervention on Social Media Use Contingent on Adherence

All but one participant achieved at least one target on each of the 20 treatment days (Table 2), resulting in a strong negative correlation between the two types of target achievement ($r = -.998$, $p < .001$). Excluding the participant with no target achievement did not alter the results, so the full sample was retained. As shown in Figure 2, participants with higher dual-target achievement (top 25%; ≥ 8 days) consistently had lower social media use during both the treatment and post-treatment period compared to the full sample.

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Table 2. Total Number of Zero, Single, and Dual Target Achievement Days (All Participants)

	Zero target achievement	Single-target achievement	Dual-target achievement	Total days in treatment
Number of days	2	687	171	860

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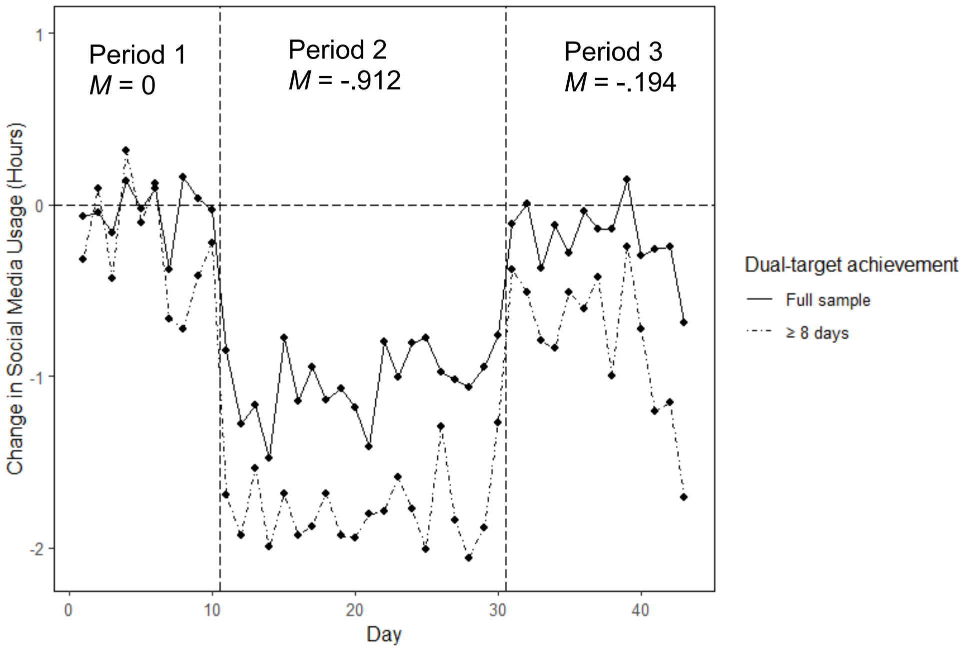

Figure 2. Social Media Usage of the Full Sample vs. Subsample with High Dual-Target Achievement

To test Hypothesis 2, we regressed the difference in social media usage between post-treatment and baseline period on (1) dual-target achievement (in days), and (2) controls (age, gender, operating system). Due to the near-perfect negative correlation between single- and dual-target achievement, only dual-target achievement was included. Using single-target achievement instead yielded nearly identical coefficients with the opposite sign. Regression estimates (Table 3) indicate that each *additional day* of dual-target achievement was associated with a reduction of 4.7 minutes (p = .002) in social media usage during the post-treatment period, supporting H2. Given the near-perfect negative correlation between single- and dual-target achievement, this effect represents the marginal benefit of both reducing social media and increasing language learning, relative to reducing social media alone. For example, an individual with ten dual-target days (vs. five) would use social media about 23.4 minutes *less* per day in the post-treatment period, assuming equal baseline use.

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Table 3. Dual-Target Achievement is Associated with Lower Post-Treatment Social Media Use

	Dependent variable: Post – Pre social media usage (hour)	p-value
Dual-target achievement (days)	-0.078 (0.022)	.002
Age	-0.002 (0.070)	.980
Gender (Female)	0.017 (0.277)	.952
Operating System (iOS)	0.381 (0.397)	.343
Constant	-0.174 (1.642)	.917
Observations	43	
R^2	0.257	
Adjusted R^2	0.179	
Residual Std. Error	0.784 (df = 38)	
F Statistic	3.286 (df = 4; 38)	

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Target Replacement Ratio

To test Hypothesis 3, we examined whether participants with higher target replacement ratio and dual-target achievement had lower post-treatment social media use compared to baseline. The language learning target was fixed at a 20-minute increase. The social media reduction target varied as a percentage of baseline use, producing different target replacement ratios (language learning target ÷ social media target). We regressed post-treatment social media use on the target replacement ratio and dual-target achievement (Table 4, Model 1) and added their interaction in Model 2. The interaction between target replacement ratio and dual-target achievement was negative and significant (β = -.005, p = .039), supporting Hypothesis 3. For interpretation, we plotted a post-estimation graph of the effect of dual-target achievement on change in social media usage at the 25th and 75th percentile of target replacement ratio (Figure 3). This graph shows that participants with a higher target replacement ratio showed larger reduction in social media use as dual-target achievement increased during the treatment period. This is reflected in the steeper negative slope at the 75th percentile of the target replacement ratio. Dual-target achievement was most effective in reducing post-treatment social media use when a greater share of this undesired behavior was replaced with language learning.

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Table 4. OLS Regression of Post-Treatment Social Media Usage: Target Replacement Ratio and Dual-Target Achievement Jointly Predict Post-treatment Social Media Reduction.

	Dependent variable = Post – Pre social media usage (hour)					
	Model 1	p-value	Model 2	p-value	Model 3	p-value
Target replacement ratio	0.020 (0.009)	.032	0.035 (0.011)	.004	0.020 (0.014)	.153
Dual-target achievement (days)	-0.072 (0.021)	.002	0.019 (0.047)	.684	0.023 (0.046)	.619
Target replacement ratio × Dual-target achievement			-0.005 (0.002)	.039	-0.005 (0.002)	.026
Baseline social media (hours)					-0.386 (0.211)	.076
Age	-0.00002 (0.067)	.999	-0.022 (0.064)	.734	-0.049 (0.064)	.450
Gender (Female)	-0.112 (0.269)	.680	-0.115 (0.257)	.658	-0.120 (0.249)	.633
Operating system (iOS)	0.373 (0.377)	.330	0.407 (0.361)	.267	0.454 (0.350)	.204
Constant	-0.573 (1.573)	.718	-0.419 (1.503)	.782	1.296 (1.732)	.460
Observations	43		43		43	
R^2	0.345		0.419		0.470	
Adjusted R^2	0.257		0.322		0.364	
Residual Std. Error	0.746 (df = 37)		0.712 (df = 36)		0.690 (df = 35)	
F Statistic	3.899 (df = 5; 37)		4.330 (df = 6; 36)		4.432 (df = 7; 35)	

Because participants with higher baseline social media use tended to have lower replacement ratios, given that the social media target (70% of baseline use) forms the denominator, we also tested whether the effect was simply driven by baseline use. When baseline social media use was added as a control (Model 3), the interaction remained significant, indicating that the target replacement ratio captures a unique replacement effect beyond baseline use (additional robustness check in Web Appendix A, Table W5).

Intent-to-treat Effect of Intervention on Perceived Social Media Addiction

To test the effect of reducing social media on perceived social media addiction, we conducted a paired-sample t-test comparing scores before (M = 2.86, SD = 0.69) and after the treatment period (M = 2.65, SD = 0.73). Results showed a significant reduction in perceived social media addiction, $t(42)$ = -2.18, p = .035, Cohen's d = 0.33.

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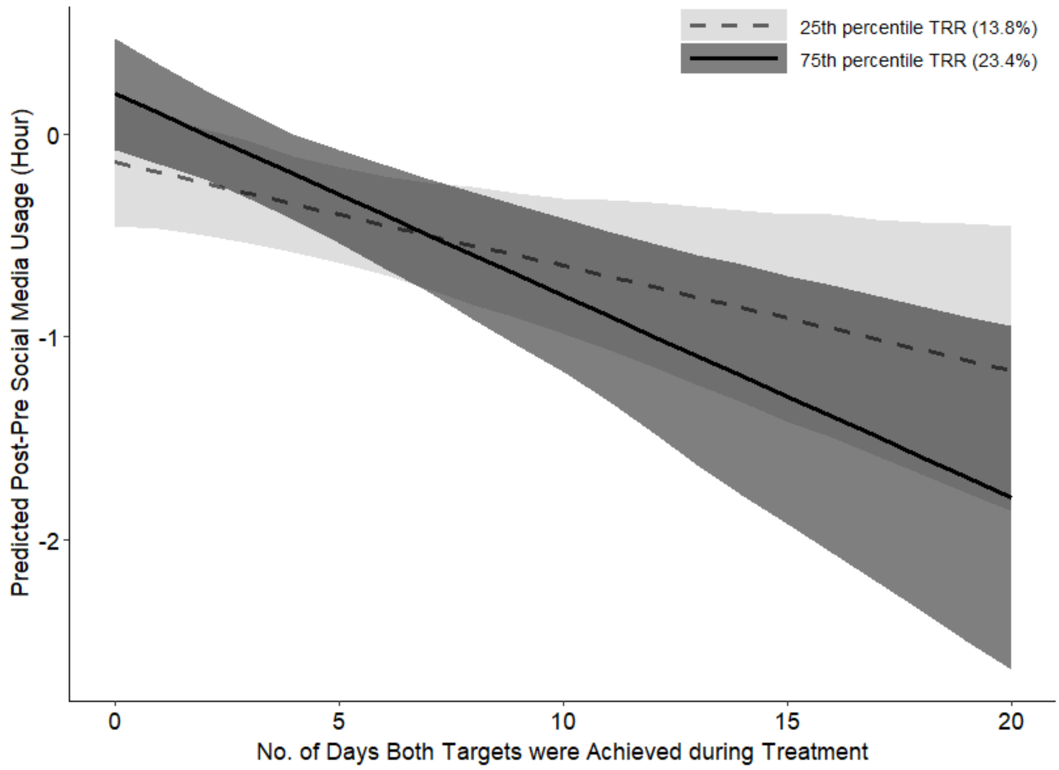

Figure 3. Post-estimation Graph of Model 2 (Table 4) at High (75th percentile) and Low Target Replacement Ratio (25th Percentile)

Per-Protocol Effect of Dual-target Achievement on Perceived Social Media Addiction

Consistent with our expectation that achieving both targets would more effectively reduce social media addiction, regression results (Table 5) showed that dual-target achievement was significantly associated with higher reductions in self-reported social media addiction (p = .037), supporting Hypothesis 4.

Intent-to-treat effect of intervention on subjective well-being

Social media usage was negatively correlated with subjective well-being at baseline (r = -.35, p = .022; Web Appendix A, Table W2). A paired-sample t-test comparing the subjective well-being index before (M = 4.37, SD = 1.09) and after the treatment period (M = 4.62, SD = 1.09) showed a significant improvement, $t(42)$ = 2.03, p = .049, Cohen's d = 0.31, supporting Hypothesis 5.

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Table 5. Dual Target Achievement Predicts Reduction in Social Media Addiction, but not Well-being

	Dependent variable			
	Addiction (Post-Pre)	p-value	Well-being (Post-Pre)	p-value
Dual-target achievement (days)	-0.038 (0.018)	.037	-0.018 (0.023)	.452
Age	-0.025 (0.055)	.653	-0.025 (0.073)	.733
Gender (Female)	-0.221 (0.217)	.315	0.373 (0.287)	.202
Operating System (iOS)	-0.425 (0.311)	.181	0.144 (0.412)	.729
Constant	1.010 (1.288)	.438	0.463 (1.707)	.788
Observations	43		43	
R^2	0.181		0.078	
Adjusted R^2	0.095		-0.019	
Residual Std. Error	0.615 (df = 38)		0.815 (df = 38)	
F Statistic	2.104 (df = 4; 38)		0.802 (df = 4; 38)	

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Per-Protocol Effect of Dual-target Achievement on Subjective Well-being

Dual-target achievement did not lead to significantly greater improvements in well-being than single-target achievement (Table 5). This suggests that reductions in social media use, irrespective of achieving the alternative activity, may improve well-being. However, this evidence is correlational.

Discussion

Our pilot study shows that participants who achieved the dual target more frequently and had a higher target replacement ratio were more likely to sustain lower social media use in the post-treatment and reported feeling less addicted to social media. Together, these findings suggest that engaging in a meaningful alternative activity may support long-term goal achievement. Additionally, reductions in social media were associated with improvements in subjective well-being. Because well-being outcomes could be influenced by participants' initial motivation to reduce social media (Lee and Hancock 2024), we tested whether baseline willingness-to-reduce predicted well-being improvements. Regression results (Web Appendix A, W1) showed no significant associations, indicating that well-being improvements were not driven by initial motivation. Due to the nearly perfect negative

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correlation between dual-target and single-target achievements, our per-protocol results should be interpreted as the difference between these two types of targets.

Self-selection is an important concern. Participants opted into the study, and baseline social media use was negatively correlated with baseline well-being, suggesting that heavier users with lower perceived well-being may have been more motivated to participate. This could partly explain the observed reductions in perceived addiction and improvements in well-being. However, baseline social media use was not significantly correlated with changes in either well-being or perceived addiction, indicating that self-selection is unlikely to fully account for the pre–post differences.

The pilot has several additional limitations. First, our screen time tracking did not capture social media use on other devices (e.g., PCs, tablets), although post-treatment qualitative data (Web Appendix A, W2) suggests that device substitution was not a major factor. Second, participants self-selected not only into the study but also into the daily incentive schemes, raising the possibility that unobserved factors (e.g., stronger motivation, greater well-being concerns) influenced outcomes. Third, because nearly every day involved some target achievement, we could not compare the effect of no target achievement vs. single- or dual-target achievement. Our experimental study addresses these limitations through random assignment, reducing self-selection bias and providing causal evidence.

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Experimental Study: Reducing Smartphone Usage in Combination with Walking

We extend our investigation with a randomized design comparing a single-target and dual-target intervention to a no-incentive control condition. This study tracks participants over a longer post-treatment period, including an early (immediately after the treatment) and late (40 days after the treatment) post-treatment. In addition, we introduce several changes motivated by theoretical and practical considerations.

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First, we broaden the focus from social media to smartphone screen time. While scholars argue that social media and general smartphone use should be distinguished (Lowe-Calverley and Pontes 2020), research shows they are closely intertwined. Smartphone use serves as the gateway through which social media and other app-related habits form (Schnauber-Stockmann and Naab 2019). Moreover, non-social media apps, such as games, can similarly impair productivity and well-being (Chiang et al. 2019). Targeting total screen time therefore prevents substitution of social media with other non-constructive smartphone activities and provides a more stringent test of intervention effectiveness, given that overall smartphone use may be harder to change (Schnauber-Stockmann and Naab 2019).

Second, we chose walking as the alternative activity because it is a simple, health-promoting activity (Lee and Buchner 2008) that can be tracked objectively via mobile apps. Walking may be particularly effective in reducing smartphone use by creating physical distance from sensory cues (e.g., notifications) that trigger phone pickup (Laibson 2001; Schnauber-Stockmann and Naab 2019). Physical activity may also help reduce smartphone dependency by regulating neurobiological processes involved in addiction (Li et al. 2020).

Third, we equalized incentives (€2 per day) across the dual- and single-target conditions as a more conservative test of the dual-target intervention's effectiveness. Building on the pilot and the theoretical rationale above, we hypothesize:

H6: Participants in the dual-target condition reduce their post-treatment screen time more compared to those in the single-target condition.

H7: Each additional day of dual-target achievement will lead to greater reductions in post-treatment screen time than each additional day of single-target achievement.

Methods

Study design and procedures

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The procedure was similar to the pilot, except for random assignment, the seven-week duration, the early and late post-treatment periods, as well as the daily step count measure (see Web Appendix B, Figure W7 for example screenshots).[5] Figure 4 shows the design.

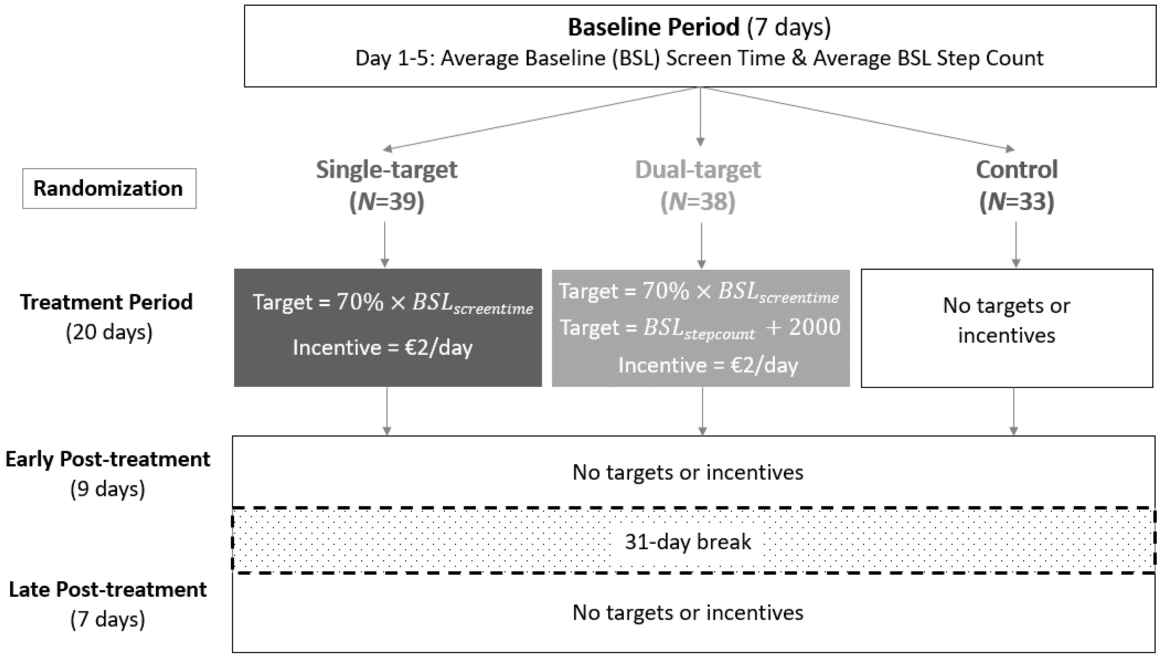

Figure 4. Design of the Experimental Study

The study (4,098 observations, N = 110; 58.2% females, 41.8% males; M_{age} = 24.4, SD = 3.53) was approved by the Institutional Review Board at a large European university. We followed the same recruitment strategy, advertising the study about smartphone usage, without revealing its focus on reductions, to avoid attracting students who were highly motivated to reduce screen time. Interested students were informed that they would receive a €15 Amazon voucher and were eligible for a lottery worth €150. In addition, they could earn an extra payment of up to €40. Rewards were distributed after data collection.

At the start of the baseline, we asked student participants to install or activate the screen time tracking app and the step count app and verify setup by uploading screenshots. At the

[5] For iPhone users, Apple's inbuilt [iOS Health app]() was used. For Android users, [Google Fit](), which could be downloaded free of costs, was used.

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end of each week during the seven-week study, participants reported their daily mobile screen time and step count for the preceding seven days in an online survey. To validate responses, participants submitted screenshots of their screen time and step count tracking apps.

During the 7-day baseline period, participants had no targets and used their phone as usual. Afterwards, we calculated each participant's screen time and step count, and randomly assigned them to one of three conditions: 1) control, 2) single-target treatment, 3) dual-target treatment. Participants in the control condition ($N = 33$) had no targets or incentives. Those in the single-target treatment ($N = 39$) earned €2 each day during the treatment period if their screen time was at least 30% below their baseline use. Participants in the dual-target condition ($N = 38$) earned €2 each day that their screen time was at least 30% below their daily baseline use *AND* their step count exceeded their baseline by 2,000 steps. We chose an increment of 2,000 steps as it is feasible (Tudor-Locke et al. 2011) with benefits for weight loss and blood pressure (Bravata et al. 2007).[6]

At the start of the treatment, participants were informed via email about their baseline average screen time and step count, along with information about benefits of reducing screen time and increasing step count (OSF Materials, S3). We confirmed understanding of the instructions with comprehension checks including baseline values, target levels, and daily incentives for single- and dual-target achievement.

In the treatment conditions, we used the average screen time and step count over the first five days (out of seven) of the baseline period to determine participants' targets. We informed participants in both treatment conditions about their screen time targets. In the dual-target condition, they were additionally informed about their step count target. In the post-treatment period (Period 2), we removed the targets and incentives, but participants continued

[6] We did not choose a relative target for step count (e.g., 30% of baseline) because of large variations in daily step count (range: 363 - 21,428 steps). A relative target would have been challenging for participants with high baseline step count, and vice versa.

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reporting screen time and step count for nine days. Thirty-one days later (40 days after the end of the treatment), participants completed a final screen time report constituting the late post-treatment (seven days). We chose this duration due to the limited time window to finish collecting data (i.e., end of the academic semester).

Surveys

Participants completed a baseline and post-treatment survey at the start of the corresponding period. In the baseline survey, beside demographic and mobile usage characteristics, we measured willingness to reduce smartphone use, which was considerably high ($M = 5.05$, $SD = 1.44$, 7-point Likert scale; one-sample t-test vs. mid-point: $t(109) = 7.64$, $p < .001$). 75% had previously attempted to reduce their smartphone use and rated it to be difficult ($M = 4.59$, $SD = 1.41$, 7-point Likert scale; one-sample t-test vs. mid-point: $t(81) = 3.75$, $p < .001$).

We measured self-reported productivity, and used anxiety experienced when separated from one's smartphone ("nomophobia") as a proxy for smartphone addiction, acknowledging ongoing debates about the construct's validity (Lowe-Calverley and Pontes 2020; Panova and Carbonell 2018). Based on Cappelen et al. (2017), we included health-related measures such as physical activity levels, height and weight, sleeping pattern, number of tired days, satisfaction with life and health (OSF Materials, S4). Baseline descriptive statistics are available in Web Appendix B, Table W8 and W9.

Analyses and Results

The following sections present results from intent-to-treat and per-protocol analyses, addressing H6 and H7, respectively.

Intent-to-treat Effect of Treatment Assignment on Screen Time

Average screen time during the baseline, intervention, and post-treatment period is reported in Table 6. There was no difference in baseline screen time across conditions. To

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assess the effect of treatment assignment on screen time, we conducted a mixed model ANOVA, with *Condition* as between-subjects factor and *Period* as within-subjects factor.

Table 6. Average Screen Time across Conditions and Periods (Standard Deviation in Brackets).

	Control	Single-target	Dual-target
Baseline	5.15 (1.80)	4.92 (1.72)	4.78 (2.00)
Period 1 (Treatment)	5.23 (1.93)	3.59 (1.56)	3.93 (1.78)
Period 2 + 3 (Early + Late Post-Treatment)	5.36 (1.68)	4.52 (2.07)	4.50 (1.60)

The 3 (Condition: control, single-target, dual-target) x 3 (Period: baseline, treatment, post-treatment) mixed ANOVA revealed a marginal main effect of Condition ($F(2,99) = 2.75$, $p = .069$) and a significant main effect of Period ($F(2, 198) = 19.61$, $p < .001$). Pairwise t-tests with Bonferroni correction indicated that screen time was significantly lower during the treatment period ($M = 4.20$ hours) than during baseline ($M = 4.94$ hours; $t(108) = 5.80$, $p < .001$, Cohen's $d = 0.56$), but did not differ significantly between baseline ($M = 4.94$ hours) and post-treatment ($M = 4.76$ hours, $t(101) = 1.55$, $p = .125$, Cohen's $d = 0.15$). Refer to Web Appendix B, Figure W8.1–8.2 for timeline graphs.

Importantly, the Condition × Period interaction was significant, $F(4,198) = 5.60$, $p < .001$. To test H6, we conducted pairwise t-tests with Bonferroni correction comparing the three conditions within each period (see Web Appendix B, Table W10 for full results). Participants in both treatment conditions reduced their screen time more than those in the control condition during the treatment period, but these reductions were not sustained post-treatment. Post-treatment screen time did not differ significantly between the single-target and control condition ($t(65) = -1.83$, $p = .072$, Cohen's $d = 0.44$), or between the dual-target and control condition ($t(61) = -2.10$, $p = .040$, Cohen's $d = 0.52$), using a Bonferroni-corrected alpha of .0055. Thus, H6 was not fully supported. A difference-in-differences regression yielded similar results (Web Appendix B, Table W11).

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We also used pairwise t-tests with Bonferroni correction to explore the change in screen time between baseline and post-treatment period in each treatment condition. Neither the single-target ($t(36) = -1.73$, $p = .091$, Cohen's $d = 0.29$) nor the dual-target condition ($t(34) = -1.68$, $p = .102$, Cohen's $d = 0.28$) showed a significant difference in screen time when comparing baseline and post-treatment periods.

Per-Protocol Effect of Treatment Adherence on Screen Time

To form a habit, a behavior should be performed repeatedly and consistently over time (Harris and Kessler 2019). Thus, consistent *adherence* to the target(s) is likely to be necessary for post-treatment reductions in screen time. We operationalize adherence as the number of days targets were achieved during the treatment period. Adherence was lower in the dual- (152 days) than single-target condition (408 days; Web Appendix B, Figure W9).

To test Hypothesis 7, we use target achievement to predict post-treatment effects. Because target achievement is endogenous, OLS estimates may be biased (Angrist and Imbens 1995). Thus, we employ an instrumental variable approach using 2-SLS regression. Prior RCTs have used this analysis to address treatment compliance (Penrod, Goldstein, and Deb 2009; Somasundaram, Zimmermann, and Pham 2025; Angrist et al. 2025).

We chose *Condition* as the instrumental variable, as it meets two criteria: it predicts target achievement during treatment (relevance), and it is not correlated with the error term ϵ_i due to random assignment and the absence of post-treatment tasks (exclusion restriction). This method allows us to infer a causal relationship between target achievement during treatment and post-treatment screen time reductions, by addressing potential unobservable confounding factors (Wooldridge 2013). In addition, it rules out reverse causality where participants expecting lower post-treatment use were more motivated to achieve target(s) during the treatment. This per-protocol analysis could not be conducted in the pilot because

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random assignment, required for the instrumental variable, was not implemented. We ran the following two regressions:

(1)

Second stage: $$PostTx\ usage\ change_{it} = \alpha + \beta_{single}(No.\ days\ achieved(single) in\ P1\hat{}_i) + \sum_{j=2} \beta_j\ (controls) + \epsilon_i$$

First stage: $$No.\ days\ achieved(single)\ in\ P1_i = \alpha_1 + \beta'(Condition_i) + \sum_{j=2} \beta_j\ (controls) + \epsilon'_i$$

(2)

Second stage: $$PostTx\ usage\ change_{it} = \alpha + \beta_{dual}(No.\ days\ achieved(dual) in\ P1\hat{}_i) + \sum_{j=2} \beta_j\ (controls) + \epsilon_i$$

First stage: $$No.\ days\ achieved(dual)\ in\ P1_i = \alpha_1 + \beta'(Condition_i) + \sum_{j=2} \beta_j\ (controls) + \epsilon'_i$$

where $PostTx\ usage\ change_{it} = PostTx\ usage_{it} - baseline_i$. Controls include gender, age, and operating system. Results of the second stage of each regression are in Table 7.

We find that greater adherence in both conditions leads to lower post-treatment screen time relative to baseline. However, the coefficient for dual-target adherence is larger than for single-target adherence (β_{dual} = -.21 vs. β_{single} = -.12). To test whether this difference is statistically significant, we conducted a Wald Chi-square test comparing the unconstrained model with a constrained model assuming $\beta_{dual} = \beta_{single}$. The test was significant (*Wald* χ^2 (1, 2642) = 4.78, p = .029), indicating that adherence in the dual-target condition had a significantly stronger effect on reducing post-treatment screen time, supporting Hypothesis 7.

Figure 5 illustrates this effect with a steeper slope for dual-target achievement, reflecting a larger marginal reduction in post-treatment smartphone use compared to baseline. As a robustness check, we used *step count* during the treatment period as a more granular measure of dual-target adherence and employed it as the endogenous predictor of post-

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treatment screen time in a set of instrumental variable regressions. The results (OSF Materials, S5) show that higher step counts significantly predicted reductions in post-treatment screen time for participants in the dual-target, but not for those in the single-target condition, relative to the control condition.

Table 7. Instrumental Variable Regressions (2nd stage) Predicting Post-Treatment Screen Time Reductions with Single- and Dual-Target Achievement.

	Dependent variable = Post-treatment usage - Baseline (hour)			
	Model 1	p-value	Model 2	p-value
Single Target: predicted number of days achieved in P1 (β_{single})	-0.12 (0.02)	< .001		
Dual target: predicted number of days achieved in P1 (β_{dual})			-0.21 (0.04)	< .001
Gender (1 = Male, 0 = Female)	-0.06 (0.13)	.631	0.05 (0.12)	.655
Age	-0.03 (0.02)	.039	-0.04 (0.02)	.016
Operating system (1 = Android; 0 = iOS)	0.24 (0.14)	.080	0.09 (0.13)	.472
Observations	1326		1326	
R^2	0.08		0.02	
Adjusted R^2	0.08		0.02	

Notes: Baseline corresponds to average mobile use during the baseline period. Standard errors (in parentheses) are robust and clustered at the participant level. In the 1st stage (Web Appendix B, Table W12) Condition significantly predicts target achievement; dual-target condition had more dual-target achievement days than single-target or control condition.

Intent-to-treat Effect of Treatment Assignment on *Perceived Smartphone Addiction*

To assess the effect of treatment assignment on perceived smartphone addiction (nomophobia item), we conducted a 3 (Condition: control, single-target, dual-target) x 2 (Period: baseline, post-treatment) mixed ANOVA with *Condition* as between-subjects factor and *Period* as within-subjects factor. The analysis revealed a significant main effect of Period ($F(1,97) = 14.27$, $p < .001$) but no significant main effect of Condition ($F(2,97) = 1.88$, $p = .159$), or Condition × Period interaction ($F(2,97) = 0.69$, $p = .503$). A paired t-test confirmed that participants reported lower smartphone addiction (or nomophobia) post-treatment ($M = 4.46$) than at baseline ($M = 4.94$; $t(99) = -3.87$, $p < .001$, Cohen's $d = 0.29$).

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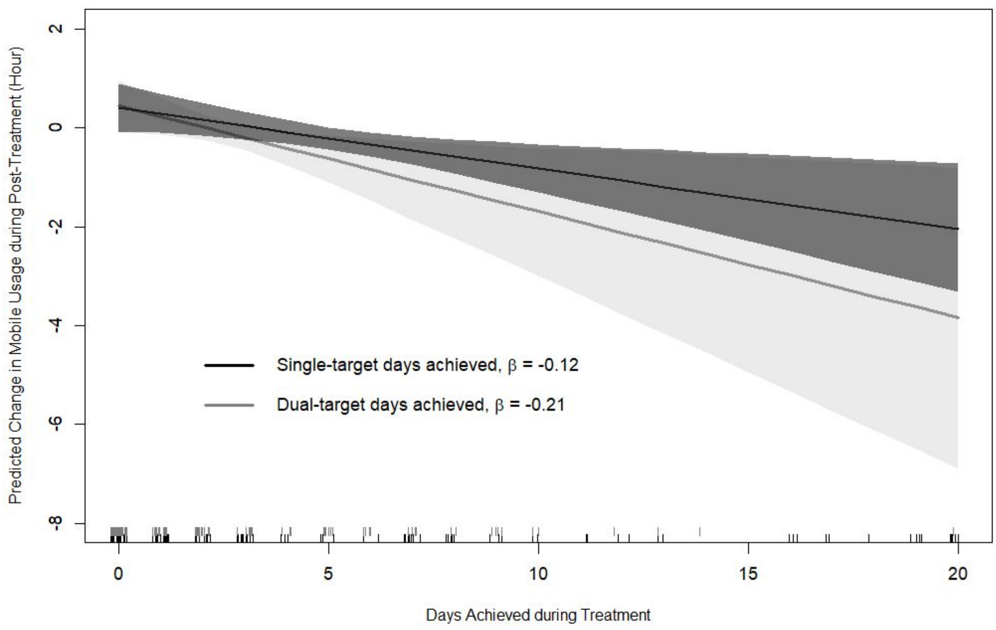

Figure 5. Post-Estimation of 2SLS Instrumental Regression. Each additional day of dual-target adherence results in a significantly greater marginal reduction in post-treatment screen time compared to single-target adherence (p = .029).

Per-protocol Effect of Treatment Adherence on Perceived Smartphone Addiction

We conducted 2SLS instrumental variable regression, analogous to the screen time analysis, to examine the effect of treatment adherence on perceived smartphone addiction. Adherence to either the single- or dual-target treatment did not predict lower post-treatment smartphone addiction relative to baseline. This suggests that while the study reduced perceived addiction overall, it was not affected by the condition or by differential adherence. The second stage results are in Appendix B.

Intent-to-treat Effect of Treatment Assignment on Subjective Well-being

Finally, we examine treatment effects on four well-being measures: weekly tired days, weekly late-sleeping days, health satisfaction, and life satisfaction. Descriptive statistics are in Web Appendix B, Table W9. Four mixed model ANOVAs were conducted, with *Condition* (control, single-target, dual-target) as between-subjects factor and *Period* (baseline, post-treatment) as within-subjects factor. No significant effects were found for weekly late-sleeping days or life satisfaction. For weekly tired days, the analysis revealed a

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significant main effect of Period ($F(1, 97) = 9.92$, $p = .002$), but no main effect of Condition ($F(2, 97) = 0.13$, $p = .876$), or Condition × Period interaction ($F(2, 97) = 0.86$, $p = .427$). A paired t-test showed that participants reported fewer tired days during post-treatment ($M = 3.62$) than at baseline ($M = 4.33$; $t(99) = -3.24$, $p = .002$, Cohen's $d = 0.38$). For health satisfaction, the analysis revealed a significant main effect of Period ($F(1,97) = 4.51$, $p = .036$), but no main effect of Condition ($F(2, 97) = 0.48$, $p = .618$), or Condition × Period interaction ($F(2, 97) = 0.21$, $p = .808$). A paired t-test showed that participants reported higher health satisfaction during post-treatment period ($M = 4.24$) than at baseline ($M = 3.95$; $t(99) = 2.17$, $p = .032$, Cohen's $d = 0.23$).

Per-Protocol Effect of Treatment Adherence on Subjective Well-being

We conducted 2SLS instrumental variable regressions, analogous to those we used for screen time and smartphone addiction, to examine the effect of treatment adherence on the four well-being outcomes. Second stage results are in Appendix B. Greater adherence to either the single- or dual-target treatment did not improve post-treatment well-being outcomes, relative to baseline. As in the pilot, we ruled out the possibility that participants' willingness to reduce screen time influenced perceived well-being in the post-treatment with a set of regressions. The results are reported in OSF Materials S6.

Discussion

This study randomly assigned participants to the treatment conditions with incentives tied to the conditions. While the intent-to-treat analysis showed no significant post-treatment advantage of the dual-target vs. single-target intervention, the per-protocol analysis revealed the following: participants with higher dual-target adherence exhibited more sustained reductions in post-treatment screen time relative to baseline than those with higher single-target adherence. This suggests that, although engaging in an effortful alternative activity such as walking may be more demanding, it could enhance the long-term impact of behavior

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change once incentives are removed. Smartphone addiction (nomophobia) and some well-being outcomes (tired days, health satisfaction) improved from baseline to the post-treatment period. However, no significant differences were observed across conditions (Web Appendix B, Figure W10).

General Discussion

Although many consumers want to reduce their smartphone usage, ingrained habits make this goal difficult to attain and sustain (Anderson and Wood 2021). Following periods of reduced usage, consumers often revert to previous consumption patterns, a phenomenon known as the triangular relapse pattern (Wood and Neal 2016). This research aimed to address this challenge by examining whether substituting smartphone or social media use with an alternative, beneficial activity could promote more lasting usage reductions.

Using a longitudinal, quasi-experimental design, our pilot study did not find sustained reductions in social media use across the overall sample following the intervention. However, participants with higher dual-target achievement maintained significantly lower post-treatment social media use relative to baseline. This finding aligns with prior studies that suggested alternative activities to complement social media reductions (Brailovskaia et al. 2022; Esmaeili and Ahmadi 2018; Reed, Fowkes, and Khela 2023). Taken together, the findings suggest that any longer-term reductions were contingent on participants successfully adhering to both the intervention goals.

Extending previous work, our research provides greater empirical control by objectively tracking behaviors and providing daily incentives to encourage consistent engagement in both targeted behaviors, moving beyond reliance on self-report and self-initiative. The dual-target approach was more effective when the alternative activity occupied a larger proportion of the time spent on social media (i.e., higher target replacement ratio). Target replacement ratio and dual-target achievement jointly predicted lower social media

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usage in the pilot study. The more consumers filled the time saved by reducing social media with an alternative activity (i.e., learning a new language), the more successfully they maintained lower post-treatment social media use.

In our experimental study, we extend the dual-target approach to reducing overall smartphone use and increasing physical activity (via step count). With the randomized design, we found no difference in post-treatment screen time when comparing the dual- vs. single-target intervention. However, consistent with the pilot study, consumer heterogeneity again played an important role. Among individuals with higher target adherence during the treatment, the dual-target intervention was more effective. Accounting for the endogeneity of target achievement through instrumental variable regression, we found that each additional day of dual-target achievement led to greater post-treatment reductions in smartphone usage compared to each additional day of single-target achievement.

Consistent with our reasoning that consumers may self-signal reduced social media dependence when engaging in alternative activities, individuals with high dual-target achievement, but not those with high single-target achievement, reported lower perceived social media addiction in our pilot. We emphasize that these results are correlational and reflect participants' *self-rated* perceptions of "addiction", not a clinical diagnosis. Excessive social media use is not considered a behavioral addiction in the Diagnostic and Statistical Manual of Mental Disorders (5th edition), and researchers caution against pathologizing technology use by adopting addiction terminology when it might be better understood as a habit (Aagaard 2021). Researchers should distinguish between habitual smartphone use and its detrimental consequences rather than conflating the two (Meier, 2022). Our findings speak to this debate. Two exploratory mediation analyses showed that perceived addiction in both of our studies did not mediate the relationship between social media / smartphone use and perceived well-being (results available upon request). While "addiction" may not be an

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appropriate label for excessive smartphone use, interventions grounded in addiction frameworks can still help consumers reduce technology habits they perceive as problematic.

Most participants did not continue the alternative activities in the post-treatment period. This might be due to two reasons. First, dual-target adherence was lower than single-target adherence in both studies. Without regular repetition, participants are unlikely to form stable habits that persist beyond the intervention. Second, although the alternative activities were beneficial, they may not have aligned with intrinsic preferences or interests, limiting motivation to continue.[7] Nevertheless, assigning a uniform alternative activity enabled objective and comparable measurements across conditions.

Lee and Hancock (2024) show that a person's mindset can influence how they perceive the effect of social media on well-being. People who believe in the benefits of social media (or have a positive valence mindset) feel well-being is improved by social media. People with an agentic mindset believe in their ability to manage social media use adequately so it does not become problematic and harm well-being. Accordingly, well-being outcomes in our studies might have been affected by participants' mindset. We examined this using baseline willingness-to-reduce as a proxy for mindset. However, controlling for it in the analysis did not affect post-treatment well-being. Still, because willingness-to-reduce reflects behavioral intentions more than the nuanced mindset construct by Lee and Hancock (2024), our findings do not allow for definite conclusions on the role of mindset.

Our findings on well-being are mixed and inconclusive. In the pilot study, participants who reduced social media use reported improvements in well-being following the intervention. However, this result is correlational and may be driven by confounding factors

[7] In our pilot, we asked participants at the end of the intervention whether they continued using the language learning app after the treatment period. Only 35% affirmed this (Web Appendix A, Table W13.1). Participants provided various reasons why they thought the language learning app might (or not) have helped to reduce social media (Web Appendix A, Table W13.2).

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such as temporal changes (e.g., end of the semester) or demand effects. In contrast, our randomized experimental study, which incentivized reductions in overall smartphone screen time rather than social media use specifically, found no effects on well-being. While this difference may reflect the distinct roles of social media vs. general smartphone use in shaping wellbeing (Panova and Carbonell 2018; Lowe-Calverley and Pontes 2020), the two studies are not directly comparable and our data does not allow us to draw conclusions about this. Given the limited and mixed evidence from our studies, any conclusions regarding the effects of smartphone or social media reduction on well-being should be interpreted with caution.

Differences across our studies may also reflect sample composition. In our pilot, participants who reduced social media reported improvements in well-being. While self-selection could partly explain these results (i.e., heavier users reported lower baseline well-being), baseline social media use was not correlated with changes in outcomes, making this explanation unlikely. By contrast, our experimental study, which targeted overall smartphone screen time, eliminates concerns about selection bias and found no evidence for well-being improvements. Overall, we find little to no evidence that the intervention improved well-being. While participants in the treatment condition did change behavior, these did not seem to translate into measurable psychological benefits.

Practical Implications for Policy, Businesses and Consumers

Following Andrews et al. (2022), we identified three policy-relevant stakeholders that might benefit from our findings: educational institutions, grassroot movements, and social media firms. First, our findings have practical implications for education policy, particularly in managing smartphone and social media use among students. Smartphone bans in schools are gaining traction, especially in European countries, but also globally (Chadwick 2024). UNESCO's Global Education Monitoring Report (2025) states that 79 countries have implemented some form of smartphone ban in schools. However, bans are often not feasible

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or perceived as limiting personal freedom. Recent research also suggests bans might not improve students' mental health (Goodyear et al. 2025). Instead of bans, education stakeholders could promote structured behavior change programs. For instance, institutions could introduce challenges modeled on our dual-target approach, setting screen time reduction goals alongside curricular or extra-curricular activities (e.g., step counts, reading time, or creative projects). Such programs can be low-cost as incentives can take non-monetary forms. Our findings suggest that combining screen time reduction goals with alternative activities may be a promising approach for participants who successfully adhere to both goals. Participants with higher dual-target adherence showed more sustained reductions in screen time relative to baseline. However, intervention assignment itself did not produce sustained reductions after the intervention period ended. Thus, educational institutions could consider the dual-target approach as one potential strategy for encouraging healthier technology habits, while recognizing that adherence is likely to be critical. Even with monetary incentives, our data suggests dual-target interventions are cost-effective. In both studies, single-target achievement was significantly higher than dual-target achievement, resulting in greater cumulative single-target payments. Yet, participants with higher dual-target adherence showed more sustained reductions in screen time. Thus, educational institutions could justify the dual-target approach not only on behavioral impact but also on long-term cost-efficiency and habit sustainability. A caveat from the results of our interventions is that education institutions ought to emphasize on the adherence of both goals; otherwise successful outcomes may not be guaranteed.

Second, dual-target interventions can serve as a practical tool for grassroot movements and special interest groups. The OECD (2025) describes such behavioral strategies as part of a broader policy toolbox that can be adapted by both formal institutions and informal community actors. For instance, in response to growing concerns over youth social media

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use, parent-led groups in the UK and elsewhere have recently advocated for blanket bans of social media for children under 16 (Banfield-Nwachi 2024). While grassroots initiatives often act more quickly than formal policy processes, they may lack evidence-based strategies. Home-based programs could be created with a dual-target structure, encouraging reduced screen time in combination with engaging, alternative activities. In doing so, grassroots actors can promote healthier digital habits without waiting for legislative change.

Third, social media platforms (e.g., Meta, TikTok) are under increasing scrutiny from regulators worldwide, with several governments proposing stronger regulations (e.g., Ofcom 2024; SMART Act 2019; United States Senate Committee on the Judiciary 2024). As a concrete example, the Australian government has become the first to make social media platforms deactivate accounts of children under 16 (Kaye and Pal 2026). To address these concerns, tech firms could apply the dual-target approach as a design principle for ecosystems of products and services, encouraging users to balance social media engagement with beneficial activities. Such approaches may be promising when users actively engage with and adhere to both goals. Proactively exploring such approaches may help firms demonstrate responsible self-regulation and reduce regulatory pressure.

Finally, for consumers, focusing on alternative activities may be useful for breaking undesired technology habits. However, again, adherence is key. Consumers should set realistic targets with achievable schedules to stay motivated and accountable. Results from an additional study (OSF Materials, S7) capturing consumers' preferences for dual-target interventions indicate that consumers prefer having multiple (rather than one) alternative activities to engage in when experiencing the urge to use their smartphone or social media.

Moreover, providing beneficial alternative activities might also help prevent compensatory addictions. Often, consumers replace one dependency with another. Melumad and Pham (2020) show that recent smoking-quitters grew more attached to their smartphones

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for stress relief, while Dey et al. (2019) found that problematic smartphone use in young men was negatively associated with frequent cannabis and cigarette use. Dual-target interventions may interrupt such compensatory cycles by offering healthy alternatives that introduce a time barrier-to-entry for compensatory addictions. This highlights a market gap for social marketers to promote beneficial alternatives to segments striving to reduce smartphone use (Lee and Kotler 2015). The behavioral 'void' can be filled by productive apps (e.g., language learning) and personal enrichment programs (e.g., step count challenges). In our additional study, consumers reported to be willing to pay approximately €11 for an app that supports social media reduction through alternative activities, suggesting that the dual-target approach can be valuable for managing digital overconsumption.

Limitations and Future Research

Further research is needed to better understand the mechanisms underlying the dual-target approach. Our studies explored two potential explanations: self-signalling of lower addiction and time replacement. Participants with higher dual-target achievement reported lower social media addiction post-treatment. However, a mediation analysis using perceived addiction as a mediator, was not significant (Web Appendix A, W3). In our additional survey, consumers rated different reasons why alternative activities might help reduce social media use. Two explanations were rated significantly higher: 1) alternative activities occupy time previously spent on social media, and 2) alternative activities make consumers aware of other things they could use their free time (OSF Materials, S7.1). These findings are more in line with a replacement process (similar to the displacement hypothesis in Neuman 1988, and Kushlev and Leitao 2020). Nonetheless, future research should examine mechanisms, which are likely to vary depending on the targeted habit and the nature of the alternative activity.

Target adherence is key to habit formation. Thus, the effectiveness of the dual-target approach depends on consistent adherence. Future research should explore strategies to

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maximize adherence. For instance, gamification (e.g., streaks) or commitment devices requiring consumers to stake money may be useful (Ashraf, Karlan, and Yin 2006; Eisingerich et al. 2019). Future work could also investigate self-set vs. externally imposed incentives (e.g., parents encouraging kids with pocket money). Additionally, longer treatment periods might give consumers time to adapt, increasing adherence (Harris and Kessler 2019).

Our intervention follows past research using monetary rewards to incentivize behaviors (e.g., Charness and Gneezy 2009; Allcott, Gentzkow, and Song 2022), as well as real-world interventions by various governments (e.g., Brazil's schooling and health incentives – Cavalcanti et al. 2025; India's maternal health cash incentive – Carvalho and Rokicki 2019). However, we acknowledge that this incentivization method might be unrealistic in settings where resources are constrained and non-monetary incentives could be used instead.

Another direction for future research is to identify characteristics that make alternative activities effective substitutes. The choice of activity should consider not only its difficulty, but also, how well it distracts consumer from the cues that activate the undesired habit (Adriaanse et al. 2011; Laibson 2001). For example, walking physically distances consumers from their smartphone, shielding them from cues such as push notifications. In our additional survey, consumers rated offline activities to be more effective than other (non-social media) online activities. Future research should test whether cue distance enhances the effectiveness of alternative activities. Moreover, alternative activities may be more effective if they match the consumption pattern of the undesired habit. Smartphone use occupies many small "pockets" of time during the day, with 50% of sessions starting within three minutes of the previous one (MacKay 2019). Alternative activities that can be broken into short, spontaneous bouts may be particularly well-suited.

Finally, in line with social marketing (Lee and Kotler 2015), identifying who benefits most from dual-target treatments is an important direction for future research. Teenagers and

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adolescents represent the biggest and most vulnerable group to engage with mobile technology. In this group, problematic smartphone and social media use has been linked to lower well-being and productivity (Hisler, Twenge, and Krizan 2020; Levenson et al. 2017; McNamee, Mendolia, and Yerokhin 2021). Given concerns and calls for preventive action, future studies should examine dual-target approaches in these vulnerable populations.

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Appendix A

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Review of Past Interventions to Reduce Social Media or Smartphone Usage

Article	Intervention	Incentive structure	Alternative activity	Treatment length	Long-term follow up	Measures of screentime	Measures of alt. activity
Esmaeili & Ahmadi (2018)	Participants set their own limit of social media usage. An app suggests alternative activities to replace social media use.	N/A	Yes; activity type suggestions only	14 days	No	Objective	Subjective
Brailovskaia et al. (2022)	Participants were asked to reduce social media usage by 30 minutes per day and to increase physical activity (PA) by 30 minutes per day.	N/A	Yes; suggested increase in daily physical activity by 30 minutes	14 days	6 months	Subjective	Subjective
Reed et al. (2023)	Participants were asked to decrease social media by 15 minutes per day, and participate in another leisure activity (suggestions provided, such as reading, exercise, non-computing related)	N/A	Yes; activity type suggestions only	84 days	No	Objective	Subjective
Allcott et al. (2020)	Participants were asked to deactivate Facebook (FB)	Deactivate FB and receive $102	N/A	28 days	28 days	Objective	N/A
Allcott et al. (2022)	Participants: - set their own limit of social media usage (no incentive) Vs. - decrease by an amount and get incentivized for it (see Incentive structure).	After a period of 21 days of incentivization announcement, incentive of $2.5 per hour of social media time reduction for 21 days, for a maximum of $150.	N/A	42 days	42 days	Objective	N/A
Collis & Eggers (2022)	Participants were asked to limit social media to max 10 minutes per day.	€ 1,000 (1-in-100 chance) lottery for those students staying under 10-minute limit	N/A	70 days	77 days	Objective	N/A
Stanley et al. (2022)	Participants were asked to reduce smartphone usage by 30%/40%/50% (for 1, 1, 5 days) of which reduction of social media is 26%/33% (for 1, then 6 days)	$10 for each day reduction is achieved	N/A	7 days	21 days	Objective	N/A
This paper	- Pilot: participants chose between (a) daily decrease of 30% of social media (single-target) OR (b) single target PLUS 20 minutes of language learning on mobile app (dual-target) - Experimental Study: daily decrease of 30% of smartphone screen time (single-target) vs. single-target plus daily 2,000 steps (dual-target)	- Pilot: €1/day of single-target achievement OR €2/day of dual-target achievement - Experimental Study: €2/day of target achievement in both intervention arms	- Pilot: Yes; use Duolingo, time-tracked - Experimental Study: Yes; Walking, step-count-tracked	- Pilot: 20 days - Experimental Study: 20 days	- Pilot: 13 days - Experimental Study: 47 days	Objective	Objective

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Appendix B

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Instrumental Variable Regressions (2nd stage) Predicting Post-Treatment DVs with Single- and Dual-Target Achievement

	Dependent variable (Post-treatment – Baseline)									
	Smartphone Addiction		Tired Days		Sleeping Late Days		Health Satisfaction		Life Satisfaction	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Single Target: predicted number of days achieved in P1 (β_{single})	-0.05 (0.07) p = .423		-0.11 (0.09) p = .214		-0.05 (0.09) p = .584		0.04 (0.05) p = .484		0.06 (0.06) p = .331	
Dual target: predicted number of days achieved in P1 (β_{dual})		-0.07 (0.12) p = .544		-0.10 (0.16) p = .538		-0.03 (0.15) p = .855		0.07 (0.10) p = .479		0.13 (0.11) p = .234
Gender (1 = Male, 0 = Female)	0.58 (0.27) p = .033	0.63 (0.28) p = .024	0.48 (0.47) p = .304	0.60 (0.49) p = .221	-0.001 (0.47) p = .999	0.06 (0.44) p = .901	0.18 (0.25) p = .473	0.15 (0.24) p = .528	0.21 (0.29) p = .469	0.16 (0.29) p = .572
Age	-0.01 (0.04) p = .793	-0.01 (0.04) p = .832	-0.11 (0.06) p = .046	-0.11 (0.06) p = .063	-0.06 (0.06) p = .365	-0.05 (0.06) p = .383	0.04 (0.03) p = .184	0.04 (0.03) p = .205	0.06 (0.04) p = .086	0.06 (0.04) p = .106
Operating system (1 = Android; 0 = iOS)	-0.10 (0.42) p = .814	-0.12 (0.44) p = .781	-0.80 (0.62) p = .197	-0.91 (0.72) p = .206	0.08 (0.51) p = .881	0.006 (0.52) p = .992	-0.01 (0.35) p = .977	-0.02 (0.36) p = .954	-0.006 (0.32) p = .987	-0.05 (0.39) p = .905
Observations	100	100	100	100	100	100	100	100	100	100
R^2	0.05	-0.04	0.13	0.03	-0.002	0.01	0.03	0.01	0.09	-0.006
Adjusted R^2	0.01	-0.09	0.09	-0.01	-0.04	-0.03	-0.01	-0.03	0.05	-0.05

Note 1: Baseline corresponds to average mobile usage during the baseline period. Standard errors (in parentheses) are robust and clustered at the participant level.

Note 2: In the 1st stage (Web Appendix B, Table W12) Condition significantly predicts target achievement; dual-target condition had more dual-target achievement days than single-target or Control condition.

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Web Appendices

Make it Stick: The Role of Alternative Activities in Reducing Smartphone Usage

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Contents

Web Appendix A. Pilot Study 2

Web Appendix B. Experimental Study 17

These materials have been supplied by the authors to aid in the understanding of their paper. The AMA is sharing these materials at the request of the authors.

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Web Appendix A. Pilot Study

Figure W1. *Examples of Baseline Screenshots Submitted (Left: Social Media; Right: Duolingo). Total Usage Durations are Shown (Red Box).*

Figure W2. *SMS Template*

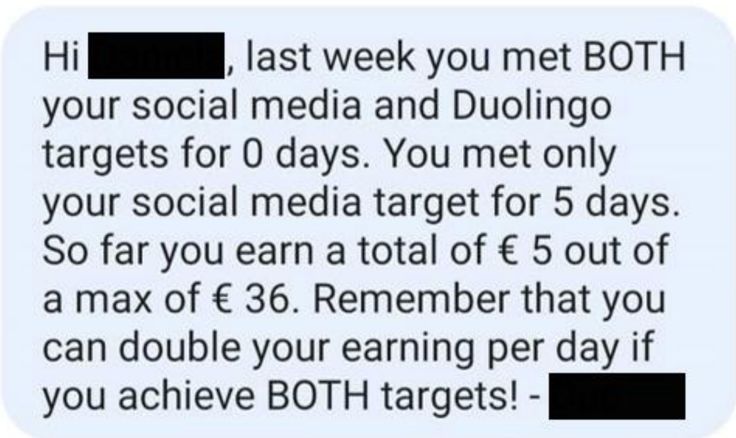

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Table W1. *Baseline Characteristics of Participants (Pilot Study)*

	Mean (SD) or Proportion
Demographics	
Age	21.6 (1.79)
Female	72.1%
Bachelor student	62.8%
Smartphone variables	
iOS (Apple iPhone)	88.4%
Owner of two phones	9.3%
Monthly data allowance	
• 5-10Gb	11.6%
• 10-20Gb	11.6%
• 20-30Gb	27.9%
• >30Gb	41.9%
Proportion of social media time using mobile	73.5% (18.98)
Proportion of mobile usage time spent on social networking	61.6% (18.48)
Willingness to reduce social media usage	4.8 (1.51)
Has previously attempted to reduce social media usage	79.1%
Frequency of notifications (1 = Not at all; 7 = Very much)	5.12 (1.58)
Language profile variables	
Number of languages with high proficiency	2.47 (0.74)
Proportion of English as a second language speakers	72.1%
Proportion of participants not learning any new language	25.6%
Proportion of participants already using Duolingo	41.9%
Willingness to use Duolingo to learn a language	4.77 (1.94)

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Table W2. *Correlation Matrix (Pilot Study)*

	1	2	3	4	5	6	7	8	9	10	11
1. Age	-										
2. Gender (Female = 1)	-0.12	-									
3. OS (Android = 1)	0.25	-0.26	-								
4. Baseline social media use (hour)	-0.14	-0.14	-0.04	-							
5. Baseline Duolingo usage (hour)	-0.13	0.24	-0.10	-0.19	-						
6. Change in social media use (hour)†	-0.06	0.07	-0.15	-0.38*	0.13	-					
7. Baseline perceived well-being	-0.17	-0.19	0.10	-0.35*	0.11	0.06	-				
8. Dual-target achievement (days)	0.05	-0.04	0.00	0.07	-0.14	-0.49***	-0.12	-			
9. Single-target achievement (days)	-0.05	0.04	0.00	-0.08	0.14	0.48**	0.13	-1.00***	-		
10. Target replacement ratio (TRR)	-0.05	0.23	-0.07	-0.72***	0.71***	0.36*	0.22	-0.13	0.14	-	
11. Change in perceived addiction†	-0.01	-0.19	0.24	0.11	-0.09	0.30	0.06	-0.32*	0.31*	-0.03	-
12. Change in perceived well-being†	-0.10	0.24	-0.13	0.06	-0.12	-0.09	-0.37*	-0.13	0.12	-0.01	-0.10

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Figure W3. *Timeline of Social Media Use Change. Error Bars are Standard Errors. Three Days were Allocated between Period 1 and Period 2 to Complete a Comprehension Check.*

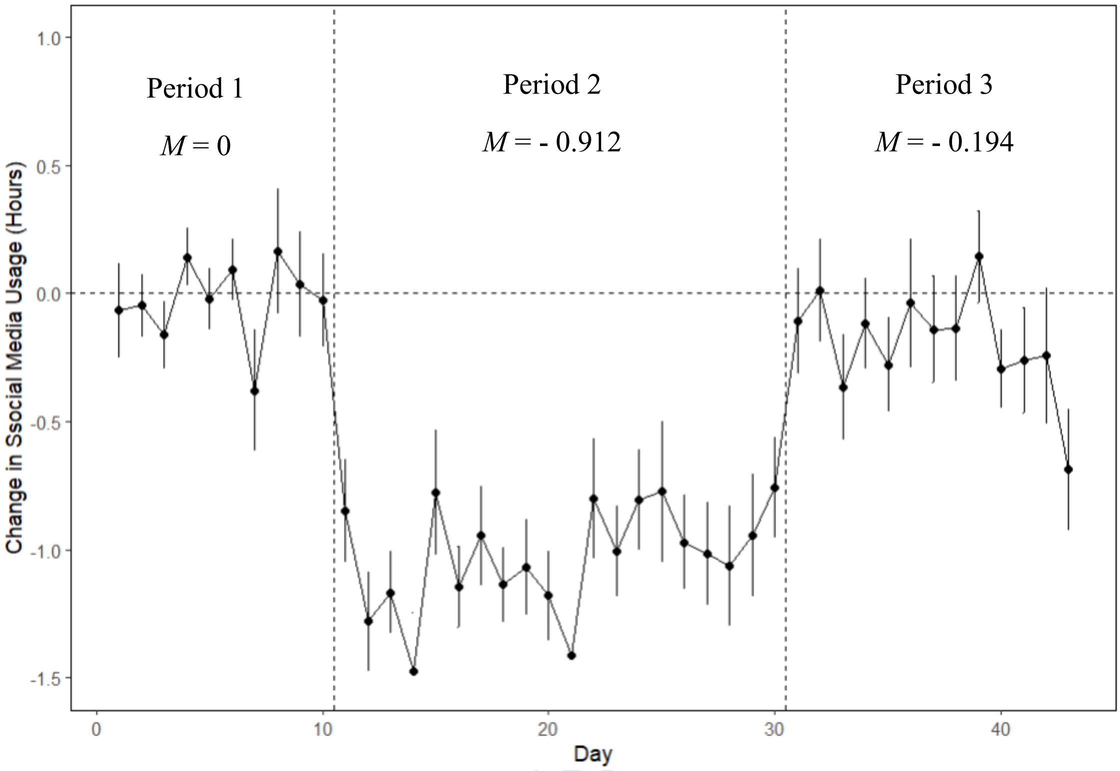

Figure W4. *Timeline of Duolingo Use Change. Error Bars are Standard Errors. Three Days were Allocated between Period 1 and Period 2 to Complete a Comprehension Check.*

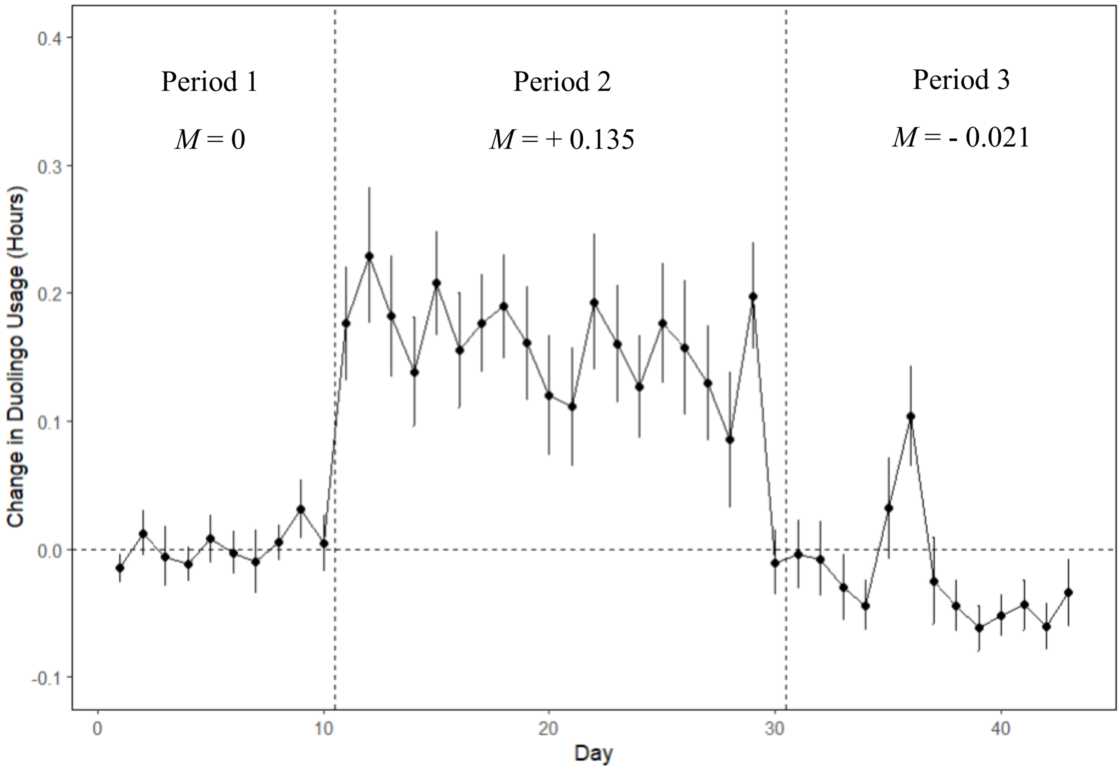

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Table W3. *Panel Regression of Social Media Use: Dual-Target Achievement Predicts Post-treatment Social Media Reduction.*

	Dependent variable = Social Media Usage (hour)	
	Model 1	Model 2
Treatment Period (Period 1)	-1.029***	-0.627***
	(0.141)	(0.159)
Post-Treatment Period (Period 2)	-0.235*	0.065
	(0.138)	(0.174)
Dual-target achievement (days)		0.012
		(0.026)
Dual-target achievement × Period 1		-0.101***
		(0.017)
Dual-target achievement × Period 2		-0.072***
		(0.024)
Constant	3.081***	3.032***
	(0.165)	(0.208)
Observations	1,588	1,588
R^2	0.085	0.154
Adjusted R^2	0.083	0.151
Residual Std. Error	1.435 (df = 1585)	1.381 (df = 1582)
F Statistic	73.272*** (df = 2; 1585)	57.659*** (df = 5; 1582)

Note: * $p < .10$; ** $p < .05$; *** $p < .01$. The base category is the baseline period. Standard errors (in parentheses) are robust and clustered at the participant level.

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Table W4. *Panel Regression of Duolingo Use (Pilot Study).*

	Dependent variable = Duolingo Use (hour)	
	Model 1	Model 2
Treatment Period (Period 1)	0.150***	0.037
	(0.032)	(0.030)
Post-Treatment Period (Period 2)	-0.025	-0.042
	(0.021)	(0.025)
AchieveBoth (days)		-0.003
		(0.002)
AchieveBoth × Period 1		0.028***
		(0.004)
AchieveBoth × Period 2		0.004**
		(0.002)
Constant	0.066***	0.078***
	(0.018)	(0.022)
Observations	1,520	1,520
R^2	0.114	0.268
Adjusted R^2	0.113	0.266
Residual Std. Error	0.234 (df = 1517)	0.213 (df = 1514)
F Statistic	97.628*** (df = 2; 1517)	110.984*** (df = 5; 1514)

Note: * $p < .10$; ** $p < .05$; *** $p < .01$. The base category is the baseline period. Standard errors (in parentheses) are robust and clustered at the participant level.

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For every additional day of dual-target achievement (instead of achieving only the social media target), participants increased their average daily Duolingo usage by 0.028 hours ($p < .001$) during the treatment period. This increase was also positive during the post-treatment (0.004 hours, $p = .039$). The increase in Duolingo use should be interpreted as the increase compared to those who achieved only the social media target for a particular day.

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Alternative Operationalization of Target Replacement Ratio x Dual-Target Achievement

We can directly examine the effect of the interaction between the target replacement ratio and dual-target achievement on post – pre (post-treatment minus baseline) social media use by substituting this interaction with the change in the ratio of Duolingo-to-social-media use from baseline to the treatment period. This change in ratio can be computed for each individual:

$$\Delta \frac{Duolingo\ usage}{Social\ media\ usage} = \frac{Duolingo\ usage_{Tx}}{Social\ media\ usage_{Tx}} - \frac{Duolingo\ usage_{bsl}}{Social\ media\ usage_{bsl}}$$

This ratio (*Social Media Replacement index*) reflects how an individual's use of Duolingo relative to their social media use changes from baseline to the treatment period. A positive sign indicates that, compared to baseline, there is a higher proportion of social media replacement using Duolingo, and vice versa. This measure resembles the interaction between the target replacement ratio and dual-target achievement in the manuscript.

We ran a linear regression predicting post – pre social media use with the ratio change. Table W5 shows the results. The coefficient for the ratio change is negative, meaning that an increase in the ratio (i.e., higher proportion of replacement) results in lower post-treatment social media use relative to baseline. This corroborates the finding that participants with higher target replacement ratio and higher dual-target achievement have lower post – pre social media use.

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Table W5. *OLS Regression of Post - Pre Social Media Use on Social Media Replacement Index. Higher Index Predicts Lower Post-Treatment Use.*

	Dependent variable = Post – Pre social media usage	
	Model 1	Model 2
Social Media replacement index	-0.85**	-0.90**
	(0.40)	(0.41)
Age		-0.02
		(0.08)
Gender (Female)		0.07
		(0.30)
OS (iOS)		0.43
		(0.43)
Constant	-0.03	-0.07
	(0.14)	(1.77)
Observations	43	43
R^2	0.10	0.13
Adjusted R^2	0.08	0.04
Residual Std. Error	0.83 (df = 41)	0.85 (df = 38)
F Statistic	4.54** (df = 1; 41)	1.47 (df = 4; 38)

Note: * *p* < .10; ** *p* < .05; *** *p* < .01.

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W1. Willingness-to-reduce social media use is not a significant predictor of post-treatment change in perceived well-being

We used baseline willingness-to-reduce (WTR) social media (in the pilot study) since this measure was conceptually most related to the Social Media Mindsets Scale (SMMS) (Lee and Hancock 2024). Table W6 shows the regression models examining change in well-being as the dependent variable. Models 1, 2, and 4 show the effect of WTR, dual-target achievement, and change in social media use (measured at baseline and post-treatment periods), respectively. Model 3 examines the interaction effect between WTR and dual-target achievement. Model 5 examines the interaction effect between WTR and change in social media use between post-treatment and baseline periods.

Model 1 indicates that WTR is not associated with a change in well-being (p = .905). Model 3 indicates there is no interaction between WTR and dual-target achievement (p = .099) on wellbeing. Model 5 shows there is no interaction between WTR and change in social media use (p = .449) on wellbeing. These results indicate that baseline WTR did not moderate improvements in wellbeing.

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Table W6. *Willingness-To-Reduce Social Media Use Does Not Predict Post-Treatment Change in Wellbeing*

	Dependent variable:				
	Well-being change (Post - Pre)				
	(1)	(2)	(3)	(4)	(5)
Willingness to Reduce social media (WTR)	-0.010 (0.083)		-0.114 (0.106)		-0.045 (0.093)
	$p = 0.905$		$p = 0.290$		$p = 0.629$
Dual-target Achievement (DTA, in days)		-0.019 (0.023)	-0.176 (0.095)*		
		$p = 0.406$	p = 0.073		
WTR x DTA			0.030 (0.018)*		
			$p = 0.099$		
Change in social media use (Post-Pre SocMed)				-0.088 (0.145)	0.436 (0.704)
				$p = 0.549$	$p = 0.540$
WTR x Post-Pre SocMed					-0.106 (0.139)
					$p = 0.449$
Constant	0.298 (0.422)	0.326 (0.154)**	0.887 (0.530)	0.234 (0.126)*	0.441 (0.461)
	$p = 0.485$	$p = 0.041$	$p = 0.103$	$p = 0.072$	$p = 0.345$
Observations	43	43	43	43	43
R^2	0.0004	0.017	0.084	0.009	0.024
Adjusted R^2	-0.024	-0.007	0.014	-0.015	-0.051
Residual Std. Error	0.816 (df = 41)	0.810 (df = 41)	0.801 (df = 39)	0.813 (df = 41)	0.827 (df = 39)
F Statistic	0.015 (df = 1; 41)	0.706 (df = 1; 41)	1.193 (df = 3; 39)	0.366 (df = 1; 41)	0.324 (df = 3; 39)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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W2. Substitution of smartphone social media use with other devices

A limitation of the screen shot data collection method is that it does not track web-based app usage, which requires browsing data. Participants may have used apps like Twitter or Facebook on both web and mobile. To address this, we provide evidence suggesting how participants reduced social media use beyond shifting to other devices.

Participants were asked to report their strategies for reducing mobile social media use with an open-ended question. We analysed 43 responses qualitatively. Table W7 provides the topics and example quotes from participants. Only one person mentioned using desktop more instead of the phone. In fact, most comments (37.73%) were related to shifting to positive alternative behaviors. This was followed by 36% of comments relating to setting time limits or better time management. Twenty two percent of comments were related to better self-awareness.

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Table W7. *Qualitative responses to "How did you reduce your mobile social media usage?"*

Positive alternatives n = 20, 37.73%	• Go outside more, hang out with other people, read more • Focus on other things beside the phone • Finish the book I'm reading rather than being on my phone • Use that time to do other things. • Maybe dedicate more time to other activities that do not require using or having a mobile phone (doing more sport, going to the cinema, church...) • Read before bed instead of using my phone • use Duolingo anytime I'm bored instead of Social Media • Spending my free time on other activities rather than scrolling through social media. • Keeping myself busy with outdoor activities and assignments
Time limits, better time management: n = 19, 35.85%	• Setting time limits on the screen app • Put restrictions on my phone • I'm going to avoid using social media during study hours and leave them for the evening. • setting time limits on the screen app, organizing my day better, avoiding phone usage late at night and early morning • I put a time limit of 1h30 for Insta, Snapchat, and WhatsApp to not go over the time. • I will use the screen time limit that is on Apple. Like this, I'm aware of social media usage and know when I should stop. • Set up the timer app on my phone which notifies me when to stop using an app
Self-awareness, self-control, self-monitoring: n=12, 22.64%	• Be more aware of the time I spend on social media • Try not to use Instagram mindlessly • Grin and bear it! • I will only go on social media upon needing to…instead of mindlessly scrolling through. • Focusing on learning rather than mindless scrolling.
Reduce notifications, delete apps, turn off phone n = 10, 18.87%	• I positioned the icon of the app in a folder that was "hidden" thus avoiding the automaticity of clicking on the app with no specific purpose. • I also set up "work mode" on my phone for when I really need to focus on other things than browsing social media. • Delete the social media apps I use the most • I will… turn off my phone when doing homework or important tasks. • Uninstall Snapchat • NOT OPEN SOCIAL MEDIA APPS • Use the different phone modes to limit app consumption. As for example in the gym (sport mode) in order to not enter any app.
Substitution: n = 1, 0.19%	• I have a 2hr limit on Instagram, but I often ignore the limit honestly. I use social media on my computer.

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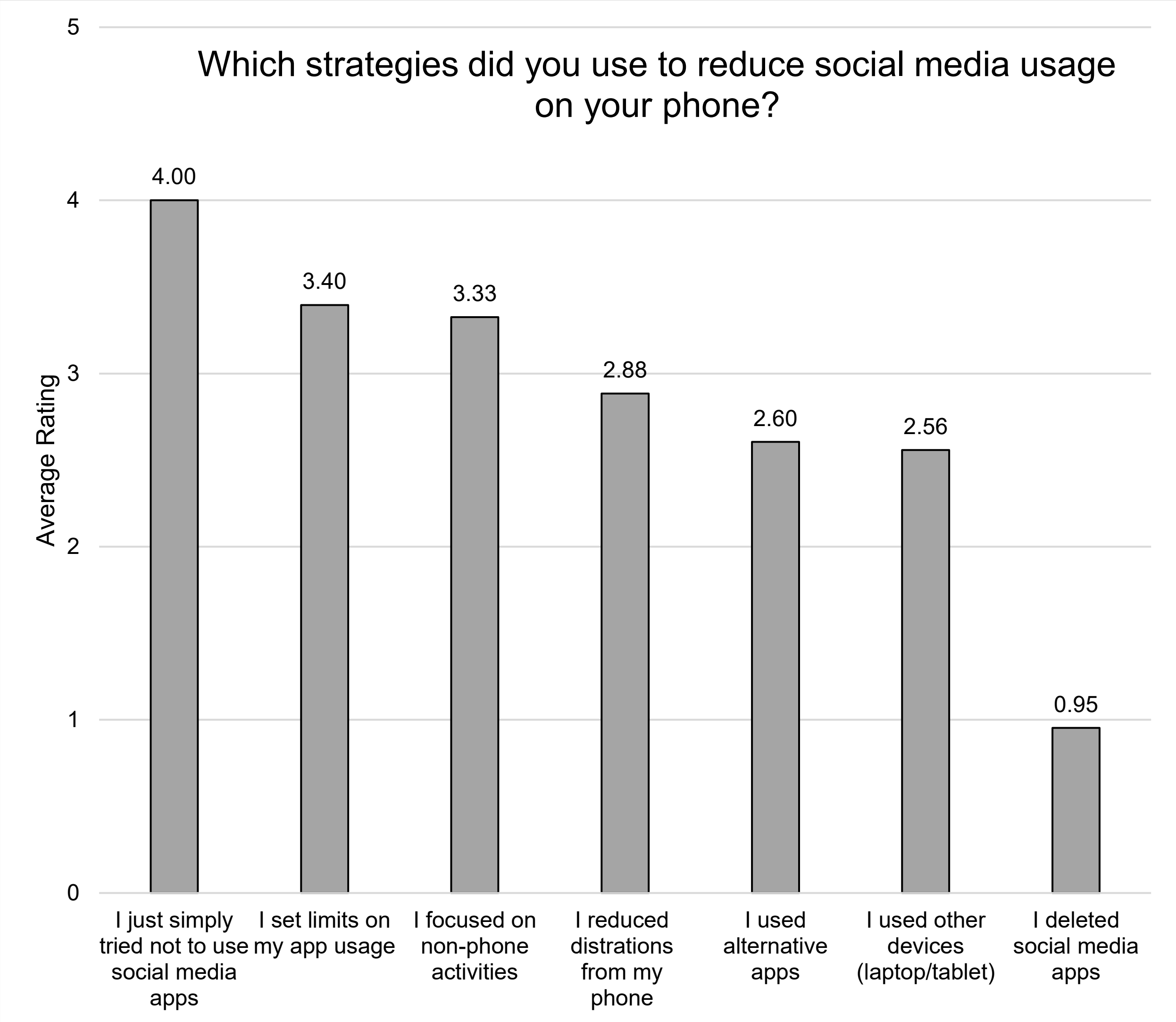
We also asked participants to rate the extent to which they used different strategies, including substitution with desktop use, to lower social media use. Figure W6 displays the results (scale from 0 = not at all, to 6 = very much). We ranked the strategies according to their average. While substitution seems to occur to some extent, it was not the main strategy that participants used (out of seven strategies, it was ranked second to last).

Figure W6. *Prevalence of strategies used to reduce mobile social media usage*



We believe that in our student sample, participants were intrinsically motivated and genuinely wanted to reduce their screen time. They had very high willingness to reduce screen time and felt that spending excessive time on the phone was negatively impacting their lives (we added a quote below to illustrate this).

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"I have realized that social media has become a source of instant gratification. I have recently deleted the app in order to be more productive and force myself not to enter Instagram the first moment I feel anxious as a way to distract myself from personal emotions. Sadly I have made this progress very late in the study, but it has been due to the level of stress and anxiety the thesis is provoking in me (social media has a huge impact on this). I am a big fan of this study, I love to participate because it is now when I give a second thought to phone usage."

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Table W13.1. *After the incentive period ended (when you no longer had any target), did you continue using Duolingo? (N = 23)*

Response	N	%
Yes	8	34.8
No, but I used a different language learning app.	2	8.7
No, and I was not using any language learning app.	13	56.5

Table W13.2. *Why do you think that using a language learning app might (or might not) help you reduce social media usage? (N = 23)*

Reason	Example quotes	N	%
Yes, replacement	Because for me clicking on the social media apps is a reflex that I have when I'm free/when I want to free my mind a bit. Replacing some of those times with the language apps takes away from those times.	7	35
Yes, distraction	For me personally, using a language app quickly became a different kind of distraction from reality (a better one in terms of what I gained, but a distraction nonetheless).	1	5
No, forced use	I had to force myself using the app and when the incentive was over I completely stopped. Social media on the other hand is always a source of entertainment and isn't forced.	1	5
No, app attached to phone	I think that the problem is actually using the phone (independently of what app) because anyways you'll end up checking social media. if i want to avoid this, i'll just avoid using the phone all in all	3	15
No, not as engaging	- It is not as fun as going to social media where you do not have to concentrate - No. It's a boring alternative	5	25
No, not enough to matter	I don't think so, not by the same amount that was imposed during the experiment	1	5
No, no use	For me, I learn Spanish from a tutor. So, App (Duolingo) didn't do anything for me	1	5
No, social media more functional	I had to use WhatsApp the majority of time simply because my peers and I communicate about homework, class questions, important exams coming, so it was hard to restrict myself…	1	5

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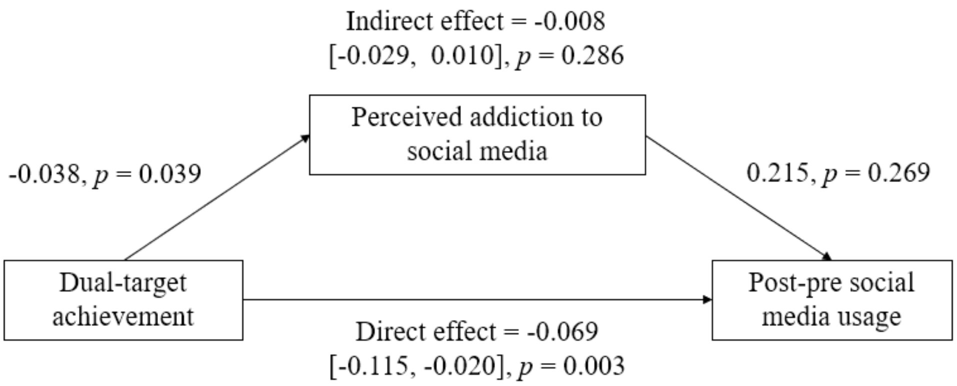
W3. Testing for mediation via perceived addiction

To test if post-treatment use social media relative to baseline (hereafter post-pre social media use) is more strongly affected by dual-target than by single-target achievement through perceived addiction to social media, we conducted a mediation analysis using the bootstrap method implemented by the R package *mediation* (Tingley et al., 2014). The model included dual-target achievement (independent variable, in days; higher dual-target achievement corresponds to lower single-target achievement), perceived addiction to social media (mediator), and post-pre social media use (dependent variable).



We observed a significant effect of dual-target achievement on perceived addiction to social media (β = -0.038, $t(41)$ = -2.130, p = .039). Perceived addiction did not have a significant effect on post-pre social media use (β = 0.215, $t(40)$ = 1.121, p = .269), while controlling for dual-target achievement. The direct effect on post-pre social media use was significant (β = -0.070, $t(40)$ = -3.029, p = .004). Finally, a 95% confidence interval (CI) (based on 10,000 bootstrapped samples) revealed that the indirect effect of dual-target achievement on post-pre social media use through perceived addiction to social media was not significant (point estimate = -0.008, 95% CI = [-0.029, 0.01], p = .286). When not controlling for dual-target achievement, the effect of perceived addiction on post-pre social media use was marginally significant (β = 0.399, $t(41)$ = 2.00, p = .052).

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Web Appendix B. Experimental Study

Figure W7. *Examples of Screenshots (Left: Screen Time; Right: Step Count)*

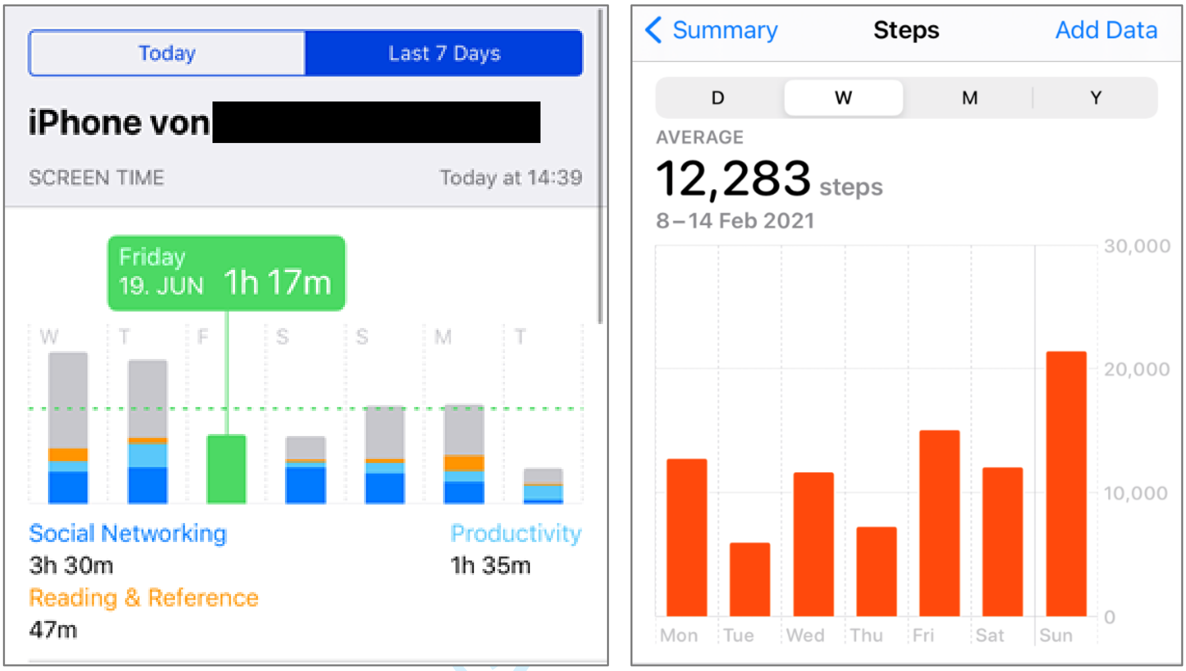

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Table W8. *Correlation Matrix of Baseline Measures (Experimental Study)*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Age	-													
2. Gender (Female = 1)	-0.33***	-												
3. OS (Android = 1)	0.10	-0.27**	-											
4. Screen time (hour)	-0.30**	0.11	-0.31***	-										
5. Step count	-0.04	0.05	-0.10	0.06	-									
6. Sleeping late days	0.06	-0.07	0.04	0.23*	0.19	-								
7. Tired days	0.14	0.00	0.09	0.09	-0.17	0.35***	-							
8. Satisfaction with health	-0.16	0.15	-0.17	-0.06	0.11	-0.19*	-0.34***	-						
9. Satisfaction with life	-0.11	0.21*	-0.15	-0.14	0.21*	-0.07	-0.26**	0.51***	-					
10. Productivity	0.13	-0.07	0.13	-0.19*	0.03	-0.20*	-0.25**	0.37***	0.47***	-				
11. Anxiety (without phone)	0.04	0.18	-0.01	0.09	0.09	0.04	-0.10	0.03	0.03	-0.06	-			
12. Positive affect	0.10	0.04	-0.02	-0.12	0.22*	-0.21*	-0.27**	0.27**	0.29**	0.42***	0.03	-		
13. Negative affect	-0.03	0.10	-0.11	0.03	-0.22*	0.04	0.21*	-0.33***	-0.35***	-0.32***	0.15	-0.18	-	
14. Delayed gratification tendency	-0.06	-0.06	-0.03	-0.03	0.05	-0.08	-0.31**	0.39***	0.28**	0.35***	-0.09	0.46***	-0.33***	-
15. Weight	0.26**	-0.69***	0.23*	-0.02	-0.02	0.07	-0.02	-0.32***	-0.27**	0.12	-0.09	0.07	0.00	-0.04

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Table W9. *Baseline Characteristics of Participants across Conditions (Experimental Study)*

	Mean (SD)			
	Control (N = 33)	**Dual-Target (N = 38)**	**Single-Target (N = 39)**	**Balance check**
Demographics				
Age	25.0 (4.19)	24.3 (3.28)	24.0 (3.18)	$F(2,107) = 0.68$, $p = 0.509$
Female	45%	58%	69%	$\chi^2(2) = 1.22$, $p = 0.544$
Smartphone variables				
Baseline screen time	5.15 (1.80)	4.92 (1.72)	4.78 (2.00)	$F(2, 107) = 0.36$, $p = 0.698$
iOS (Apple iPhone)	85%	82%	85%	$\chi^2(2) = 0.07$, $p = 0.965$
Owner of >= 1 phone	9%	11%	5%	$\chi^2(2) = 2.24$, $p = 0.326$
Proportion of mobile usage time spent on social networking	48.1%	60.5%	52.8%	$\chi^2(2) = 1.46$, $p = 0.483$
Willingness to smartphone usage	4.97 (1.59)	5.05 (1.39)	5.10 (1.37)	$F(2, 107) = 0.08$, $p = 0.927$
Has previously attempted to reduce smartphone usage	73%	87%	64%	$\chi^2(2) = 3.60$, $p = 0.165$
Health and performance variables				
Physically active	4.18 (1.88)	4.76 (1.51)	4.51 (1.34)	$F(2, 107) = 1.21$, $p = 0.304$
Weight	68.9 (13.94)	69.8 (15.82)	64.7 (13.16)	$F(2, 107) = 1.34$, $p = 0.267$
Willingness to walk more	5.27 (1.48)	5.87 (1.17)	5.59 (1.41)	$F(2, 107) = 1.71$, $p = 0.186$
Weekly sleeping late (days)	4.70 (2.48)	5.24 (1.73)	4.67 (2.07)	$F(2, 107) = 0.88$, $p = 0.419$
Weekly tiredness (days)	4.12 (2.42)	4.39 (1.70)	4.44 (2.01)	$F(2, 107) = 0.24$, $p = 0.785$
Satisfaction with life	4.82 (1.49)	4.76 (1.15)	4.92 (1.26)	$F(2, 107) = 0.15$, $p = 0.860$
Satisfaction with health	4.00 (1.41)	3.82 (1.52)	4.05 (1.12)	$F(2, 107) = 0.32$, $p = 0.730$
Productivity	4.39 (1.37)	4.21 (1.42)	4.28 (1.17)	$F(2, 107) = 0.17$, $p = 0.842$
Anxiety (without phone)	4.52 (1.84)	5.21 (1.56)	5.03 (1.81)	$F(2, 107) = 1.49$, $p = 0.230$
Delayed Gratification tendency	4.22 (1.38)	3.93 (0.92)	4.26 (0.96)	$F(2, 107) = 1.06$, $p = 0.350$
Negative Affect (PANAS)	2.26 (0.72)	2.18 (0.61)	2.13 (0.60)	$F(2, 107) = 0..40$, $p = 0.670$
Positive Affect (PANAS)	3.48 (0.71)	3.46 (0.57)	3.44 (0.73)	$F(2, 107) = 0.02$, $p = 0.976$
Belief about target achievement (before intervention; days)	-	12.3 (4.49)	12.4 (4.69)	$F(1, 73) = 0.03$, $p = 0.874$
Perceived target difficulty (before intervention)	-	4.87 (1.30)	4.92 (1.26)	$F(1, 73) = 0.03$, $p = 0.865$

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Average Change in Mobile Use across Conditions

Figure W8.1 compares the average change in mobile use (from baseline) between dual-target and control conditions. In period 1 and 2, the average reduction in the dual-target condition was 0.98 hours (59 minutes) and 0.70 hours (42 minutes), respectively, compared to the control condition. In period 3, participants in the dual-target condition lowered their usage by 0.09 hours (5 minutes) from baseline, while the control condition increased usage by 0.46 hours (28 minutes). Figure W8.2 compares the average change in mobile usage (from baseline) between single-target and control conditions. In period 1 and 2, the average reduction in the single-target condition was 1.28 hours (77 minutes) and 0.51 hours (or 31 minutes), respectively, compared to the control condition. In period 3, participants in the single-target condition lowered their usage by 0.34 hours (20 minutes) from baseline, while the control condition increased its usage by 0.46 hours (28 minutes).

Figure W8.1. *Average Daily Change in Mobile Use from Baseline (Control vs. Dual-Target). Standard Error Bars are Shown.*

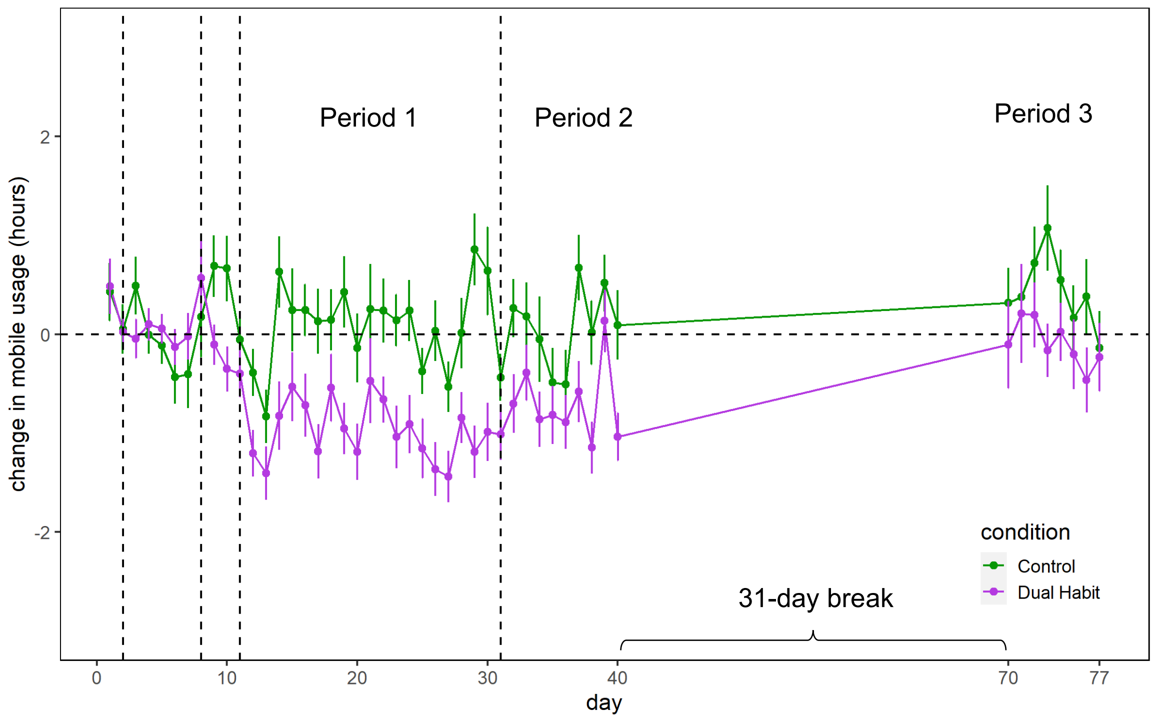

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Figure W8.2. *Average Daily Change in Mobile Use from Baseline (Control vs. Single-Target). Standard Error Bars are Shown.*

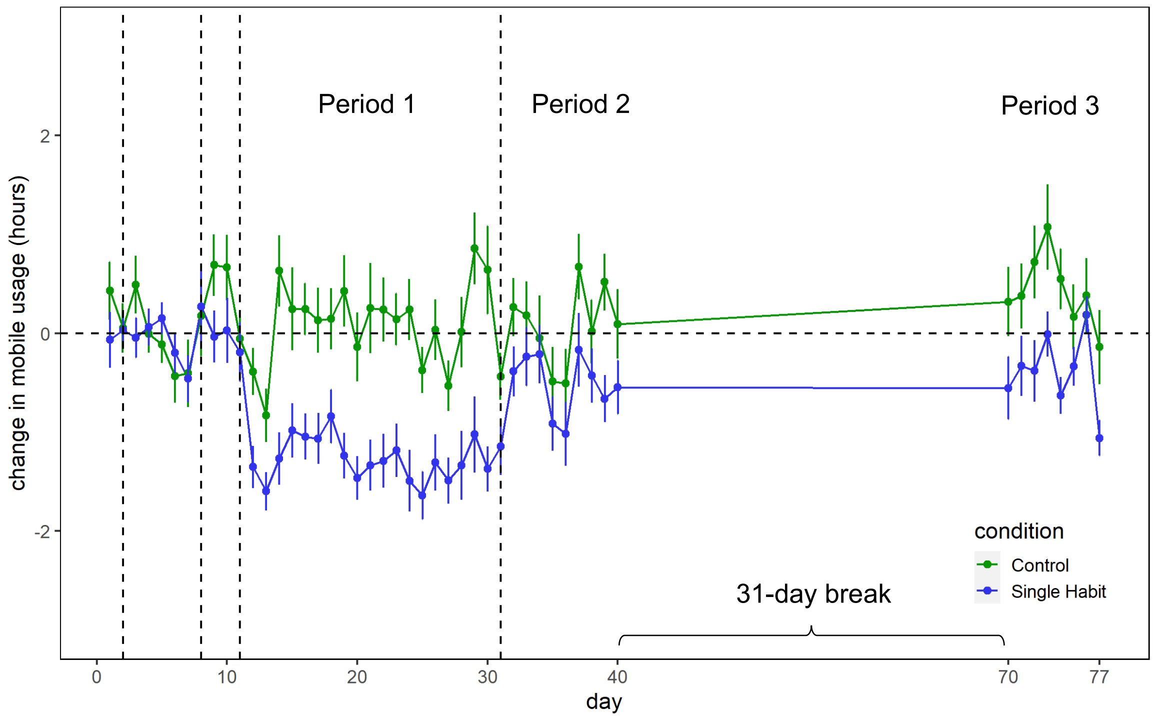

Table W10. *Pairwise t-Tests Results*

Period	Comparison groups	Mean difference (screen time, in hours)	*t*	*p*
Baseline	C – ST	0.23	0.56	0.577
	C – DT	0.37	0.82	0.415
	ST – DT	0.14	0.32	0.750
Treatment	C – ST	1.64	3.91	< .001
	C – DT	1.30	2.92	0.005
	ST – DT	-0.33	-0.87	0.387
Post-treatment	C – ST	0.84	1.83	0.072
	C – DT	0.86	2.10	0.040
	ST – DT	0.02	0.05	0.959

Note: C = control condition, ST = single-target, DT = dual-target

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Difference-in-Differences (DiD) Regression Analysis of Screen Time

We compared screen time in the three conditions using difference-in-difference ordinary least squares (OLS) regression. We regress participants' mobile usage on (1) the treatment variables (control is the base category, dual-target and single-target are dummy variables); (2) the period dummy variable which captures the change in usage across each period (period 0 or baseline is the base category); and (3) the interactions between treatment and period dummies to capture the changes in use from the baseline period in the particular treatment condition. Standard errors are clustered at the subject-level to account for potential within-subject correlation. Regression estimates are in Table W11. The treatment dummy variables are not significant, indicating no baseline difference in smartphone use. We now focus on the treatment × period interactions.

In period 1, participants in both single- and dual-target conditions decreased their use by 1.434 hours ($p < .001$) and 1.055 hours ($p < .001$), respectively, compared to the control condition. Hence, incentives were effective in reducing usage in both treatment conditions during period 1. There was no difference between the single- and dual-target conditions in period 1 ($p = .196$). In period 2, participants in both single- and dual-target conditions decreased use by 0.597 hours ($p = .07$) and 0.657 hours ($p = .054$), respectively, compared to the control condition.

In period 3, participants in the single-target condition decreased their use by 0.808 hours ($p = .048$) compared to the control condition. On the other hand, participants in the dual-target condition did not decrease their usage compared to the control condition ($p = .574$). These results might be unreliable due to high attrition in late post-treatment responses, especially for the dual-target condition (Table W15). The attrition rates of the conditions are 24% for Control, 36% for single-target, and 45% for dual-target. The results of this DiD analysis are consistent with the results of the mixed ANOVA (main manuscript).

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Table W11. *Difference-in-difference OLS Estimation (Screen Time)*

	Dependent variable – Mobile Usage (hour)
Single-target condition	-0.251 (0.409)
	p = 0.539
Dual-target condition	-0.253 (0.444)
	p = 0.569
Treatment (Period 1)	0.126 (0.149)
	p = 0.400
Early Post-treatment (Period 2)	0.010 (0.229)
	p = 0.966
Late Post-treatment (Period 3)	0.424 (0.284)
	p = 0.136
Single-target condition × Period 1	-1.434 (0.239)***
	p < .001
Dual-target condition × Period 1	-1.055 (0.271)***
	p < .001
Single-target condition × Period 2	-0.597 (0.329)*
	p = 0.070
Dual-target condition × Period 2	-0.657 (0.341)*
	p = 0.054
Single-target condition × Period 3	-0.781 (0.404)*
	p = 0.054
Dual-target condition × Period 3	-0.305 (0.454)
	p = 0.502
Constant	5.130 (0.298)***
Observations	4,098
R^2	0.080
Adjusted R^2	0.077
Residual Std. Error	2.198 (df = 4,086)
F Statistic	32.236*** (df = 11; 4,086)

Note: * *p* < .10; ** *p* < .05; *** *p* < .01. The base category is control condition in baseline period. Standard errors (in parentheses) are robust and clustered at the participant level.

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Figure W9. *Target Achievement was Higher In Single-Target (Top) Than Dual-Target Condition (Bottom). Adherence Was Lower in Dual-Target Than Single-Target Condition*

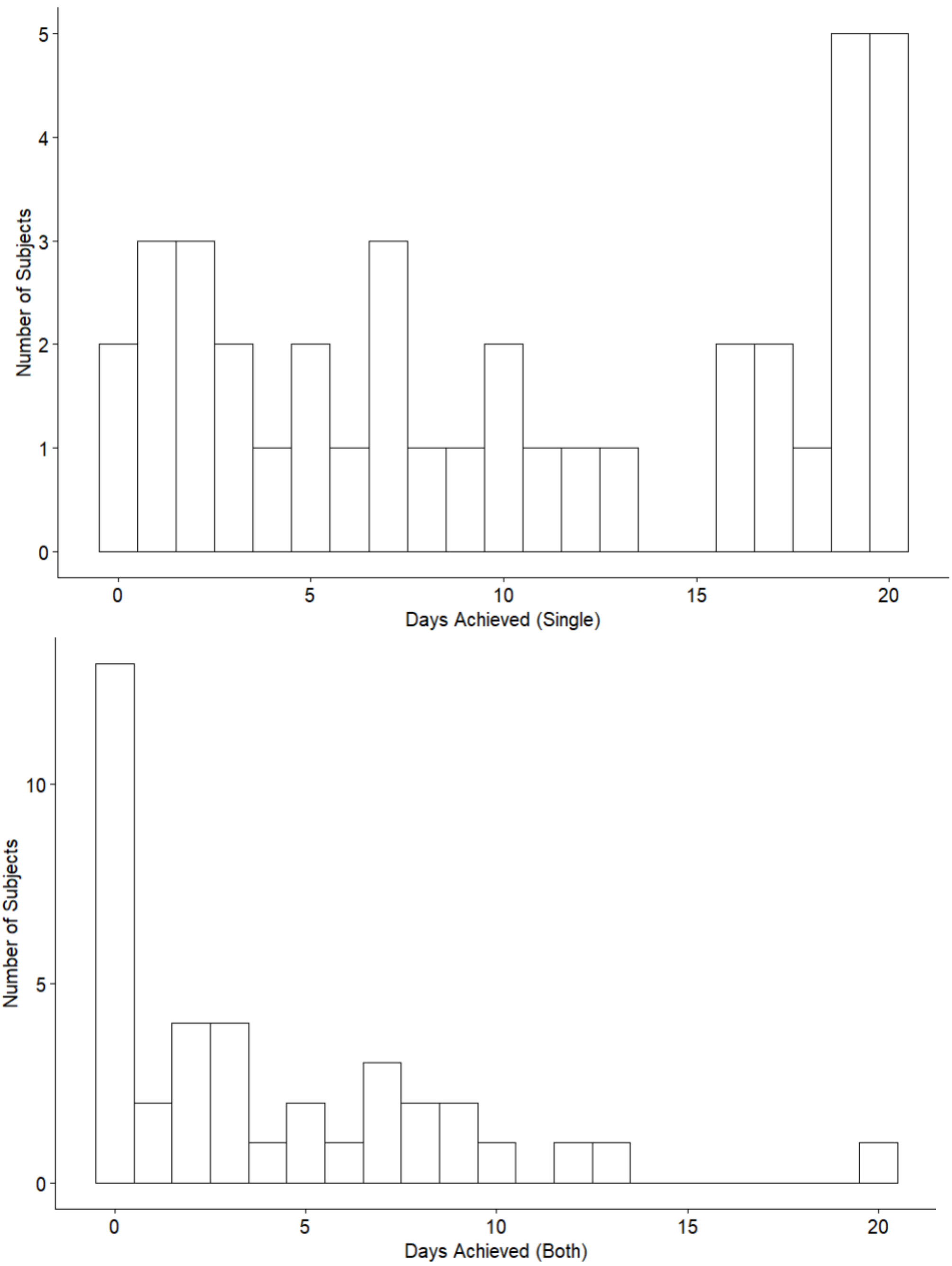

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Table W12. *Instrumental Variable Regressions (1st Stage - OLS)*

	Dependent variable Target achievement days in treatment period	
	Single Target Condition	Dual Target Condition
	Model 1	Model 2
Control condition	-2.46*** (0.18)	-2.86*** (0.19)
Single Target condition	3.02*** (0.27)	-0.89*** (0.23)
Gender (1 = Male; 0 = Female)	-0.41 (0.21)	0.07 (0.18)
Age	0.05 (0.03)	0.05* (0.02)
OS (1 = Android; 0 = iOS)	1.85*** (0.29)	1.05*** (0.21)
Observations	1,760	1,760
R^2	0.24	0.12
Adjusted R^2	0.24	0.11

Note: * *p* < .05; ** *p* < .01; *** *p* < .001. Base category is Dual-Target condition. Standard errors (in parentheses) are robust and clustered at the subject level. Condition is a good predictor of target achievement days and can distinguish between dual- and single-target condition in terms of dual-target achievement (β = -0.89, *p* < .001).

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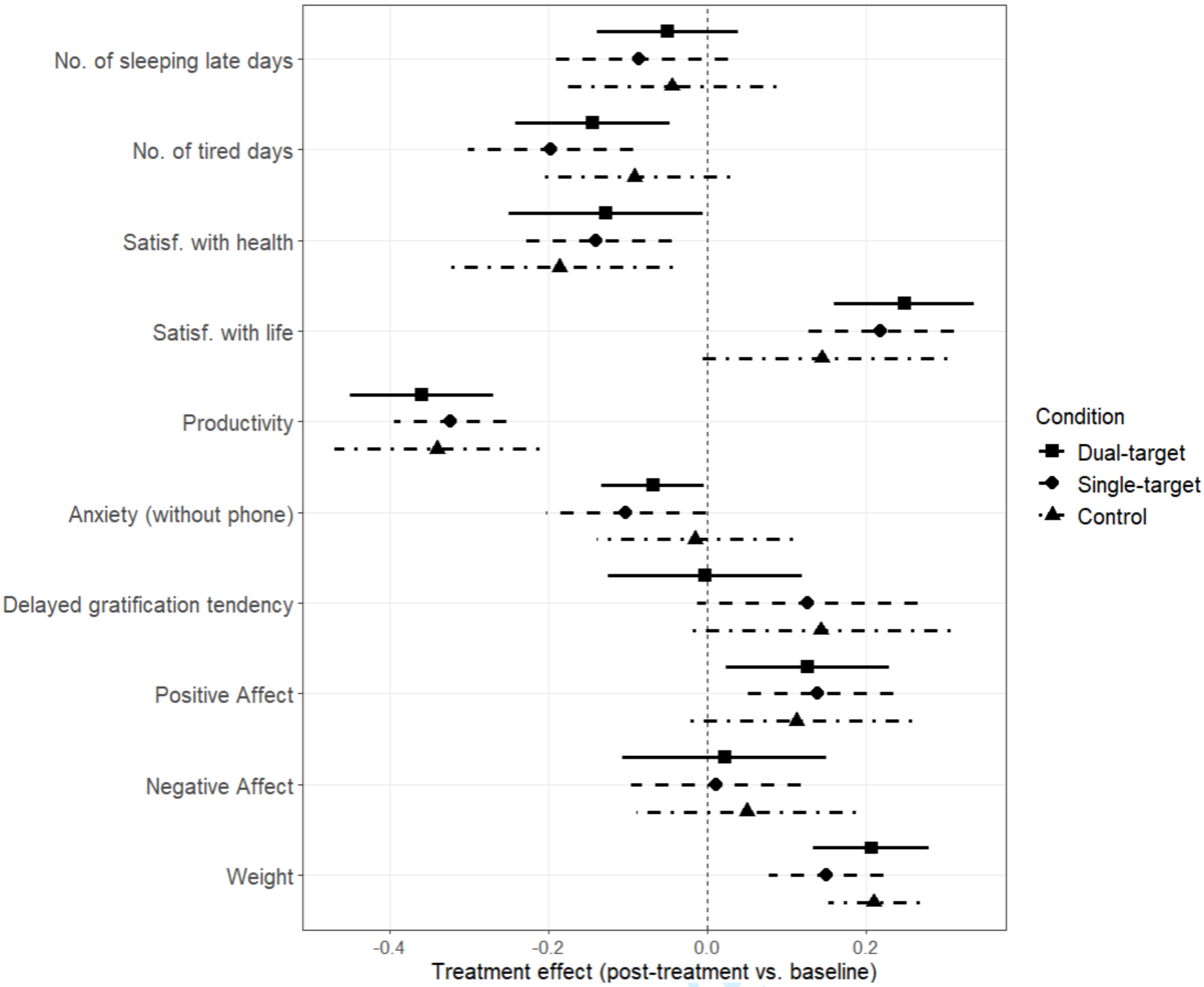
Figure W10. *Post-treatment Changes in Survey Measurements from Baseline. All Scales are Normalized to the Range [-1, 1].*



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