Self-Selected Goals Outperform Assigned Goals in Reducing Mobile Phone Usage:

Evidence from a Randomized Controlled Trial

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Abstract

Excessive smartphone use is increasingly recognized as a public-health concern, yet scalable approaches to help individuals regulate daily use remain limited. We examine whether allowing individuals to self-select reduction goals improves behavioral and psychological outcomes when incentives and average goal levels are held constant across conditions. In a twelve-week randomized controlled trial, (N = 149; over 9,000 person-day observations), participants were assigned to (i) a self-selected condition (choosing a 10%, 20%, or 30% reduction in daily phone use), (ii) an assigned condition (assigned a 14% reduction goal), or (iii) a no-goal control condition. Participants who selected their own goals reduced phone use by 26 minutes more per day **(**73% larger reduction) and achieved their goals 11 percentage points more often than those assigned goals, despite identical incentives and average goal levels.

Reductions in phone use and higher goal achievement were associated with improvements in perceived addiction, depressive, and anxiety symptoms. These psychological outcomes were secondary endpoints. Although the between-group estimates generally followed the same directional pattern as the behavioral outcomes, the sample size for these analyses was limited and the between-group differences were not statistically significant. These findings should therefore be interpreted with caution.

Overall, the results provide causal field evidence that self-selection under this goal-setting design can improve behavioral outcomes. Allowing individuals to choose their own goals may strengthen engagement and support healthier digital behavior. Incorporating opportunities for goal-selection may represent a simple addition to digital-health and public-health interventions aimed at helping individuals moderate smartphone use and improve well-being.

Key words: Digital Health; Psychological Well-Being; Smartphone Use; Self-Selection; Goal Setting; Randomized Controlled Trial; Self-Regulation.

Highlights

- RCT on whether self-selection in goal-setting improves digital health behaviors.
- Self-selected participants reduced phone use more than assigned participants.
- Self-selected participants achieved goals more often than assigned participants.
- Effects persisted despite identical incentives and average goal levels.
- Reduced phone use was associated with improved well-being.

Public significance statement

Many people feel they use their phones more than they would like, yet struggle to cut back. This study suggests that allowing individuals to set their own goals can support healthier digital habits. In a randomized field experiment, participants who selected their own phone-use reduction goals used their phones less and were more likely to meet their goals than those assigned goals with equivalent average goal levels and identical incentives. Reductions in phone use and higher goal achievement were also associated with improvements in perceived addiction, depressive, and anxiety symptoms, although psychological differences across conditions should be interpreted with caution. These findings suggest that providing simple opportunities for choice and ownership may help individuals better regulate their technology use, offering a practical and scalable approach to supporting healthier digital behavior.

1. Introduction

Smartphone use now shapes the daily routines of billions of people worldwide. Adults in many countries spend several hours per day on their mobile devices, and usage continues to rise across socioeconomic groups. Many individuals believe they spend more time on their phones than they intend to, and surveys consistently document concerns about compulsive checking, difficulty regulating use, and the emotional strain associated with heavy engagement (Lee et al., 2014; Volkmer & Lermer, 2019). From a public-health perspective, these patterns represent modifiable behavioral risks that may be responsive to low-cost, scalable interventions. In the UK, for example, half of young adults report feeling addicted to their phones and have unsuccessfully attempted to reduce their usage (Ofcom, 2020). In the U.S., the average teenager spends roughly seven hours per day consuming digital media (Gitnux, 2025).

India, which is our experimental context, exhibits these patterns in a particularly pronounced form and presents an important setting for understanding digital behavior and health. As of 2021, roughly 750 million Indians owned smartphones (Deloitte, 2022), and industry estimates suggest that many users spend more than seven hours per day on their devices (Redseer Strategy Consultants, 2022). At the same time, India faces a substantial and persistent mental-health burden: depression and anxiety rank among the most common mental disorders globally, and an estimated 197 million Indians live with a mental-health condition (Sagar et al., 2020). As digital engagement accelerates and mental-health challenges remain widespread, understanding how technology use affects well-being has become an increasingly important focus of public-health research.

A large empirical literature links intensive digital engagement to a range of psychological outcomes. Studies show that late-night smartphone use is associated with shorter sleep

duration, poorer sleep quality, and next-day fatigue and mood disturbances (Exelmans & Van den Bulck, 2016; Hisler et al., 2020). Many others find that higher daily screen time correlates with more depressive symptoms, greater anxiety, and lower subjective well-being (Thomée et al., 2011; Volkmer & Lermer, 2019). These relationships are often stronger among adolescents and among individuals who describe their use as compulsive or who frequently engage late at night (Elhai et al., 2017; Hisler et al., 2020; Twenge & Campbell, 2018).

At the same time, several preregistered reanalyses of large-scale datasets show that the associations between digital-media use and well-being can be small or highly contingent on context, age, or media type (Orben & Przybylski, 2019). Taken together, this evidence suggests that screen time is not uniformly harmful but that specific patterns of use may carry psychological risks.

Randomized experiments provide additional insights. Several studies that asked participants to reduce or temporarily deactivate social-media use report modest improvements in well-being, lower depressive symptoms, or increases in offline social interaction (Allcott et al., 2020; Allcott et al., 2018; Tromholt, 2016). These interventions typically target specific platforms rather than total smartphone use, and few evaluate changes in overall daily screen time (Somasundaram et al., 2025), which may offer a more comprehensive indicator of digital exposure. In addition, many prior studies rely on self-reported measures of digital behavior or infrequent outcome assessments, limiting our understanding of day-to-day patterns of change. Despite growing public concern about digital overuse, experimental evidence on reducing total smartphone use in real-world settings remains limited.

Goal setting represents one promising strategy for changing behavior. Classic goal-setting theory proposes that specific, challenging, and personally meaningful goals tend to increase effort, focus attention, and support persistence (Locke & Latham, 2002). A wide range of behavioral research supports this view. Goals and incentives have been shown to increase exercise participation (Charness & Gneezy, 2009), improve smoking cessation (Volpp et al., 2009), reduce energy consumption (Somasundaram et al., 2023), and shift patterns of digital use when paired with commitment devices or temporary restrictions (Allcott et al., 2022). In these settings, goals appear to work because they clarify expectations and structure self-regulation.

A longstanding question concerns whether goals should be assigned or chosen. Studies in labor and organizational settings often find that people who select their own goals work harder and perform better (Bommaraju & Hohenberg, 2018; Goerg & Kube, 2012; Incekara-Hafalir et al., 2025), although evidence from behavioral interventions remains less consistent (Adjerid et al., 2022; Woerner et al., 2025). Yet a key limitation runs through much of the self-selected goal literature. In many contexts, selecting a more ambitious goal is tied to higher rewards or stronger performance incentives, making it difficult to isolate whether the benefits arise from goal-selection itself or from the higher rewards associated with more ambitious goals. This confound limits what we can conclude about the role of goal selection.

Behavioral theories provides reason to expect autonomy to matter. Self-Determination Theory (Ryan & Deci, 2000) emphasizes that people are more likely to initiate and maintain behavior change when they feel ownership and volition. The COM-B model (Michie et al., 2011) highlights that autonomous motivation can strengthen people's capacity and willingness to adopt new habits. Therefore, self-selected goals may lead to larger behavior

change. Yet empirical evidence remains limited because few studies cleanly separate the role of goal selection from differences in expected rewards or difficulty, and very few use high-frequency, objective measures of total smartphone use.

The present study aims to address these gaps. We evaluate whether self-selected screen-time reduction goals reduce daily smartphone use more than assigned goals under equivalent average goal levels and identical incentives. Participants in the self-selected condition chose a reduction goal from predefined options. Participants in the assigned condition received a goal equal to the average goal selected by the self-selected condition. Regardless of the goal level, participants in both intervention conditions received the same monetary incentive for achieving their goal. This design reduces the typical confounding between goal levels and expected rewards and allows a direct comparison between self-selected and assigned goals under a fixed incentive structure.

We examine these questions using a twelve-week randomized controlled trial conducted among students and employees of a large academic institution in India. We randomized 149 participants across three arms, and weekly submissions of screenshots from the digital well-being application on participants' smartphones generated more than 9,000 person-day observations of daily screen time. Participants could earn small daily monetary incentives for achieving their goal. The study was preregistered on AsPredicted (ID: 142497), and the protocol is publicly available (Sharma et al., 2024). The primary outcome was daily goal achievement. Secondary outcomes included average daily smartphone use during and after the intervention, as well as psychological measures including depression (PHQ-9), anxiety (GAD-7), and perceived phone addiction. Because treatment assignment was randomized, the trial provides causal estimates of the effects of self-selection on goal achievement and screen-

time reduction within this intervention design. The mental-health outcomes were also preregistered, although causal interpretation requires caution because psychological change reflects multiple influences and follow-up response rates were lower.

By situating self-selected goal setting within a randomized design and pairing it with high-frequency, objective measures of digital behavior, this study contributes new evidence to research on digital well-being and health behavior. The findings have implications for public-health and digital-wellness interventions in workplaces, universities, and community settings that aim to help individuals regulate smartphone use. More broadly, the study adds nuance to ongoing public-health discussions about screen time and mental health by examining a theoretically grounded mechanism within a real-world population.

2. Experimental design and methodology

We conducted a three-arm randomized controlled trial among students and employees of a large academic institution in India. We preregistered the study on AsPredicted (https://aspredicted.org/hr3nn.pdf) and published a detailed data-collection and pre-analysis plan as a protocol paper (Sharma et al., 2024; protocol available [here]). All de-identified data and replication code are publicly available on the Open Science Framework (**here**) to support transparency and reproducibility.

The intervention lasted five weeks and was followed by a four-week post-intervention tracking period. This extended duration exceeds that of comparable field experiments on digital behavior (Allcott et al., 2022; Somasundaram et al., 2025) and allows us to examine patterns of goal adherence and behavioral persistence over the medium term.

2.1 Study design and participants

We recruited participants from the employee and student population of a large academic institution in India. A total of 156 individuals enrolled in the study (60 females; mean age = 31.73, SD = 7.18). Appendix Figure S2 presents the CONSORT diagram. The Institutional Review Board at the Indian School of Business (ISB) approved all procedures, and the study followed the published protocol (Sharma et al., 2024).

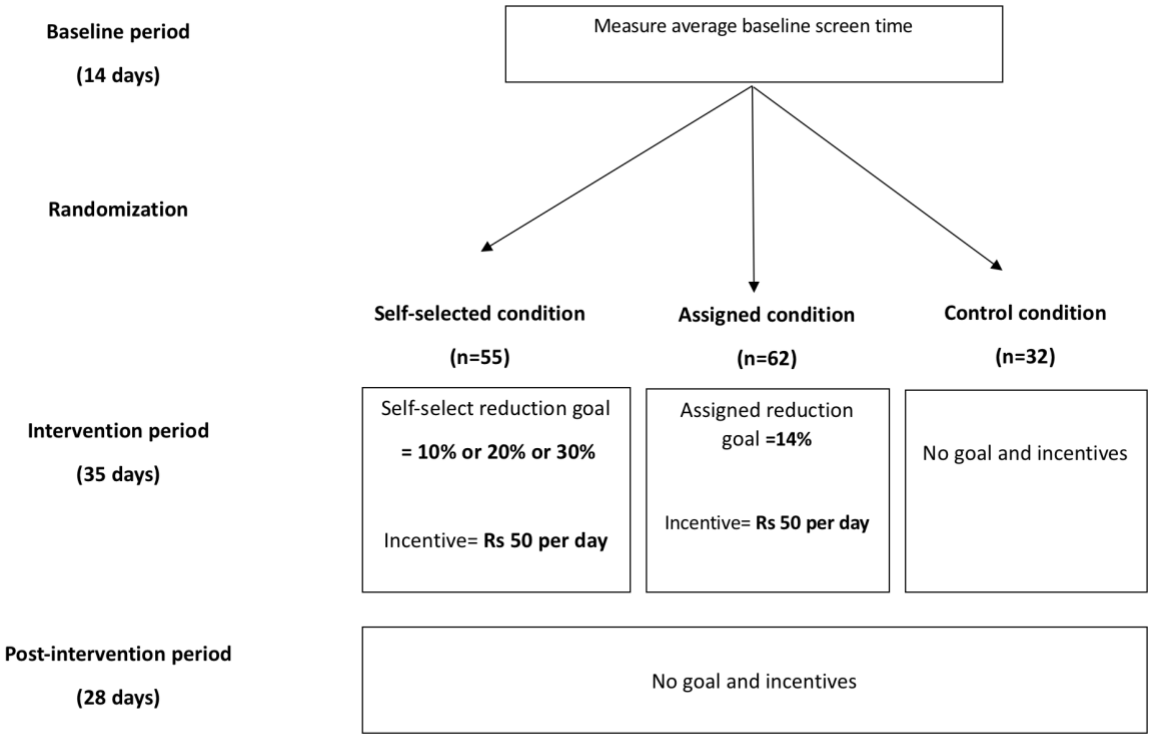
We compensated each participant with a fixed participation fee of ₹500 (approximately USD 6). Participants could earn an additional ₹0–₹1750 (approximately USD 21) during the intervention, depending on their performance. Incentive payments were made at the end of the intervention period, while the participation fees were paid after the post-intervention period. Participants who completed all surveys were also eligible for a lottery with two prizes of ₹5000 (approximately USD 60) each.

Eligibility required ownership of an Android smartphone with the built-in Digital Wellbeing app. Participants enabled the app and reported their daily screen time though a weekly survey and by uploading a screenshot.

The study lasted 84 days and comprised four phases: a 14-day pre-intervention baseline, a 7-day randomization, a 35-day intervention, and a 28-day post-intervention phase (Figure 1; see Appendix Figure S1 for the detailed timeline). During baseline, participants reported their daily phone usage without any intervention. After the baseline, we randomly assigned participants in a 2:2:1 ratio to one of three conditions: (i) self-selected goal, (ii) assigned goal, or (iii) control. Randomization was stratified by baseline phone use, gender, and employee-versus-student status.

Of the 156 individuals who enrolled, 149 completed the baseline period and were randomized across the three conditions. We allocated more participants to the intervention conditions to ensure adequate power to compare self-selected and assigned conditions (see Sharma et al., 2024, for power calculations). The final dataset contained 9,290 person-day screen-time observations.

Figure 1: Experimental design of the study.



2.2 Intervention:

Following the pre-intervention baseline and randomization, all participants received an informational handout describing the potential benefits of reducing mobile phone use. Participants in the control condition did not receive a goal or any monetary incentives.

Participants in the self-selected condition chose one of three reduction goals relative to their baseline average daily usage: 10%, 20%, or 30%. A pilot study confirmed that these goals were salient, comparable, and achievable, and the discrete set of options kept the decision simple and easy to interpret. Participants earned ₹50 (approximately USD 0.60) for each day they achieved their self-chosen goal. Although the 10% reduction goal offered the easiest path to earning incentives, several participants chose higher goals, likely using them as commitment devices to strengthen self-control (Brocas et al., 2004; Bryan et al., 2010).

Among participants in the self-selected condition, 14.5% chose the 20% goal, 11% chose the 30% goal, and the remaining participants selected the 10% goal. The resulting average chosen goal was 14 percent. During the randomization week, after participants in the self-selected condition chose their goals and before the intervention period began, we assigned this same 14 percent reduction goal to participants in the assigned condition to enable comparisons across the two conditions under equivalent average goal levels and identical incentives. Participants in the assigned condition received the same daily incentive of ₹50 for each day they achieved their goal.

2.3 Data collection

All participants completed a baseline survey at enrollment and a follow-up survey at the end of the intervention period. These surveys recorded demographic characteristics, perceived

phone addiction, and psychological well-being using validated instruments for depression (PHQ-9) and anxiety (GAD-7). Detailed descriptions of these scales appear in the published protocol (Sharma et al., 2024).

We collected phone-usage data through weekly online surveys. Participants reported their daily screen-time by entering usage for each day and uploading a screenshot from the Digital Wellbeing application for verification. The screenshots display daily usage for the entire week in the form of a bar chart (Appendix Figure S3), which allowed us to cross-check the values entered in the survey against the corresponding graphical records. Research assistants conducted random audits of submissions by comparing reported values with screenshots and, for a subset of participants, verifying usage directly on participants' phones. No systematic discrepancies were detected, and any minor inconsistencies identified during audits were resolved using the screenshot records. These procedures provide some reassurance regarding the reliability of the usage data. Similar approaches combining self-reported and device-based measures have been used in prior work (Lipman, Pogliano, et al., 2026; Somasundaram et al., 2025).

During the 28-day post-intervention period, participants continued to report their daily phone usage using the same procedure. They no longer received goals or monetary incentives during this phase, which allowed us to observe whether behavioral changes persisted after incentives were removed.

2.4 Measures

We measured psychological outcomes to assess how reductions in smartphone use affected well-being. Prior correlational studies associate higher screen time with elevated anxiety,

depressive symptoms, and perceived dependence on mobile devices (Hisler et al., 2020; Thomée et al., 2011; Twenge & Campbell, 2018; Volkmer & Lermer, 2019). Evidence on whether experimentally reducing phone use improves psychological health remains limited and mixed, and most studies rely on self-reported digital behavior (Odgers & Jensen, 2020; Orben & Przybylski, 2019). By collecting validated measures before and after the intervention, we test whether randomized reductions in phone use corresponded with measurable changes in mental health and perceived addiction.

Perceived addiction:

We assessed perceived phone addiction using an eight-item scale adapted from prior work (Allcott et al., 2022; Andreassen et al., 2012; Bianchi & Phillips, 2005). Items captured maladaptive use (for example, "I check my phone immediately after waking up") on a 1–5 Likert scale, with higher values indicating stronger feelings of dependence. The full set of items appears in the published protocol (Sharma et al., 2024).

Depression and anxiety:

We measured depressive and anxiety symptoms using the Patient Health Questionnaire (PHQ-9) and the Generalized Anxiety Disorder scale (GAD-7). Both instruments are widely validated self-report measures with strong psychometric reliability and established screening thresholds (Kroenke et al., 2001; Spitzer et al., 2006). Higher scores indicate greater symptom severity.

Depression and anxiety were measured only at baseline and at the end of the intervention, consistent with standard practice in digital well-being trials.

2.5 Estimation strategy

We analyzed treatment effects on goal achievement and daily phone use using both model-free comparisons and regression-based methods. Model-free analyses compare mean outcomes across conditions to provide transparent, unadjusted differences.

Phone usage

To estimate the adjusted effects, we estimated a difference-in-differences (DiD) ordinary least squares (OLS) model to quantify changes in daily phone usage across experimental phases and treatment arms. The specification (Sharma et al., 2024; Appendix A1) included indicator variables for treatment conditions (with self-selected as the reference), time periods (with baseline as the reference), and their interactions. The interaction terms captured the change in average usage from baseline in each condition relative to the self-selected condition. We control for age, gender, and student or employee status, and cluster standard errors at the participant level.

As a robustness check, we additionally estimated models with participant fixed effects and day fixed effects to account for within-person dependence and common time shocks. These specifications address the panel structure of the data (Appendix Table S3).

Goal achievement.

To estimate the adjusted effects, we estimated logistic regression models for both the intervention and post-intervention periods. We exclude baseline and control condition observations because they did not involve goal setting. For each period, we regressed a binary indicator of daily goal achievement (1 = goal achieved, 0 = otherwise) on a treatment indicator (with self-selected as the reference), controlling for age, gender, baseline usage, and

student or employee status. Standard errors were clustered at the subject level. We also estimated a DiD specification for goal achievement consistent with the preregistered analysis plan described in the protocol and detailed in the Appendix (Appendix Table S5).

Missing data.

The analysis uses all available daily observations under a missing-at-random (MAR) assumption. Of the 11,473 potential participant-day observations (149 × 77), approximately 19% were missing. There was no significant difference in missing observations across the conditions (Control: 21.0%, Assigned: 19.6%, Self-selected: 17.1%).

2.6 Exploring potential mechanisms

To explore potentials explanations for differences in performance between the self-selected condition and the assigned condition, we examined two theoretically relevant mechanisms:
(i) **Goal achievability,** whereby participants may have chosen goals aligned with their perceived ability, making them potentially easier to achieve; and
(ii) **Participation and ownership**, whereby the act of choosing one's own goal may have increased psychological ownership and intrinsic motivation, leading to higher goal achievement.

These analyses are exploratory and are intended to provide suggestive evidence on potential mechanisms rather than definitive tests of causal pathways.

To assess these channels, we collected two self-reported measures at the start of the intervention period:

1. Perceived goal difficulty. Participants rated the expected difficulty of their goal on a 1–7 scale (1 = very easy, 7 = very difficult). This measure captured participants' subjective perceptions of goal achievability.
2. Expected goal achievement. Participants reported how many days (out of 35) they expected to meet their goal during the intervention period. This measure reflected participants' initial beliefs about their ability to sustain behavioral change.

We compared these measures across the self-selected and assigned conditions, and across the three goal levels (10%, 20%, and 30%) within the self-selected condition. We then examined whether perceived difficulty or expected success predicted actual reductions in smartphone use and daily goal achievement. If performance gains were primarily driven by achievability, self-selected participants would be expected to report lower perceived difficulty and higher expected success. Conversely, if participation and ownership contributed to the observed differences, perceived difficulty and expectations might be similar across conditions, even if performance differed.

2.7 Smartphone use and psychological outcomes

We examined whether reductions in mobile phone usage during the intervention period were associated with changes in perceived addiction, depression, anxiety, and daily mood. All psychological outcomes (perceived addiction, depression, and anxiety) were measured at baseline and at the end of the intervention using validated self-report scales described earlier.

To capture short-term affective states, we also collected daily mood ratings. Participants received a WhatsApp prompt at a random time each day and rated their mood on a scale from

1 (“absolutely miserable”) to 10 (“absolutely happy”). This measure provided a high-frequency indicator of day-to-day emotional well-being during the intervention period.

We compared baseline and end-of-intervention psychological scores within each experimental condition. For each measure, we calculated standardized effect sizes to summarize the magnitude of change, using Cohen’s *d* for paired samples and reporting 95 percent confidence intervals. We tested within-group changes with paired *t*-tests.

To examine whether improvements in psychological outcomes are associated with behavioral change, we estimated linear regression models relating reductions in daily screen time and rates of goal achievement to changes in perceived addiction, depressive symptoms, and anxiety symptoms. These models controlled for baseline usage, age, gender, and student or employee status. This approach allowed us to assess whether individuals who reduced their phone use more substantially also reported improvements in psychological well-being, while recognizing that these associations do not alone establish causal effects on mental health.

As a complementary analysis, we also estimated regression models of post-intervention psychological outcomes as a function of treatment assignment, controlling for baseline values and demographic covariates. These models provide direct tests of between-group differences in psychological outcomes across randomized arms.

3. Results

Baseline characteristics were balanced across conditions, confirming successful randomization (Appendix Table S1). The proportion of days with missing screen-time reports did not differ significantly by condition. Table 1 summarizes average outcomes across treatment conditions.

Table 1: Averages outcomes and 95% CI by treatment and goal: usage reduction, goal achievement, and perceptions.

Condition	Goal	Intervention period reduction (minutes)	Goal achievement. rate (%)	Perceived goal difficulty (1-7)	Beliefs about goal achievement (# days out of 35)
Assigned	14% (n=62)	22.76 [6.93, 38.59]	47.2 [39.55%, 54.84%]	4.61 [4.21, 5.02]	26.75 [24.18, 29.31]
Self-selected	Overall	49.17 [29.39, 68.96]	58.3 [50.46%, 66.14%]	4.85 [4.48, 5.22]	24.57 [22.39, 26.76]
	10% (n=41)	40.67 [19.01, 62.31]	60.3 [51.87%, 68.73%]	4.8 [4.40, 5.24]	23.7 [21.27, 26.91]
	20% (n=8)	44 [-11.47, 99.46]	42.2 [22.5%, 61.7%]	5.25 [4.38, 6.11]	26.87 [21.43, 32.32]
	30% (n=6)	93.48 [36.95,150]	68.6 [44.49%, 92.71%]	4.4 [2.54, 6.46]	24.16 [18.03, 30.30]

Notes: Subgroup estimates for the 20% and 30% goals are based on small sample sizes (n=8 and n=6, respectively) and should be interpreted as illustrative only.
The 95% CI for columns 1 and 2 were computed based on standard errors clustered at subject level accounting for repeated observation of the subject i.

3.1 Model-free evidence

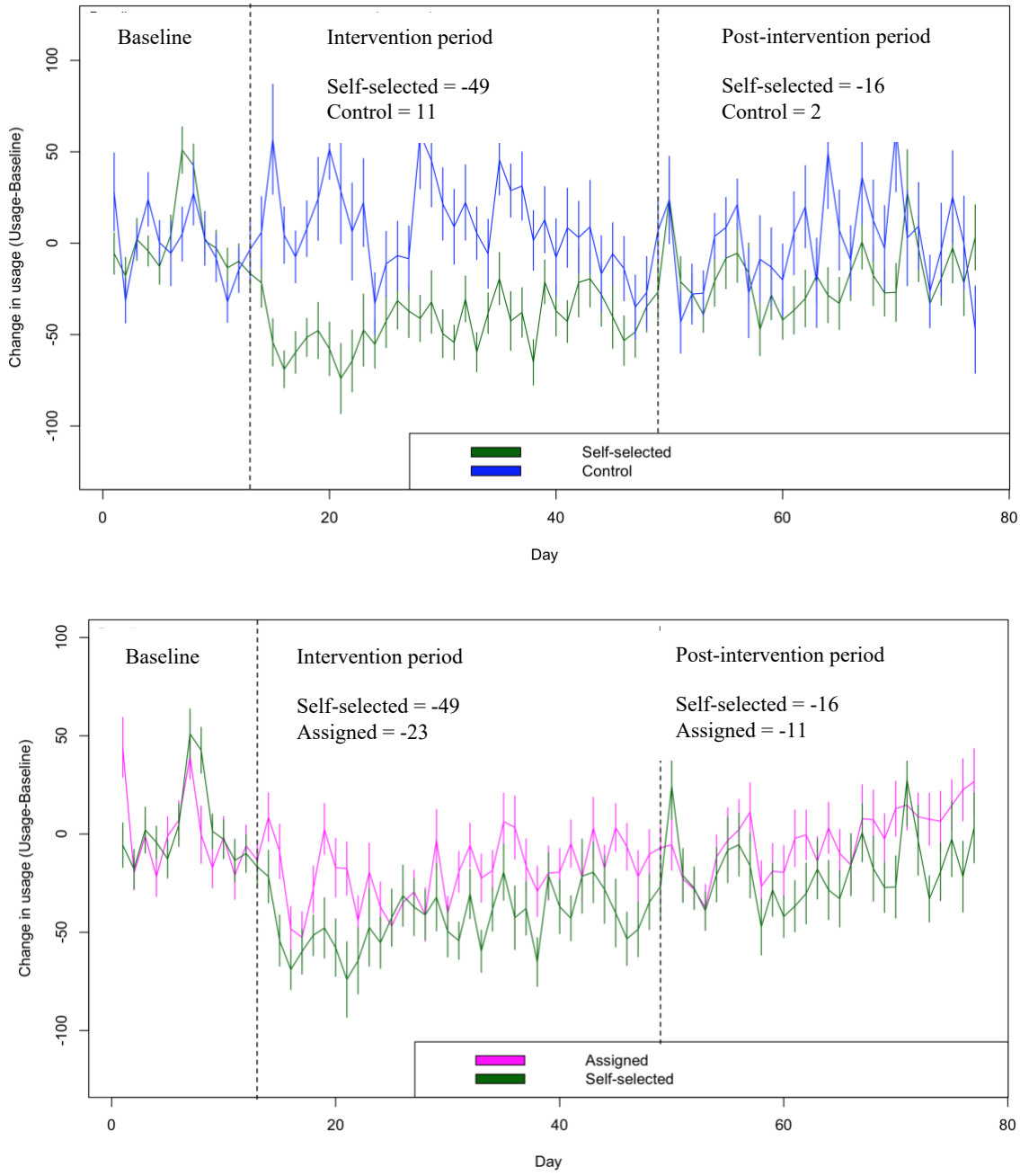
3.1.1 Reduction in usage

Figures 2a and 2b present model-free changes in daily phone use relative to baseline. Usage levels were indistinguishable across the three conditions during the baseline period ($p = .99$), confirming balance in pre-intervention behavior.

During the intervention, participants in the self-selected condition showed the largest reduction in average daily screen time. Their usage fell by approximately 49 minutes per day relative to baseline. Participants in the assigned condition reduced their daily use by an average of 23 minutes. In contrast, participants in the control condition increased their use by roughly 11 minutes per day over the same period.

Reductions in phone use persisted into the post-intervention period in both intervention conditions. Participants in the self-selected condition continued to use their phones about 16 minutes less per day than at baseline, while participants in the assigned condition used their phones about 11 minutes less per day than baseline. In contrast, phone use in the control condition was two minutes higher than baseline.

Figure 2 (a)-(b): Average change in daily phone usage relative to baseline.

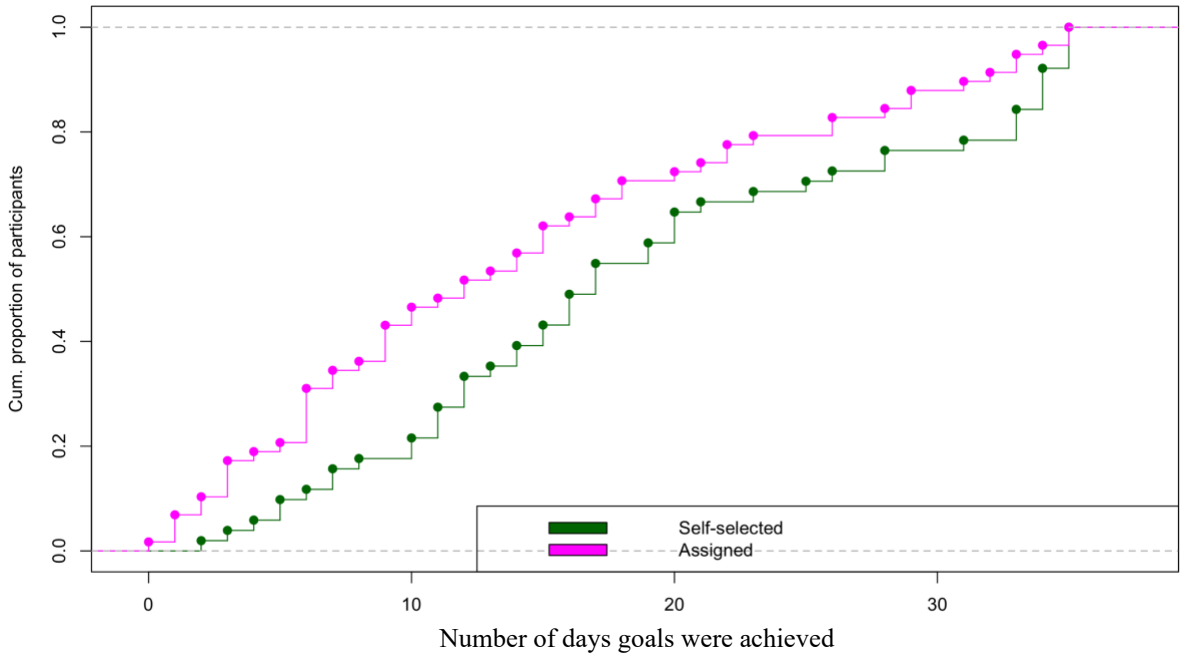


3.1.2 Goal achievement

We next compared goal achievement between the assigned and self-selected conditions. During the intervention period, the average goal achievement rate in the self-selected condition (58.3%) was 11.2 percentage points higher than in the assigned condition (47.1%, p = .03; see Table 1). The cumulative distribution functions in Figure 3 show this difference clearly. The curve for the self-selected condition lies to the right of the assigned condition

across most of the distribution, indicating that a larger share of participants in the self-selected condition achieved their goals on more days overall compared with those in the assigned condition.

Figure 3: Cumulative distribution of days participants achieved their goal (self-selected vs. assigned).



3.2 Regression analysis

3.2.1 Usage

Table 2 presents the DiD regression results for daily mobile phone usage across treatment conditions.

Table 2: Effect of treatments on daily phone usage across experimental periods.

	Dependent variable:
	Usage on day t
Control	-11.673
	(22.855)
Assigned	-4.202
	(20.292)
Intervention period	-48.314***
	(10.112)
Post-intervention period	-14.984
	(13.114)
Gender male	23.862
	(16.922)
Age	-2.395
	(1.270)
Student	-10.120
	(20.195)
Control x Intervention period	61.219***
	(17.710)
Assigned x Intervention period	26.202*
	(12.837)
Control x Post-intervention period	17.430
	(23.711)
Assigned x Post-intervention period	6.747
	(16.628)
Constant	348.536***
	(43.250)
Observations	9,290
R2	0.037
Adjusted R2	0.036
Residual Std. Error	133.252 (df = 9278)
F Statistic	32.739** (df = 11; 9278)

Notes: * p<.05 ** p<.01 *** p<.001, Standard errors clustered at subject level. Reference =Self-selected, Baseline period, Female, Employee.

Consistent with the model-free comparisons, baseline usage did not differ across conditions; the treatment-condition coefficients for the baseline period were small and statistically indistinguishable from zero.

The interaction terms between treatment and period indicators capture differential changes in usage during the intervention relative to the self-selected condition. During the intervention period, participants in the self-selected condition reduced their phone usage on average by 61.2 minutes more than the control condition ($p = .001$) and 26.2 minutes more than the assigned condition ($p = .042$). Participants in the assigned condition reduced their usage on average by 35.0 minutes more than the control condition ($p = .036$). This indicates that the reduction in the self-selected condition was approximately 73 percent greater than in the assigned condition, despite identical incentives and equivalent average goal levels.

During the post-intervention period, participants in the self-selected condition continued to use their phones less than those in the control and assigned conditions (17 minutes and 7 minutes less, respectively), although these differences were not statistically significant (ps > .40).

The results are robust to alternative specifications including models without controls (Appendix Table S2), and with participant and day fixed effects that account for within-person dependence and common time shocks (Appendix Table S3).

3.2.2 Goal achievement

Regression estimates and marginal effects are presented in Table 3, using the self-selected condition as the reference category.

Table 3: Effect of treatments on goal achievement during the intervention and post-intervention periods.

	Dependent variable: Goal achievement (1/0) on day t			
	Intervention period		**Post-intervention period**	
	Coefficients	Marginal effects	Coefficients	Marginal effects
Assigned	-0.475**	-0.112*	-0.228	-0.053
	(0.223)		(0.212)	
Gender (Male)	-0.712***	-0.15**	-0.373	-0.088
	(0.230)		(0.231)	
Age	0.025*	0.003	0.006	0.0015
	(0.013)		(0.015)	
Student	-0.371	-0.08	-0.789***	-0.18
	(0.251)		(0.284)	
Baseline	0.002	0.004	0.0001	0.000
usage	(0.001)		(0.001)	
Constant	-0.168		-0.029	
	(0.645)		(0.678)	
Observations	3,479		2,394	
Log Likelihood:	-2,297.565		-1,579.485	
AIC:	4,607.131		3,170.970	

Notes: * p<.05 ** p<.01 *** p<.001, Standard errors clustered at subject level. Reference = Self-selected, Baseline period, Female, Employee. Control condition and baseline period is excluded from the analyses as they do not have goals

During the intervention period, participants in the self-selected condition achieved their daily goals on average 11.2 percentage points more often than those in the assigned condition ($p <$ .05), even though both conditions faced equivalent average goal levels and identical monetary incentives.

During the post-intervention period, participants in the self-selected condition continued to achieve their goals more frequently, by an average of 5.3 percentage points. This difference

was not statistically significant (p = .28), but it is directionally consistent with the intervention-period pattern.

Overall, the results mirror the usage reduction findings. The results remain robust across alternative model specifications, including logit models estimated without covariates (Appendix Table S4) and difference-in-differences linear probability and logit models (Appendix Tables S5–S6) detailed in the protocol paper.

3.3 Exploring potential mechanisms

We next examine whether the superior performance in the self-selected condition can be explained by differences in goal achievability or by the effects of participation and ownership. Table 1 summarizes goal achievement, reduction in phone usage, perceived goal difficulty, and expected goal attainment across conditions.

Average perceived difficulty did not differ significantly between the self-selected and assigned conditions (self-selected: 4.85 vs. assigned: 4.61; $p = .38$), suggesting that participants viewed their goals as similarly achievable. We also compared perceived difficulty across the three self-selected goal levels (10%, 20%, 30%) and the assigned condition (14%). None of these differences were statistically significant (10% = 4.8; 20% = 5.25; 30% = 4.4; assigned = 4.61).

Expectations about success also did not vary across conditions. On average, participants in the self-selected condition expected to achieve their goals on 24.6 of 35 days, compared with 26.8 days in the assigned condition ($p = .20$). Within the self-selected condition, expected goal achievement did not show a clear pattern across goal levels (10% = 23.7 days; 20% =

26.9 days; 30% = 26.0 days). Across conditions, participants reported similar expectations about goal attainment.

These subgroup comparisons are based on small numbers of participants in the higher goal categories and should be interpreted as illustrative only.

These patterns suggest that differences in perceived achievability or expected success are unlikely to fully explain the higher goal achievement observed in the self-selected condition. However, these measures are based on self-reports and the subgroup comparisons rely on relatively small samples, limiting the strength of inference. We discuss the potential mechanisms further in the Discussion.

3.4 Reductions in smartphone use and psychological outcomes

We assessed whether reductions in daily smartphone use were associated with changes in perceived addiction, anxiety, and depression. These psychological outcomes were secondary endpoints. Baseline averages for PHQ-9, GAD-7, and perceived addiction differed slightly across conditions, so we interpret the results with appropriate caution.

Of the 149 randomized participants, 93 completed both the baseline and end-of-intervention mental-health assessments. Attrition was balanced across treatment arms and showed no systematic association with baseline phone use, demographics, or treatment status. Among these respondents, the pattern of reductions in smartphone use closely matched the full sample: participants in the self-selected condition showed the largest average decline in daily use, followed by those in the assigned condition, while usage in the control condition remained largely unchanged (Appendix Table S7).

This subsample allows us to examine within-person changes in psychological outcomes in relation to reductions in phone use. Although the study was not powered to detect small changes in mental-health scores, the consistency of behavioral patterns across the full sample and the balanced attrition provide some reassurance about the comparability of participants who completed follow-up. Even so, the mental-health findings should be viewed as suggestive rather than definitive, and we interpret them as preliminary evidence on how reductions in smartphone use may relate to changes in perceived dependence and psychological well-being.

As a complementary analysis, we estimated regression models of post-intervention outcomes as a function of treatment assignment, controlling for baseline values and demographic covariates. The estimated differences are directionally consistent with larger improvements in the self-selected condition but are imprecisely estimated and not statistically significant (Appendix Table S8).

3.4.1 Perceived Addiction

Perceived addiction scores declined from baseline to the end of the intervention in both treatment conditions. Participants in the self-selected condition reported a statistically significant reduction (Cohen's d = 0.33, 95 percent CI [0.06, 0.60], p = .02), and those in the assigned condition showed a similar decrease (Cohen's d = 0.26, 95 percent CI [0.01, 0.52], p = .03). Perceived addiction did not change in the control condition (Cohen's d = 0.25, 95 percent CI [-0.11, 0.63], p = .17) (Appendix Table S7).

Reductions in daily phone use were associated with lower perceived addiction, even after adjusting for baseline usage, age, gender, and student or employee status. Each hour of reduced screen time corresponded to a 0.12-point decline in perceived addiction (p = .04). Goal achievement showed a similar pattern. Each additional day a participant achieved their goal was associated with a 0.019-point reduction in perceived addiction (p = .02; Appendix Tables S9 and S10).

Taken together, these findings indicate that both reducing daily phone use and consistently meeting one's goal were linked to modest decreases in perceived addiction.

3.4.2 Mental health

Depression

We assessed changes in depressive symptoms using the PHQ-9 scale. Scores declined significantly from baseline to the end of the intervention in the self-selected condition (Cohen's d = 0.39, 95% CI [0.02, 0.76], p = .03), but not in the assigned (Cohen's d = 0.17, 95% CI [-0.07, 0.42], p = .16) or control conditions (Cohen's d = 0.16, 95% CI [-0.06, 0.39], p = .14) (Appendix Table S7). These within-group changes are directionally consistent with the larger reductions in phone use observed in the self-selected condition.

Reductions in daily phone use were significantly associated with improvements in depressive symptoms after controlling for baseline usage, age, gender, and employment status. Each minute of reduced phone use corresponded to a 0.016-point decrease in the PHQ-9 score (p = .04), implying that a sixty-minute reduction in daily use was associated with approximately one-point improvement in PHQ-9 score. Goal achievement showed a similar pattern. Each

additional day a participant reached their daily goal was associated with a 0.16-point decrease in PHQ-9 score (p = .02; Appendix Tables S11–S12).

These results suggest that both reductions in phone use and consistent goal attainment were associated with lower depressive symptoms, with larger within-group changes observed in the self-selected condition.

Anxiety

We measured anxiety symptoms with the GAD-7 scale. Anxiety declined significantly from baseline in the self-selected condition (Cohen's d = 0.62, 95% CI [0.21, 1.04], p = .002), while changes in the assigned (Cohen's d = 0.005, 95% CI [-0.28, 0.29], p = .90) and control conditions (Cohen's d = 0.29, 95% CI [-0.04, 0.64], p = .09) (Appendix Table S7) were not statistically significant.

Patterns differed from those observed for depression. Reductions in phone use were not significantly associated with changes in anxiety (β = 0.003, p = .75). Instead, goal achievement showed a stronger association with anxiety symptoms. Participants who met their goals more frequently showed greater reductions in GAD-7 scores (β = −0.13, p = .03). Over the thirty-five-day intervention, achieving goals on eighteen days was associated with an improvement of roughly 2.3 points on the GAD-7 scale (Appendix Tables S13–S14).

These results suggest that goal attainment was more strongly associated with reductions in anxiety symptoms than reductions in phone use.

3.4.3 Mood

We also examined daily mood using a 10-point rating scale collected through a WhatsApp prompt delivered at random times during the day. Average mood did not change significantly from baseline to the end of the intervention in any of the three conditions, and mood levels were not meaningfully associated with overall reductions in screen time or with average goal attainment (Appendix Table S15). However, participants in better moods were more likely to meet their goals on a given day ($p = .048$; Appendix Table S16), suggesting that positive affect may facilitate short-term goal achievement even if not directly influenced by the intervention.

Across behavioral and psychological outcomes, participants in the self-selected condition reduced daily phone use more and showed the largest within-group declines in perceived addiction, depressive, and anxiety symptoms. However, between-group differences in psychological outcomes were imprecisely estimated and do not support strong conclusions about differences across conditions. Taken together with the behavioral analyses, these findings are consistent with the possibility that larger reductions in phone use may be associated with improvements in psychological outcomes.

4. Discussion and Conclusion

This randomized controlled trial evaluated whether allowing individuals to choose their own smartphone-use reduction goals leads to stronger behavioral and psychological outcomes than assigning comparable goals. When average goal levels and incentives were held constant, participants who selected their own goals reduced their daily phone use more than those who were assigned goals. They also achieved their goals more frequently and showed

larger within-group improvements in perceived addiction, depression, and anxiety. Participants in the self-selected condition reduced their daily usage by an average of 61 minutes relative to baseline, compared with a 35-minute reduction in the assigned condition (approximately 26 minutes more, or about 73% larger than the assigned condition), and achieved their daily goals 11 percentage points more often.

These findings suggest that allowing individuals to choose their own goals may strengthen engagement and support healthier digital behavior. Even modest opportunities for choice, introduced within a structured intervention, produced meaningful changes in daily phone use. This pattern is consistent with research in health psychology, which identifies autonomy and ownership as key drivers of sustained behavior change (Ryan & Deci, 2000). Interventions that incorporate opportunities for user choice may help individuals align their technology use with personal intentions, an increasingly important aim in digital-health practice.

We conducted exploratory analyses to examine potential explanations for the superior performance observed in the self-selected condition. Participants who selected their own goals did not view them as easier or expect to meet them more often than those who received assigned goals. These similarities suggest that perceived achievability alone is unlikely to fully account for the observed differences. However, several other mechanisms could also explain these differences (Lipman, Alvarez Colic, et al., 2026), and our study was not designed to distinguish among them. One possibility is participation and ownership, whereby selecting a goal increased participants' sense of ownership, which may have enhanced intrinsic motivation and engagement in pursuing the goal. Another possibility is sorting, whereby self-selection allowed participants to choose goals that better matched their individual preferences and circumstances. Another possibility is commitment following goal

selection, whereby selecting a goal strengthened commitment to that choice, making participants more likely to follow through on it. Because our design does not directly measure these mechanisms or separately identify the effects of sorting into goal levels from the effects of self-selection, we interpret the results as reflecting the combined effect of self-selection under this design rather than any single underlying mechanism. Future research could further disentangle these mechanisms.

A related design consideration is that goal difficulty may not scale linearly with percentage reductions in screen time. Although we match the average goals across intervention conditions, differences in the distribution and structure of goals may still translate into differences in experienced difficulty if reductions are not proportional in effort. The goal structure also differed across conditions: participants in the self-selected condition chose from a discrete set of options, whereas participants in the assigned condition received a single goal. Our measures of perceived difficulty and expected success do not indicate systematic differences across conditions, although they may not fully capture such dynamics. An alternative approach would be to randomly allocate participants in the assigned condition across the same set of goal levels as those available in the self-selected condition. Such a design would require additional structure to separately identify the effects of goal levels and self-selection, and we view this as a useful direction for future research.

Although mental-health outcomes were secondary endpoints, the psychological outcomes followed a broadly similar pattern, although these analyses were less precisely estimated. Participants in the self-selected condition reported reductions in perceived addiction, depressive, and anxiety symptoms, while changes in the assigned and control conditions were smaller or not statistically significant. These patterns should be interpreted cautiously, as

even though the between-group estimates in psychological outcomes followed the same directional pattern as the behavioral outcomes, the sample size for these analyses was limited and the between-group differences were not statistically significant. Nonetheless, the consistency between behavioral and psychological patterns is consistent with the possibility that improved self-regulation may be associated with better well-being. This interpretation aligns with evidence linking heavy or compulsive smartphone use with emotional distress (Hisler et al., 2020; Thomée et al., 2011; Twenge & Campbell, 2018; Volkmer & Lermer, 2019a). The effect sizes observed here fall within the range reported for brief digital or behavioral interventions targeting mental health (Howarth et al., 2018; Ly et al., 2014; Svärdman et al., 2022).

From a public-health perspective, the findings contribute in several ways. Given the global rise in daily smartphone engagement, autonomy-supportive goal-setting may represent a promising behavioral tool for improving digital self-regulation across diverse populations. First, the results provide causal evidence on a scalable strategy that may help individuals who wish to moderate their smartphone use. Many adults and adolescents report that they spend more time on their phones than they intend to, and they express a desire for support in regulating daily use. Prior interventions have relied on externally imposed limits or large financial incentives. For example, Allcott et al. (2022) offered substantial compensation for reduced use, and Somasundaram et al. (2025) assigned a fixed 30 percent reduction goal. Both achieved reductions of roughly one hour per day. In this study, participants with self-selected goals achieved a comparable reduction despite smaller incentives and more moderate goals. These findings indicate that incorporating opportunities for goal selection can produce sizable reductions in total daily phone use and may be feasible to implement within existing digital-health tools, workplace wellness programs, or educational settings.

Second, the study contributes to ongoing debates about screen time and mental health by moving beyond correlational associations. Total daily phone use captures a broad set of digital activities, including communication, entertainment, browsing, and social media. It may therefore serve as a more comprehensive indicator of overall digital exposure than platform-specific metrics. Although the mental-health findings should be interpreted with caution, the direction and magnitude of changes observed here are consistent with the possibility that reducing total smartphone use may be associated with improvements in psychological well-being for some individuals.

Third, the results highlight the importance of participatory approaches in digital-health interventions. Incorporating even limited opportunities for choice may enhance adherence and engagement. These insights may extend to other health domains where motivation and self-regulation are central, such as physical activity, diet, sleep, and stress management.

The findings also provide practical guidance for public-health intervention design. Allowing individuals to set their own behavioral goals may strengthen adherence even when incentives and average goal levels remain constant. Because opportunities for goal selection are relatively easy to incorporate into digital-health tools and wellness programs, self-selection may offer a scalable approach to promoting healthier digital behavior.

The study has limitations. First, although the intervention lasted five weeks and was followed by four weeks of post-intervention tracking, long-term persistence remains uncertain. The self-selected condition continued to show reduced use during the post-intervention period, but the differences were not statistically significant. Longer engagement or periodic

reinforcement may be required to sustain change. Second, the study population consisted of students and employees of a single academic institution. This setting provided a relatively controlled setting and high compliance, but generalizability to other populations should be examined in future work. Third, only 63 percent of participants completed both mental-health assessments. Although attrition was balanced across conditions and unrelated to baseline characteristics, the reduced sample limits statistical power for detecting psychological effects. Finally, we measured total daily phone use rather than specific categories of use. While total use is a policy-relevant outcome, future research could investigate whether changes in particular types of digital activity have distinct effects on well-being (Collis & Eggers, 2022). Requiring participants to upload screenshots may also have increased participant burden and could affect representativeness, although attrition rates were similar across conditions.

An additional limitation concerns the interpretation of comparisons with the control condition. Participants in the control condition did not receive goals or monetary incentives. As a result, comparisons between the treatment conditions and the control condition reflect a combination of goal-setting, incentives, and engagement, and do not isolate the effect of goal-setting alone. Our primary analysis focuses on the comparison between the self-selected and assigned goal conditions, where incentives are held constant.

Despite these limitations, the findings provide evidence that allowing individuals to choose their own goals can enhance digital self-regulation and support well-being. Goal selection is a simple feature that can be incorporated into a wide range of digital-health tools and public-health programs. As digital engagement continues to rise and concerns about dependence and mental health grow, interventions that incorporate user choice may offer an effective and scalable pathway toward healthier digital habits.

Future research should examine dynamic or adaptive goal-setting strategies, evaluate longer-term effects, and test such interventions in more diverse populations. Understanding how goal-selection interacts with feedback, social support, and environmental cues will advance both theory and practice in digital health and behavioral self-regulation.

Declaration of competing interest

The authors declare no competing interests.

Data and code availability

The data and code supporting the study is available at the OSF link here.

Use of AI

During the preparation of this work the author(s) used ChatGPT in order to improve language and readability of the article. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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