Leveraging Intrinsic Motivation and Readiness to Change to Address User Attrition in Digital Self-Control Tools: A Quasi-Experimental Study of Nudge Reconfiguration Interventions

Awen Kidel Peña--Albert, Sandy Ingram, Yasser Khazaal, Léo Litrico, Juan Carlos Farah, Denis Gillet

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Abstract

Background: Digital self-control tools have emerged as technological interventions to address excessive smartphone usage and promote digital wellbeing. However, these tools face persistent challenges with user attrition and sustained engagement, compromising their long-term effectiveness. Current literature lacks understanding of the psychological mechanisms that drive user retention and meaningful interaction with DSCTs, particularly how intrinsic motivation and readiness to change influence sustained engagement patterns.

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Methods: We conducted a quasi-experimental study (n=252) targeting passive users at risk of churning from a DSCT mobile application. Participants were randomly assigned to receive an invitation to reconfigure their nudge settings during daily check-ins (experimental group, n=138) or to a control condition (n=114, no intervention). The experimental group was further classified into acceptance and rejection subgroups based on their response to the intervention. Data collection included system usage logs, self-reported questionnaire responses, and semi-structured user interviews. We analyzed user-nudge interaction ratios, nudge configuration parameters, daily goal selections, and behavioral patterns using t-tests and Cohen's d for effect sizes, at P<.05.

Results: Of the experimental participants, 46% (63/138) accepted the nudge reconfiguration invitation. The acceptance group showed pre-existing behavioral indicators of higher readiness to change, including 21.53% shorter consecutive usage durations and 20.56% longer cooldown periods compared to the rejection group. Post-intervention, the acceptance group exhibited a temporary surge in user-nudge interaction from 24% to 65%, while the rejection group showed sustained decline below 20%. Behavioral divergence between groups widened significantly (Cohen's d increasing from -0.47 to -0.67, P=.002). Notably, acceptance group participants demonstrated significantly lower tendency to select leisure-oriented daily goals compared to the rejection group (15.6% vs 26.2%, P=.001). Self-reported measures of screen time goals and scrolling regret showed no predictive value for intervention acceptance (P>.1).

Conclusions: Observable behaviors, rather than stated intentions, effectively predict intervention receptiveness in DSCTs. The study reveals a significant intention-behavior gap, highlighting that behavioral analytics provide superior predictive value compared to self-report measures. Sustainable DSCT engagement requires alignment with users' intrinsic motivation and readiness to change, as evidenced by pre-existing behavioral patterns. These findings suggest that effective DSCT design should incorporate adaptive systems that recognize and respond to users' evolving motivational states while preserving autonomy, rather than relying on static interventions or self-reported preferences.

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Conclusions: Observable behaviors, rather than stated intentions, effectively predict intervention receptiveness in DSCTs. The study reveals a significant intention-behavior gap, highlighting that behavioral analytics provide superior predictive value compared to self-report measures. Sustainable DSCT engagement requires alignment with users' intrinsic motivation and readiness to change, as evidenced by pre-existing behavioral patterns. These findings suggest that effective DSCT design should incorporate adaptive systems that recognize and respond to users' evolving motivational states while preserving autonomy, rather than relying on static interventions or self-reported preferences.

Keywords: digital self-control tools, digital wellbeing, smartphone addiction, nudge interventions, self-determination theory, behavior change, user attrition, intrinsic motivation, mobile applications, smartphones, screen time

Introduction

The digital revolution—marked by transformative milestones, including the establishment of the Internet (1983), the emergence of social media platforms such as Facebook (2004), and the proliferation of smartphone applications (2008)—has fundamentally reshaped human communication and social interaction patterns. While telephony initially revolutionized interpersonal communication by transcending geographical constraints in the 20th century, the Internet has exponentially accelerated global interconnectedness, profoundly altering social behaviors and technological dependencies.

The evolution of communication devices, progressing from stationary computers to mobile phones and ultimately to smartphones, represents a central component of this digital transformation. These portable devices, offering unprecedented accessibility and persistent connectivity, have become fundamental to contemporary social interaction [1]. The proliferation of smartphone technologies through mobile applications has permeated daily life, encompassing diverse domains, including media consumption, social networking, gaming, education, and health management [2,3]. This technological integration has necessitated the conceptualization of new terminology such as *digital wellbeing*. Digital wellbeing refers to the equilibrium—or lack thereof—that individuals maintain in their relationship with mobile devices and has gained prominence in scientific literature as a public health concern, particularly regarding potentially maladaptive relationships between individuals and their mobile devices, often characterized through excessive screen time metrics that may reflect difficulties in the self-control use of such tools and their prioritization over other leisures and duties [4,5].

Since their introduction, smartphone apps have become the primary means through which we engage with our devices and establish our digital habits [6]. The ubiquitous adoption of social media applications has particularly amplified digital dependencies, especially among digital natives—individuals who have grown up with internet access [7]. Social media platforms have evolved into multifaceted spaces that simultaneously function as crucial nodes of contemporary social networks and entertainment hubs [8]. Driven by commercial imperatives centered on user engagement metrics and profit optimization [9], these platforms have developed increasingly sophisticated recommendation algorithms specifically engineered to maximize screen time and user interaction [10] This creates an environment where users' conscious intentions to moderate their digital consumption compete against scientifically designed engagement mechanisms [11], potentially exacerbating concerns about digital wellbeing and mental health [12]. These dynamics also contribute to broader public health concerns regarding digital wellbeing and smartphone addiction.

Digital Self-Control Tools

In response to these emerging public health challenges, researchers and developers have explored technological solutions to promote digital wellbeing and self-regulation. These attempts led to the emergence of digital self-control tools (DSCTs) designed to help users monitor and regulate their digital activities [13,14]. These tools embody a paradoxical approach: utilizing technology to regulate technology, using digital interventions that modify users' decision-making environments [15]. DSCTs operate across various platforms and contexts, from browser extensions that modify YouTube's user interface by removing recommendation feeds [16] to mobile applications designed to address excessive smartphone usage [14].

So far, studies on screen time apps have yielded mixed results, with one study finding that such interventions lacked perceived effectiveness [17]. While a meta-analysis found that control tools may be linked to reduced smartphone use, it did not address whether disconnection alone fosters digital wellbeing [15]. Current implementations of these tools face substantial limitations, particularly in maintaining sustained user interaction [18], which is a common issue for digital and smartphone-based interventions [19–21]. The prevalent approach of implementing pre-scheduled interventions often results in a misalignment between users' initial motivations and their subsequent behavioral patterns, sparking a feeling of helplessness or annoyance to the user and ultimately compromising the long-term effectiveness of these tools [22]. The primary challenge lies in developing interventions that not only initiate but also maintain behavioral change while preserving user autonomy throughout the process.

One notable example in the mobile DSCT landscape is *One Sec*, which implements delayed gratification principles [23]. The application intercepts attempts to access target applications with a deliberative interface combining messaging, temporal friction, and the option to cancel the access attempt. This approach aims to introduce consciousness into habitual app-opening behaviors. While a study has demonstrated One Sec's effectiveness over a six-week period [23], the high-friction nature of such interventions can generate user resistance, potentially compromising long-term effectiveness [22]. The combination of friction-based interventions and limited proactive interaction opportunities could exemplify why many DSCTs experience significant attrition rates.

The challenge of user retention extends beyond DSCTs to the broader mobile health (mHealth) application sector [24]. A 2022 study on mHealth attrition identified multiple abandonment factors: 21% of users found alternative solutions, 19% expressed disappointment with application features, and 32% reported motivational decline [25]. While product abandonment can stem from various factors, DSCT attrition appears particularly sensitive to intervention design [18]. Excessive or unreliable interventions might precipitate tool abandonment.

Current literature identifies two critical research priorities in DSCT development: implementing effective blocking strategies and encouraging users to maintain properly configured limit settings that generate meaningful nudges over time. Our study primarily focuses on investigating the latter. Specifically, we address the challenge of user attrition and sustained engagement with digital self-control tools, which remains a persistent obstacle to their long-term effectiveness.

The gap in current research lies in understanding the psychological mechanisms that drive user retention and meaningful interaction with DSCTs. While technical functionality has received considerable attention, the motivational factors that determine whether users continue to engage with nudges over time remain underexplored. Leveraging these factors is essential for developing interventions that not only initiate behavioral change but sustain it through continued user engagement.

Goal of This Study

This study investigates how intrinsic motivation and readiness to change—operationalized through users' daily goal priorities—can be strategically leveraged to address user attrition in DSCTs. We investigate strategies for sustaining user-nudge interactions to promote digital wellbeing over time. Through a quasi-experimental protocol, we target users who are at risk of churning —defined as those with no user-nudge interaction who may subsequently discontinue their mandatory daily check-ins and ultimately uninstall the application. We invite these passive users to reconfigure their nudge settings to increase frequency. Through the analysis of observable behaviors—such as system usage logs and self-reported questionnaire responses—we infer participants' intrinsic motivation and readiness to change, as reflected in their daily goal priorities. These behavioral indicators are leveraged as actionable proxies for the psychological determinants of self-regulation and sustained engagement with DSCT nudges. The findings aim to inform the design of more effective digital wellbeing interventions by integrating motivational insights into user retention strategies.

Methods

Digital Self-Control Tool

Tool Development

Detox [26] is an iOS application launched in November 2023 designed to foster sustainable digital wellbeing by implementing targeted application-blocking mechanisms. The app specifically targets excessive smartphone use over short durations, a behavior commonly associated with *doomscrolling* —the excessive consumption of short-form content on smartphone apps [27]. While the term originally emerged during the COVID-19 pandemic to describe the excessive consumption of negative news, it has since evolved in colloquial usage to refer more broadly to the inability to disengage from endless or infinite scrolling interfaces displaying short-form videos on social media [28].

The development of Detox followed an iterative methodology inspired by the lean startup model [29]. An initial prototype was created prior to conducting user interviews or engaging early adopters. Once the first version was released, usage patterns of early adopters were monitored, and approximately 50 in-depth user interviews were conducted to refine the product. Feedback from these interviews highlighted that Detox effectively mitigated excessive social media engagement, particularly patterns linked to doomscrolling, thereby guiding the app's evolution to better meet user needs.

Over a 12-month period, Detox evaluated various behavioral modification strategies by adjusting the "friction coefficient" of smartphone app access including social media access. This involved experimenting with restrictive interventions—such as blocking access to applications until the following day after excessive use—and more lenient approaches—such as only sending reminders in the form of notifications to stop scrolling—. By November 2024, insights from over 8,000 users supported the creation of a theory-informed and empirically anchored framework of digital interventions, drawing on behavioral data, interviews, and Self-Determination Theory. These interventions were meticulously calibrated to address maladaptive social media interaction patterns to promote healthier digital habits.

Conceptual Framework

The theoretical underpinning of Detox's intervention framework prioritizes user autonomy in self-regulation over the imposition of restrictive measures [30,31]. Grounded in self-determination theory (SDT), Detox emphasizes three core psychological needs—autonomy, competence, and relatedness—which are widely recognized as critical components of applications designed to facilitate behavior change [30,32,33]. These constructs are conceptualized as follows:

Autonomy: The need to perceive oneself as the originator of one's actions, with behaviors aligned to personal values and interests.

Competence: The need to feel proficient and effective in one's endeavors. When competence is satisfied, individuals gain confidence in their ability to master tasks and attain desired outcomes, thereby bolstering motivation and engagement.

Relatedness: The need to experience meaningful connections and a sense of belonging within interpersonal relationships. Fulfillment of this need fosters psychological wellbeing and sustains motivational processes.

According to SDT, the satisfaction of these three needs enhances intrinsic motivation, promotes personal growth, supports sustained behavior change, and contributes to psychological wellbeing. This framework aligns closely with contemporary theories of behavioral modification that advocate for sustainable change [34]. By embedding these principles, *Detox*'s approach offers a theoretically robust foundation for addressing phone addiction while respecting individual agency.

Intervention Design

For each intervention, users maintain the agency to decide which apps they want to monitor. *Detox* implements three distinct categories of interventions, as illustrated in Figure 1.

The Daily Check-In: This serves as the primary forced intervention mechanism. Beginning at 4 AM daily, the system automatically restricts access to monitored applications until users complete their Daily Check-In within the Detox interface. During this process, users establish a daily objective (e.g., "Study," "Leisure," or "Work"), which informs subsequent intervention protocols throughout the day (Figure 1, second panel).

The Anti-Doomscrolling Reminder: This represents a user-configured nudging mechanism that is activated based on continuous usage patterns. The intervention triggers when usage duration exceeds a user-defined threshold (e.g., five minutes of continuous engagement), resulting in a temporary restriction period (e.g., one minute). Both the continuous usage threshold and restriction duration are customizable parameters determined by the user (Figure 1, third panel).

The Timer Block/Overnight Block: These functionalities enable temporal restriction of monitored applications for user-specified durations (Figure 1, fourth panel).

For clarity and consistency throughout the remainder of this paper, we will employ the following terminology: "daily check-in" will continue to be referred to as such; "The Anti-Doomscrolling Reminder" will be referred to as the "nudge feature"; and "The Timer Block/Overnight Block" will be referred to as "manual app blocking." These designations will facilitate precise discussion of each intervention type and its respective effects on user behavior.

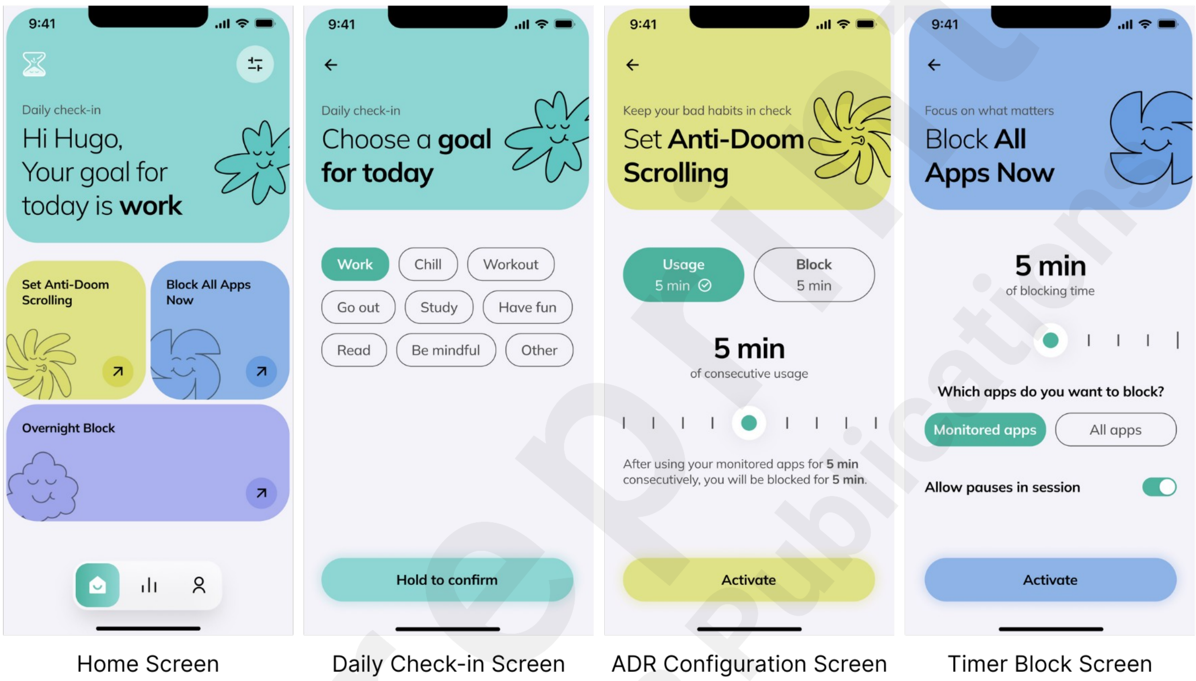

Figure 1. Main screens of the Detox application demonstrating the user interface design grounded in self-determination theory, featuring customizable intervention parameters that preserve user autonomy while facilitating digital self-regulation.

Study Design

Participant Recruitment

The study population consisted of users from the DSCT user base who engage with the application through mandatory daily check-ins. Within this population, we distinguish between active users—those who demonstrate regular user-nudge interaction on a weekly basis by receiving nudges—and passive users—those who complete daily check-ins but do not receive any nudges. Our recruitment specifically targeted passive users who showed no user-nudge interaction in the three days preceding enrollment, as these users were considered at risk of churning.

The total DSCT user base comprised 472 daily check-in users: 252 (53.4%) were passive users meeting our eligibility criteria, while 220 (46.6%) were active users with regular nudge interactions and thus ineligible for this experiment. We successfully recruited all 252 eligible passive users through a rolling enrollment protocol over three days (November 22–25, 2024), with each participant receiving exactly one invitation during this period. This sample represents the maximum possible recruitment from the target population.

Participants were allocated to one of three groups that form the core of our experimental design. The experimental group (n=138, 54.8%) received an invitation to reconfigure their nudge settings during their daily check-in. Within this group, those who accepted the invitation were subsequently classified as the acceptance group, while those who declined formed the rejection group. The control group (n=114, 45.2%) consisted of passive users who met the same eligibility criteria but received no intervention, serving as a baseline for comparison.

Randomization between experimental and control groups was performed automatically at the device level, with allocation decisions executed independently for each participant. Although the study protocol targeted an equal distribution (50%) between groups, the observed imbalance resulted from the decentralized randomization process, which operated without global coordination and allowed for independent assignment variations across devices.

Procedure

Participants were recruited through a rolling enrollment protocol over three days (November 22–25, 2024). Each eligible user received a single invitation during their mandatory daily check-in.

The experimental group (n=138) was presented with the intervention before completing their daily goal selection. Based on their response to the intervention, they were classified into acceptance or rejection groups. Group assignment remained fixed throughout the study period.

The control group (n=114) completed their daily check-in without receiving any intervention, maintaining access to all application features.

Usage data was collected continuously for five weeks: one week pre-intervention and four weeks post-intervention.

Intervention

The intervention consisted of three screens integrated into the daily check-in flow as depicted in Figure 2. The detailed user journey of the experiment design can be found in Figure S1 in Multimedia Appendix 1. The intervention screens are as follows:

Introduction Screen: Presented before daily goal selection, this screen highlighted the user's lack of recent nudge activity with the message "Review my configuration" and prompted them to "Set Anti-Doom Scrolling."

Choice Screen: Displayed a suggested nudge configuration of ten-minute consecutive usage followed by a one-minute cooldown period. Users could accept ("Give it a try!") or decline ("I prefer not to") this configuration.

Survey Screen: A mandatory single-choice questionnaire captures the user's rationale for their decision, with response options including "Kept forgetting," "Looked motivating," and "Other."

Experimental participants maintained complete autonomy regarding intervention acceptance. To isolate engagement patterns from potential confounding effects of blocking interventions, we implemented a brief blocking period for the nudge setting, which minimized user frustration [22] while enabling focused analysis of engagement dynamics.

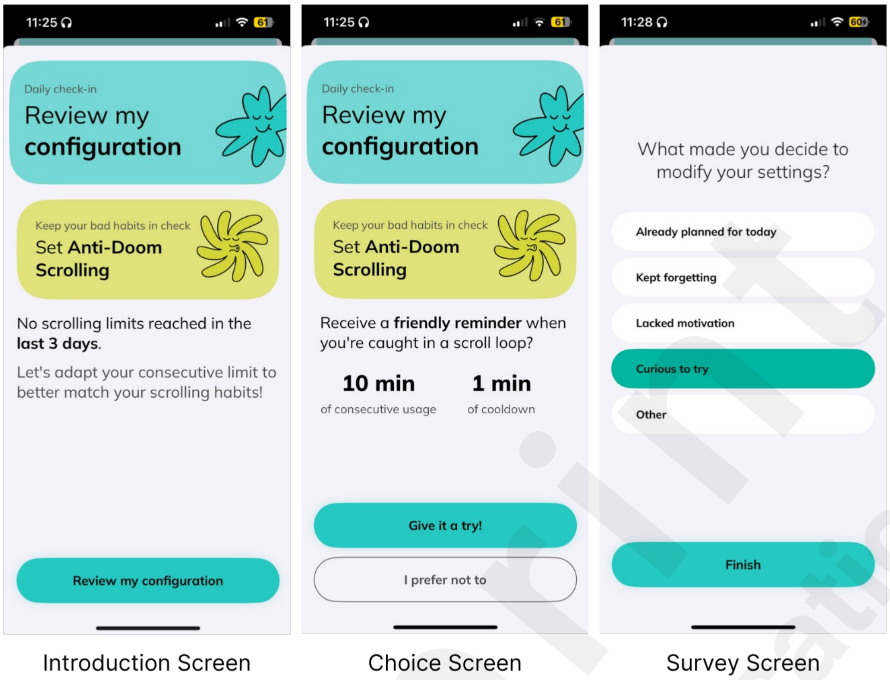

Figure 2. Experiment screens illustrating the quasi-experimental protocol for nudge reconfiguration invitation, highlighting the preservation of user autonomy through voluntary participation and the systematic data collection framework.

Data Collection and Instruments

In this study, we analyzed system usage logs and self-reported questionnaire data to infer users' readiness to change and intrinsic motivation, with a focus on individuals at risk of churn. Data collection was conducted through the Mixpanel analytics platform, which implemented event-based logging protocols to systematically record user interactions.

Usage logs captured several key interactions: completions of the daily check-in feature with associated timestamps; date and time at which users received nudges for extended time spent on monitored apps; updates to nudging configuration settings; and interactions with manual app blocking features. These metrics provided detailed insights into the frequency and temporal distribution of user engagement with the DSCT.

Self-reported data were gathered through multiple modalities:
1: Daily check-in responses: Users selected personal goals for the day, which were later reminded to them. This collected ongoing qualitative data, enabling longitudinal analysis of user intentions.
2: Onboarding surveys: Participants completed assessments of their device usage patterns, including daily screen time, intended screen time goals within the DSCT, frequency of regretted scrolling sessions, and contexts in which such regret occurred.
3: User interviews: These were conducted to develop deeper insights into user profiles, including types of apps being blocked, motivations for downloading the tool, and objectives for using the DSCT.

Demographic data were collected through multiple methodological approaches: age and gender data were obtained via DSCT onboarding surveys, geographical location was determined through Mixpanel analytics tools, and user seniority was extracted from DSCT interaction records.

Related to the nudge reconfiguration invitation, experimental response data documented the temporal sequence of intervention-related events with precise timestamps. The platform recorded intervention acceptance or rejection, subsequent nudge settings adjustments, and post-intervention interaction patterns.

The daily engagement framework, facilitated by the mandatory daily check-in feature, ensured consistent participation and enabled measurement of daily user interaction and attrition rates. Together, these mechanisms established a robust environment for examining variations in user interaction and self-regulation outcomes.

Data Analysis

For our data analysis, we implemented a multi-tiered approach to examine observable behaviors from both usage logs and self-reported questionnaire data to infer readiness to change and intrinsic motivation.

The first analysis examined usage logs and the user-nudge interaction ratio. For each day, we calculated the proportion of users receiving at least one nudge relative to those completing daily check-ins. This analysis revealed temporal engagement patterns across three cohorts: the acceptance group, the rejection group, and the control group. Time-series analysis identified significant cohort-specific variations in user-nudge interaction trends.

The second analysis investigated usage logs with feature configuration parameters across groups. This included nudge setting adjustments, interaction with manual app-blocking features, and modifications to monitored app selections. We employed paired t-tests to assess pre- and post-intervention changes within experimental groups, while independent t-tests evaluated differences between experimental and control groups.

The third analysis focused on self-reported data, including daily check-in goal selections, post-intervention survey responses from the experimental group, and onboarding survey responses. Given the structured format of these responses, we utilized t-tests to determine the significance of differences between groups, ensuring a thorough qualitative evaluation supported by statistical rigor.

All statistical analyses were conducted by exporting Mixpanel data into a Jupyter Notebook environment for detailed correlation analysis. The study applied a statistical significance threshold of $P<.05$, with correlations exceeding this threshold treated as non-significant. Effect sizes were calculated using Cohen's d to quantify the magnitude and practical significance of between-group differences. This rigorous analytical framework provided a comprehensive evaluation of intervention effectiveness while addressing the multifaceted nature of user behavior.

Ethical Considerations

Participants provided informed consent during the application’s onboarding process, which explicitly outlined the potential use of their data for research purposes. To safeguard anonymity, no personally identifiable information was collected. The application's architecture incorporated a tokenization system compliant with Apple's privacy guidelines for app monitoring, ensuring that researchers could not identify specific applications restricted by participants. User autonomy was preserved throughout the study: participants retained full control over their engagement with the application and could withdraw at any time by discontinuing use of the Detox tool. The research design prioritized transparency regarding all application features, allowing participants to adjust usage parameters according to their preferences without researcher interference.

Results

Nudge Reconfiguration Response and User-Nudge Interaction

Of the 138 participants assigned to the experimental group, 46% accepted the invitation to reconfigure their nudge settings. User-nudge interaction ratios were analyzed across acceptance, rejection, and control groups, as illustrated in Figure 3. At the time of the experiment, the baseline user-nudge interaction ratio among all DSCT users was 50%, serving as a reference point for evaluating participant engagement.

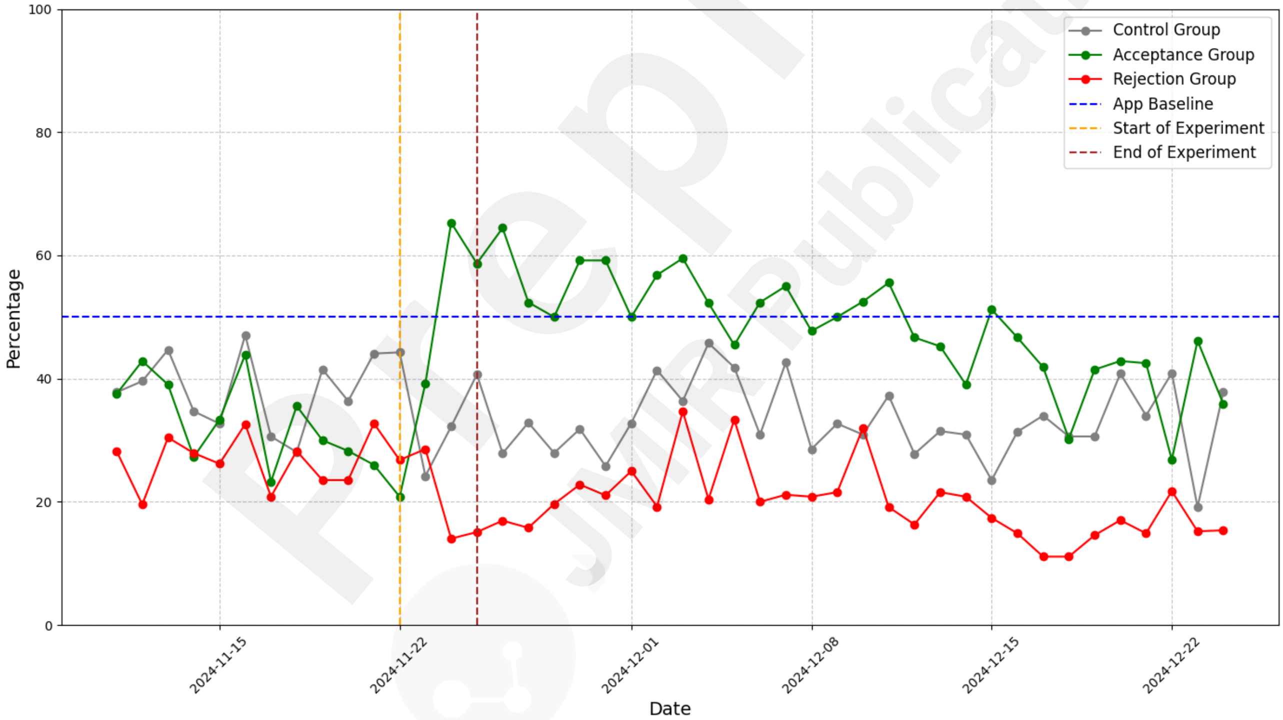

Figure 3. Temporal evolution of user-nudge interaction ratio across experimental groups, revealing significant post-intervention behavioral divergence, with the acceptance group demonstrating a temporary but substantial increase from 24% to 65% engagement, while the rejection group exhibited sustained decline below 20%.

Acceptance Group Outcomes

The acceptance group exhibited significant changes in user-nudge interaction following intervention. Pre-intervention, these participants maintained a consistent interaction ratio of 24%. Post-intervention, this ratio surged to 65%. This elevated engagement persisted above baseline levels for approximately two weeks before gradually declining, converging with control group levels by the one-month mark.

Rejection Group Outcomes

The rejection group displayed distinctive behavioral patterns. While their pre-intervention interaction ratio mirrored other groups, post-intervention engagement dropped below 20%. Throughout the observation period, this group consistently demonstrated the lowest engagement rates across all cohorts.

Control Group Performance

The control group maintained stable user-nudge interaction ratios throughout the observation period. Notably, the acceptance group's interaction ratio converged with the control group's approximately one month post-intervention.

Demographic Analysis

Analysis of participant demographics confirmed alignment with the broader DSCT user base, with consistent distributions across all experimental groups. Key demographic characteristics included: concentration in the 16-20 age range, gender composition of 60% male participants, 70% of users with greater than one month usage history, and geographical distribution indicating 15% of participants from the United States.

Evolution of Usage Patterns Following Nudge Reconfiguration Invitation

Nudge Settings Configuration

Three days pre-reconfiguration invitation, the acceptance group configured shorter consecutive usage durations (-21.53%) and longer cooldown periods (+20.56%) compared to the rejection group. This disparity widened significantly one week post-invitation, from (t=2.19, P=.03, d=-.47) to (t=3.28, P=.002, d=-.67), as depicted in Figures 4 and 5 (data from November 20 and 29, 2024). Acceptance group participants largely maintained their reconfigured nudge settings (median=10.0) post-intervention.

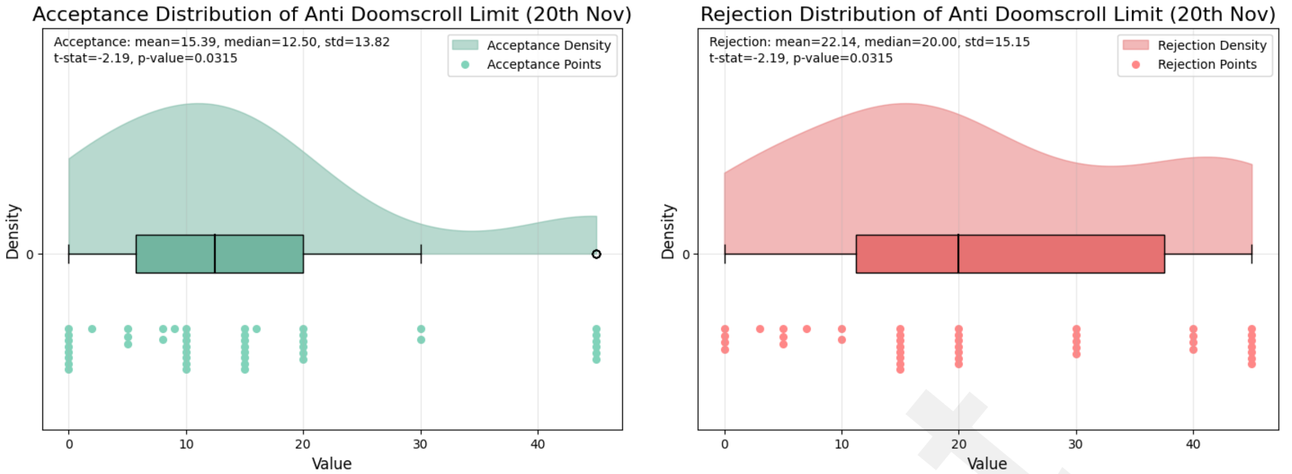

Figure 4. Nudge limit distribution comparison between acceptance and rejection groups (November 20, 2024) demonstrating pre-existing motivational differences, with acceptance group participants configuring 21.53% shorter consecutive usage durations, indicating higher baseline readiness for digital self-regulation.

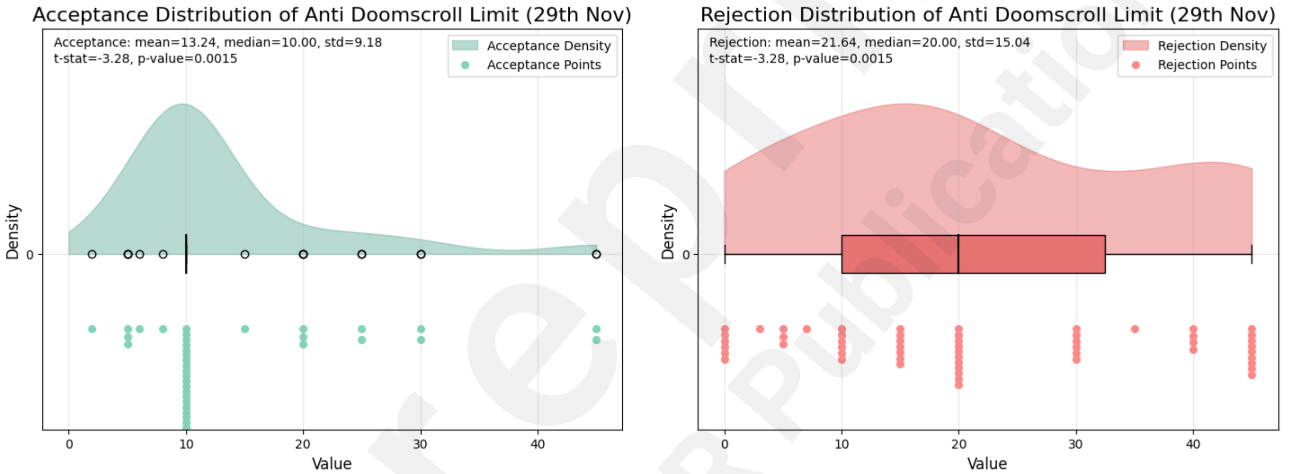

Figure 5. Nudge limit distribution comparison between acceptance and rejection groups (November 29, 2024) showing widening behavioral differentiation post-intervention, with effect size increasing from *d*=-.47 to *d*=-.67, confirming sustained commitment to stricter self-regulatory settings among successful adopters.

Manual App Blocking Interaction

Although the reconfiguration invitation targeted nudge settings rather than manual blocking interactions, the distribution of manual app blocking behaviors between acceptance and rejection groups diverged during the post-invitation observation period. This divergence increased from November 20 (t=1.82, *P*=.07, *d*=.39) to November 29 (t=2.58, *P*=.01, *d*=.49). Cohen's *d* increased from 0.39 to 0.49, demonstrating the growing magnitude of effect, as shown in Figure S2 in Multimedia Appendix 1. The significance threshold shifted from above 0.05 (0.07) to below this value (0.01), further highlighting the increasing separation between group behaviors.

Self-Reported Questionnaire Data Analysis

Daily Check-In Goals

Compared to the rejection group, acceptance group participants demonstrated a significantly lower tendency to select "Chill" as a daily goal (15.6% vs. 26.2%; t=-3.46, *P*=.001, *d*=.13), as illustrated in Figure S3 in Multimedia Appendix 1.

Onboarding Survey Analysis

Analysis of onboarding survey responses regarding current screen time and screen time reduction goals revealed no significant differences (*P*>.1) between acceptance and rejection groups, as depicted in Figure S4 and S5 in Multimedia Appendix 1.

Further analysis of responses regarding scrolling regret frequency and associated emotional responses also yielded no significant differences (*P*>.1) between groups, as shown in Figure S6 and S7 in Multimedia Appendix 1. While response patterns were similar, both distributions exhibited comparable trends, evidenced by the similar distribution of the "Disappointed" response for scrolling-associated emotions.

Post-Intervention Survey

Post-intervention survey data showed no statistically significant patterns (*P*>.05) and were consequently excluded from further analysis.

Qualitative Insights from User Interviews

Twelve semi-structured interviews were conducted with participants who had used the DSCT for at least one month prior to the nudge reconfiguration invitation. Participants ranged in age from 16 to 30 years. Interviewees primarily reported monitoring social media applications as their main source of distraction, with some also identifying mobile games, dating platforms, or streaming services as secondary targets.

Participants consistently cited a desire to make better use of leisure time as their primary motivation for reducing screen time. Several interviewees acknowledged habitual patterns of continuous scrolling from workday end until dinner time. These participants expressed preference for the DSCT's blocking functionality during these vulnerable periods, enabling redirection of attention toward activities such as sports, chess, or creative pursuits.

Discussion

Interpretation of Key Findings

Our study reveals critical insights into the psychological determinants of sustained user-nudge interaction and engagement with digital self-control tools. The 46% acceptance rate for nudge reconfiguration among at-risk users suggests that nearly half of passive users possess latent readiness to re-engage with DSCTs when prompted. However, the divergent trajectories between acceptance and rejection groups illuminate deeper motivational dynamics underlying DSCT effectiveness.

The pre-intervention behavioral differences between groups are particularly noteworthy. Acceptance group participants configured 21.53% shorter consecutive usage durations and 20.56% longer cooldown periods compared to the rejection group, even before receiving the intervention invitation. This finding suggests that readiness to change manifests through observable behaviors rather than self-reported intentions. The widening of this behavioral gap post-intervention (Cohen's *d* increasing from -0.47 to -0.67) indicates that the nudge reconfiguration invitation served to amplify existing motivational differences rather than create new ones, potentially by reinforcing participants' autonomy and self-regulatory capacity among those already disposed toward behavioral change.

The temporal pattern of user-nudge interaction in the acceptance group—surging from 24% to 65% immediately post-intervention before gradually declining—demonstrates both the potential and limitations of external prompts. While the intervention successfully reactivated engagement, the subsequent decline suggests that extrinsic motivators alone cannot sustain long-term behavioral change without corresponding intrinsic motivation. This aligns with self-determination theory, which posits that sustainable behavior change requires the satisfaction of autonomy, competence, and relatedness needs [30].

Particularly revealing is the disconnect between self-reported measures and behavioral outcomes. Despite no significant differences in stated screen time reduction goals or scrolling regret frequency between groups, behavioral indicators clearly differentiated those who would successfully re-engage with the DSCT. This intention-behavior gap [35] underscores the limitations of relying solely on self-reported data when predicting DSCT effectiveness and highlights the importance of behavioral analytics in understanding user engagement patterns.

The spillover effects observed in manual app blocking behaviors, despite the intervention targeting only nudge settings, suggest that successful re-engagement with one DSCT feature may catalyze broader self-regulatory behaviors. This finding aligns with theories of behavioral momentum, where small successful changes can facilitate larger behavioral modifications.

Implications for DSCT Design and Implementation

Our findings challenge conventional approaches to DSCT user engagement. The 46% acceptance rate among passive users and subsequent boost in user-nudge interaction challenge the binary classification of users as either engaged or disengaged, suggesting instead that engagement exists on a continuum with opportunities for reactivation even among seemingly passive users. This perspective encourages DSCT developers to implement proactive reengagement strategies rather than simply accepting attrition as inevitable.

These proactive reengagement strategies have proven more effective for users with higher readiness to change. Our pre-intervention data revealed that acceptance group participants configured stricter self-regulatory parameters (21.53% shorter usage durations, 20.56% longer cooldown periods), indicating that observable behaviors can predict intervention receptiveness. In this context, DSCTs aiming to offer personalized experiences should leverage behavioral markers to enable precise identification of users most likely to benefit from re-engagement prompts, thereby optimizing intervention effectiveness.

However, the temporary nature of increased engagement reveals a critical limitation. While our intervention successfully boosted user-nudge interaction from 24% to 65%, the subsequent decline demonstrates that extrinsic motivators alone cannot sustain behavioral change. Sustainable engagement requires progressive feature designs that transition users from external prompts to self-directed regulation through adaptive goal-setting, competence-building feedback, and autonomy-supportive interfaces.

Throughout these design considerations, the preservation of user autonomy emerges as a fundamental principle. DSCTs must navigate the inherent tension between providing behavioral support and avoiding paternalistic control. This delicate balance requires thoughtful intervention framing, opt-in mechanisms, customizable parameters, and transparent communication about the rationale behind nudges and restrictions. Only by respecting user agency can DSCTs foster the intrinsic motivation necessary for lasting behavior change, as our divergent group outcomes clearly demonstrate.

Limitations

This study faces several limitations that inform the interpretation of our findings. Our quasi-experimental design constrains causal inference, as pre-existing behavioral differences between acceptance and rejection groups—particularly in nudge configurations—suggest self-selection biases dynamics [36] that complicate attribution of outcomes solely to the intervention. While these baseline differences provide valuable insights about readiness indicators, they prevent definitive conclusions about intervention causality.

Beyond design constraints, our reliance on behavioral proxies for psychological constructs introduces measurement limitations. Although usage patterns and configuration choices offer objective indicators, they cannot fully capture the complexity of intrinsic motivation or readiness to change.

Additionally, generalizability constraints arise from our sample characteristics. Participants were drawn exclusively from a single DSCT (Detox) with a specific design philosophy, predominantly young users (16-20 years), and limited geographical diversity. These factors may limit the applicability of our findings to other DSCTs, age groups, or cultural contexts where digital self-regulation practices differ.

Furthermore, we cannot determine whether the decline in user-nudge interaction observed in Figure 3 represents a successful change in behavior that reduces reliance on the tool or disengagement from self-regulation efforts, as we lack direct measures of participants' real-world digital wellbeing behaviors outside the DSCT environment.

Future Research Directions

Our findings illuminate critical avenues for advancing DSCT effectiveness research. The convergence of acceptance and control groups after one month raises fundamental questions about intervention durability. This pattern suggests that single-prompt interventions have limited sustainability, pointing toward the need for longitudinal studies investigating optimal intervention cadences. Research should test whether periodic re-engagement at empirically-determined intervals can maintain elevated user engagement without inducing prompt fatigue.

Building on our identification of behavioral readiness indicators, predictive modeling represents a promising research direction. While our study identified several acceptance predictors, comprehensive models incorporating temporal patterns, contextual factors, and usage trajectories could enable dynamic, personalized intervention timing. Machine learning approaches could identify complex behavioral signatures that signal optimal intervention moments, moving beyond static threshold rules to recognize when users are most receptive to change. Future research may integrate comprehensive psychological assessments, ecological momentary assessments of human–device interaction, objective and longitudinal measures of smartphone and app use (e.g., usage logs), as well as contextual data on physical and social environments to better understand how these factors jointly influence digital wellbeing.

Furthermore, comparative effectiveness research across theoretical frameworks is essential for establishing evidence-based DSCT design principles. Our study examined one SDT-based approach, but the field would benefit from systematic comparisons of different intervention philosophies. Understanding which approaches work best for different user segments, cultural contexts, and problematic usage patterns could guide the development of more personalized and effective interventions.

These research directions collectively aim to transform DSCTs from static tools to adaptive systems that recognize and respond to users' evolving motivational states while preserving the autonomy essential for lasting behavioral change.

Conclusion

This study indicates that successful engagement with digital self-control tools is fostered when these tools align with users' priorities—particularly when intrinsic motivation and readiness to change are supported by features that enhance users’ sense of agency and self-control. Through our quasi-experimental investigation of passive users at risk of churning, we observed that a substantial portion accepted nudge reconfiguration invitations, with acceptance predicted by pre-existing behavioral indicators rather than self-reported intentions. The acceptance group exhibited shorter consecutive usage durations and longer cooldown periods before intervention, revealing that readiness to change manifests through observable behaviors rather than stated goals. This intention-behavior gap underscores the critical importance of behavioral analytics over self-report measures in understanding user engagement with digital wellbeing interventions

Our findings suggest that the future of effective DSCT design lies not in creating more restrictive or feature-rich tools, but in developing adaptive systems tailored to the needs of specific population clusters and based on SDT principles, that recognize and respond to users' motivational states while preserving their autonomy, increasing their competence and reinforcing relatedness. As digital wellbeing becomes an increasingly critical public health concern, understanding the psychological mechanisms underlying successful self-regulation in digital contexts becomes essential for developing interventions that create lasting positive change.

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Data availability

Data supporting the findings of this study are available from the corresponding author upon reasonable request.

Authors' Contributions

LL and AKPA developed the mobile application and conducted participant recruitment, screening, data collection, and patient interviews. AKPA performed the data analysis. AKPA, SI, YK, JCF, and DG contributed to result interpretation and discussion. AKPA drafted the original manuscript. All authors reviewed and revised the final version of the manuscript.

Conflicts of Interest

While AKPA and LL developed the mobile application used in this study, participants were recruited from the broader user base and were not personally known to the researchers. AKPA and LL maintained complete separation from user decision-making processes to ensure study integrity and prevent any potential bias that could compromise the validity of the results. All other authors report no conflicts of interest.

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Abbreviations

DSCT: digital self-control tool
SDT: self-determination theory
mHealth: mobile health
COVID-19: Coronavirus Disease 2019
ADR: anti-doomscrolling reminder
iOS: iPhone Operating System

Supplementary Files

Multimedia Appendixes

Detailed nudge reconfiguration settings, participant inclusion criteria, and supplementary statistical analyses.
URL: http://asset.jmir.pub/assets/5e4979ef9d22ad0c6c19b33edf1ac2df.pdf