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APMH ARCHIVES OF PSYCHIATRY AND MENTAL HEALTH
ISSN 2766-2721

Research Article

One Week to Wellness: A Pre–post Experimental Study on the Effects of a Seven-day Digital Detox Intervention on Psychological Well-being, Cognitive Functioning, and Life Satisfaction in University Students

Sora Pazer*

IU International University of Applied Science, Germany

More Information

***Corresponding author:** Sora Pazer, IU International University of Applied Science, Germany, Email: sorapazer@gmail.com

Submitted: February 20, 2026
Accepted: March 03, 2026
Published: March 04, 2026

Citation: Pazer S. One Week to Wellness: A Pre–post Experimental Study on the Effects of a Seven-day Digital Detox Intervention on Psychological Well-being, Cognitive Functioning, and Life Satisfaction in University Students. Arch Psychiatr Ment Health. 2026; 10(1): 025-031. Available from: https://dx.doi.org/10.29328/journal.apmh.1001063

Keywords: Digital detox; Screen time reduction; Psychological well-being; Procrastination; University students; Cognitive performance; Self-regulation; Life satisfaction; Mental health intervention

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Abstract

Digital media overconsumption has emerged as a pervasive behavioral phenomenon with substantial implications for mental health, cognitive performance, and subjective well-being among university student populations. Despite a growing body of literature documenting the deleterious effects of excessive smartphone and social media use, empirical evidence on the efficacy of short-term, voluntarily initiated digital detox interventions remains scarce. The present pre–post study examined the psychological consequences of a structured seven-day screen time reduction protocol in a sample of N = 77 undergraduate and graduate students. Participants were instructed to limit daily screen time to a maximum of two hours across all non-academic digital devices. Objective screen time data were collected via integrated device usage tracking applications, and self-report measures assessed positive affect, concentration, sleep quality, procrastination, perceived stress, subjective productivity, social connectedness, and life satisfaction on Likert-type scales (1–5) at baseline (Day 0) and post-intervention (Day 7). Results revealed a dramatic and statistically significant reduction in mean daily screen time (from M = 6.48 to M = 2.03 hours; Cohen's d = 3.05). All psychological outcome variables showed large-to-very-large intervention effects (Cohen's d range: 1.41–2.28). Structural equation modeling confirmed a coherent pathway from reduced screen time through stress reduction and improved concentration to enhanced productivity and life satisfaction (CFI = .96; RMSEA = .048). Moderation analyses demonstrated that participants with the highest baseline screen usage (> 7 hours/day) exhibited the most pronounced concentration gains (d = 0.57). These findings provide robust evidence for the rapid psychological benefits of even short-term digital self-regulation and carry direct implications for university mental health programming and digital literacy interventions.

Introduction

The proliferation of smartphones, social media platforms, and always-on digital connectivity has fundamentally reshaped patterns of human behavior, social interaction, and attentional resource allocation across all age groups, with university students representing a particularly vulnerable population [1]. Contemporary estimates indicate that young adults in industrialized nations spend between six and nine hours per day interacting with digital screens outside of occupational or academic obligations, a figure that has risen continuously over the past decade and accelerated markedly during and following the COVID-19 pandemic [2,3]. The ecological and psychological consequences of this profound behavioral shift have attracted substantial scientific attention, with converging evidence from longitudinal cohort studies, experience sampling methodologies, and laboratory-based experiments linking excessive digital media use to impaired executive functioning, elevated symptoms of anxiety and depression, disrupted sleep architecture, and diminished academic achievement [4-7].

Procrastination is among the most consistently documented behavioral correlates of excessive digital engagement among student populations. Smartphone accessibility functions as a virtually inexhaustible source of immediate reinforcement that systematically competes with effortful academic tasks requiring sustained cognitive engagement [8,9]. Notifications, infinite-scroll content feeds, and intermittent variable reward mechanisms embedded within major platforms exploit established principles of operant conditioning to produce compulsive checking behaviors that fragment attentional focus and disrupt deep work states [1,10,11]. The neurological substrates underlying this dynamic include dopaminergic dysregulation within prefrontal-striatal circuits, partially analogous to mechanisms implicated in behavioral addiction [12,13].

Sleep represents another critical domain of impairment associated with heavy digital device use. The penetration of smartphones into the bedroom and the prevalence of pre-sleep screen exposure have been extensively documented as contributors to circadian rhythm disruption, delayed sleep onset, and reduced total sleep duration through blue-light-mediated melatonin suppression and the arousing effects of social and emotional content consumption [14-17]. Poor sleep quality in turn exerts cascading negative effects on mood regulation, cognitive performance, and stress reactivity, creating self-reinforcing cycles of psychological deterioration [18].

In response to growing public and clinical concern, the concept of the "digital detox"—defined as a deliberate, time-limited abstinence from or significant reduction of digital device usage—has attracted considerable popular and scientific interest [19]. However, empirical research on the psychological effects of structured digital detox interventions remains limited and methodologically heterogeneous. Existing studies vary substantially in operationalization of the intervention (full abstinence vs. partial reduction), measurement modalities (self-report vs. objective tracking), intervention duration (ranging from single days to several weeks), and outcome domains assessed [20-23]. Notably, Hunt, et al. [22] demonstrated that limiting social media use to 30 minutes per day over three weeks produced significant reductions in loneliness and depression among undergraduate students—one of the most methodologically rigorous investigations to date. Similarly, Tromholt [23] found that Facebook abstinence for one week significantly improved affective well-being relative to a control condition in a large Danish sample.

The current study addresses several gaps in the extant literature by examining a broader multidimensional outcome profile across a seven-day intensive screen time reduction protocol, employing objective device-based behavioral measurement in conjunction with self-report psychological assessments, and implementing structural equation modeling to map the mechanistic pathways through which digital self-regulation exerts its beneficial effects. Grounded in self-determination theory [24], cognitive load theory [25], and the strength model of self-control [26], we hypothesized that a seven-day reduction of screen time to ≤ 2 hours per day would produce significant improvements across all assessed psychological domains, with concentration and stress reduction serving as key mediating mechanisms linking behavioral change to enhanced life satisfaction.

Method

Participants and study design

A total of N = 77 university students (Mage = 23.4 years, SD = 3.1; 61% female, 37% male, 2% other/non-binary) enrolled at a German private university participated in the present study. Participants were recruited via in-class announcements and the institutional learning management system. Inclusion criteria required active enrollment in a degree program and a baseline daily screen time of at least four hours as verified by device usage data at screening. Participants with self-reported diagnoses of attention-deficit/hyperactivity disorder (ADHD) or current pharmacological treatment affecting attention were excluded to reduce confounding. All participants provided written informed consent before enrollment, and ethical approval was obtained from the institutional review board. No monetary compensation was provided; participants received partial course credit. The study employed a single-group pre–post design with assessments administered at baseline (Day 0) and immediately following the seven-day intervention period (Day 7). While the absence of a randomized control group represents a methodological limitation (discussed below), this design was selected to maximize ecological validity and feasibility within a naturalistic educational setting.

Intervention

Participants were instructed to reduce their daily screen time across all personal digital devices—including smartphones, tablets, and personal computers used for non-academic purposes—to a maximum of two hours per day for seven consecutive days. Devices used exclusively for university coursework (e.g., accessing course materials, submitting assignments) were exempt from the restriction. At the initial study session, participants received a standardized protocol document specifying the intervention rationale, behavioral guidelines, and recommended strategies for managing digital cravings and structuring screen-free time. Strategies drawn from the self-regulation and behavioral intervention literature included implementation intention formation [27], notification management, physical device separation during work and sleep periods, and substitution with offline leisure activities. Objective compliance monitoring was implemented via integrated screen time tracking applications available on iOS (Screen Time) and Android (Digital Wellbeing) operating systems. Participants were required to enable these features and submit daily screenshots of their usage statistics to a designated secure digital repository. This procedure yielded a continuous, objective behavioral record supplementing self-report measures, consistent with recommendations for multi-method behavioral assessment in digital health research [28].

Measures

Screen time (objective). Daily total screen time in hours was recorded via device-native tracking applications across all personal applications, excluding designated academic tools. Both applications have demonstrated adequate concurrent validity against more intensive experience sampling and passive sensing methodologies [29].

Psychological outcomes (self-report). Eight psychological constructs were assessed using purpose-developed five-item Likert-type scales (1 = does not apply at all; 5 = applies completely): (a) positive affect/mood, (b) concentration and attentional control, (c) sleep quality, (d) procrastination tendency, (e) perceived stress, (f) subjective productivity, (g) social connectedness, and (h) life satisfaction. For procrastination and stress, higher scores reflected greater frequency/intensity, with improvement defined as a score reduction. Items were informed by validated instruments, including the Pittsburgh Sleep Quality Index [30], the Perceived Stress Scale [31], the Pure Procrastination Scale [32], and the Satisfaction With Life Scale [33]. Internal consistency for all scales at baseline ranged from $\alpha = .76$ to $\alpha = .89$ (M = .82), indicating acceptable to good reliability. To facilitate transparency and future replication, representative sample items for each scale are provided: positive affect/mood ("I feel emotionally balanced and in good spirits"), concentration ("I can focus on a task without being distracted"), sleep quality ("I feel rested and refreshed after sleeping"), procrastination ("I delay tasks I intended to complete"), perceived stress ("I feel overwhelmed by the demands placed on me"), subjective productivity ("I feel that I am accomplishing what I set out to do"), social connectedness ("I feel meaningfully connected to the people around me"), and life satisfaction ("I am satisfied with my life as a whole").

Statistical analysis

All analyses were conducted using R [34]. Paired-samples t-tests were computed to assess pre–post differences for each outcome variable. Effect sizes were calculated as Cohen's d with pooled standard deviations. Pearson product-moment correlation coefficients were computed among post-intervention psychological outcome variables to characterize the intercorrelational structure of the outcome domain. Hierarchical multiple regression was employed to model post-intervention life satisfaction as a function of post-intervention concentration, positive affect, and perceived stress. Moderation analysis examined whether baseline screen time level (operationalized as a median split: Group A > 7 h/day, n = 29; Group B ≤ 7 h/day, n = 48) moderated the magnitude of concentration improvement, tested via an independent-samples t-test on post-intervention concentration scores. Structural equation modeling (SEM) was implemented in lavaan [35] to evaluate the hypothesized mediated pathway model. Model fit was assessed using the Comparative Fit Index (CFI; acceptable ≥ .95), Root Mean Square Error of Approximation (RMSEA; acceptable ≤ .06), and Standardized Root Mean Square Residual (SRMR; acceptable ≤ .08). All significance tests were evaluated at $\alpha = .05$, two-tailed.

Results

Mean daily screen time decreased from M = 6.48 hours (SD = 1.31) at baseline to M = 2.03 hours (SD = 0.27) at Day 7, representing an absolute reduction of 4.45 hours per day. This reduction was highly statistically significant, $t(76) = 26.74$, $p < .001$, with an exceptionally large effect size (Cohen's d = 3.05), indicating near-universal and substantial behavioral change across participants. The convergence of pre-intervention means toward the intervention ceiling (≤ 2 h/day) was further reflected in the markedly reduced post-intervention standard deviation, demonstrating high compliance fidelity (Table 1).

Table 2 presents descriptive statistics and Δ scores for all eight psychological outcome variables. Across all domains, the pattern of change was consistent with hypothesized directions: positive affect, concentration, sleep quality, subjective productivity, social connectedness, and life satisfaction all increased substantially, while procrastination and perceived stress decreased markedly. The largest absolute change was observed for concentration (Δ = +1.74) and subjective productivity (Δ = +1.74), with procrastination demonstrating the largest magnitude decrease (Δ = −1.67).

Paired-samples t-tests confirmed that all pre-to-post differences were statistically significant at $p < .001$ (Table 3). Effect sizes were uniformly large to very large (Cohen's d range:

Table 1: Objective Screen Time at Baseline and Post-Intervention.

Time Point	M (hours/day)	SD
Pre-Intervention (Day 0)	6.48	1.31
Post-Intervention (Day 7)	2.03	0.27

Note: Assessed via device-native screen time tracking applications (iOS Screen Time/ Android Digital Wellbeing). Reduction: −4.45 h/day; $t(76) = 26.74$, $p < .001$, Cohen's d = 3.05.

Table 2: Pre–Post Descriptive Statistics for All Psychological Outcome Variables (N = 77).

Variable	Pre M	Pre SD	Post M	Post SD	Δ
Positive Affect	2.54	0.66	4.18	0.58	+1.64
Concentration	2.37	0.72	4.11	0.61	+1.74
Sleep Quality	2.61	0.71	3.98	0.65	+1.37
Procrastination	3.88	0.76	2.21	0.69	−1.67
Perceived Stress	3.74	0.73	2.29	0.64	−1.45
Subjective Productivity	2.48	0.69	4.22	0.56	+1.74
Social Connectedness	2.69	0.75	3.87	0.70	+1.18
Life Satisfaction	2.72	0.68	4.07	0.59	+1.35

Note: Scores reflect Likert-type scales (1 = does not apply at all; 5 = applies completely). For Procrastination and Perceived Stress, lower post-intervention scores indicate improvement. Δ = Post M − Pre M.

Table 3: Paired-Samples t-Tests and Effect Sizes for Pre–Post Comparisons (N = 77).

Variable	t	df	*p*	Cohen's d
Positive Affect	17.92	76	< .001	2.04
Concentration	19.11	76	< .001	2.17
Sleep Quality	14.82	76	< .001	1.69
Procrastination	18.47	76	< .001	2.10
Perceived Stress	15.33	76	< .001	1.74
Subjective Productivity	20.05	76	< .001	2.28
Social Connectedness	12.41	76	< .001	1.41
Life Satisfaction	15.96	76	< .001	1.82

1.41 – 2.28), with subjective productivity demonstrating the largest effect (d = 2.28) and social connectedness the smallest, though still large, effect (d = 1.41). These magnitudes are notably robust and exceed typical effect sizes reported in general psychotherapy outcome research (d ≈ 0.80) [36], underscoring the potency of even a brief and ecologically embedded behavioral intervention.

To supplement parametric analyses, we examined the proportion of participants endorsing scale values of 4 or 5 at post-intervention on key items reflecting subjective improvement. Results indicated that 89% of participants endorsed noticeably improved concentration, 92% endorsed being more productive than before the intervention, 87% reported feeling emotionally more stable, 94% reported procrastinating less, and 81% reported improved sleep quality. These distributional findings confirm that large effect sizes were not driven by outliers but reflect a near-universal response to the intervention across the sample.

Table 4 presents the Pearson correlation matrix among four central post-intervention outcome variables. All correlations were statistically significant at $p < .001$. Particularly strong positive associations were observed between concentration and productivity ($r = .83$) and between positive affect and productivity ($r = .79$), consistent with theoretical models positing that attentional control and affective state serve as proximal determinants of productive behavior [37,38]. Perceived stress exhibited moderate-to-strong negative correlations with all three other variables, ranging from $r = -.68$ (with positive affect) to $r = -.71$ (with concentration).

Regression analysis: Predictors of life satisfaction

A hierarchical multiple regression analysis examined the predictive utility of post-intervention concentration, positive affect, and perceived stress for post-intervention life satisfaction. The final model was statistically significant, $F(3, 73) = 47.18$, $p < .001$, $R^2 = .66$, indicating that 66% of the variance in life satisfaction was jointly explained by these three predictors. Concentration ($\beta = .38$, $p < .001$) and positive affect ($\beta = .36$, $p < .001$) emerged as the strongest positive predictors, with perceived stress contributing a significant negative independent effect ($\beta = -.21$, $p = .009$). These findings highlight the central role of cognitive and affective recovery in translating digital self-regulation into subjective life quality improvements.

Independent-samples t-test comparing post-intervention concentration between participants with high (> 7 h/day; Group A: $n = 29$, M = 4.29, SD = 0.49) and low (≤ 7 h/day; Group B: $n = 48$, M = 3.99, SD = 0.66) baseline screen time revealed a statistically significant group difference, $t(75) = 2.46$, $p = .016$, d = 0.57. Participants with initially higher screen time engagement exhibited greater post-intervention concentration gains, consistent with a diminishing marginal returns model of digital self-regulation: individuals with the greatest behavioral excess may derive proportionally stronger cognitive benefits from reduction [20].

Table 4: Pearson Correlation Matrix for Key Post-Intervention Outcome Variables ($N = 77$).

Variable	1. Positive Affect	2. Concentration	3. Productivity	4. Stress
1. Positive Affect	—	.74**	.79**	–.68**
2. Concentration	.74**	—	.83**	–.71**
3. Productivity	.79**	.83**	—	–.69**
4. Perceived Stress	–.68**	–.71**	–.69**	—

Note: ** $p < .001$.

The hypothesized structural pathway model positing that screen time reduction influences life satisfaction through sequential mediation via stress reduction, concentration improvement, and subjective productivity demonstrated excellent fit to the observed data: CFI = .96, RMSEA = .048 (90% CI [.031, .065]), SRMR = .042. All specified direct paths were statistically significant. Screen time reduction predicted both lower stress ($\beta = .58$, $p < .001$) and higher concentration ($\beta = .62$, $p < .001$). Concentration strongly predicted productivity ($\beta = .79$, $p < .001$), which in turn predicted life satisfaction ($\beta = .68$, $p < .001$). These findings provide support for the proposed sequential mediation structure and lend specificity to the mechanisms through which digital self-regulation produces distal psychological benefits.

Discussion

The present investigation provides compelling evidence that a structured seven-day digital detox intervention—characterized by limiting recreational screen time to ≤ 2 hours per day—produces rapid, robust, and practically significant improvements across a wide spectrum of psychological outcomes in university students. The pattern of findings is consistent across behavioral (objective screen time), self-report (psychological outcomes), and latent structural (SEM pathway) levels of analysis, offering a convergently validated picture of intervention efficacy.

The magnitude of observed effect sizes (Cohen's d = 1.41–2.28 across outcomes) warrants careful interpretation. While such values are exceptional by conventional benchmarks in psychological intervention research [39], they are contextually interpretable when considered alongside the extreme behavioral change achieved (mean screen time reduction of 4.45 hours per day, d = 3.05) and the deliberately constructed intensity of the short-duration protocol. Participants were not merely reducing incidental scrolling but fundamentally restructuring their daily behavioral ecology within a compressed timeframe, plausibly generating correspondingly intense subjective contrast effects [40]. Furthermore, the pre-intervention baseline scores suggest substantial initial impairment on well-being-related variables (e.g., concentration M = 2.37; productivity M = 2.48 on a 1–5 scale), creating favorable conditions for large improvement effects from a psychometric floor perspective [41].

The finding that procrastination showed the largest magnitude of reduction ($\Delta = -1.67$; $d = 2.10$) is theoretically meaningful. Smartphone use and social media browsing have been consistently identified as primary procrastination vehicles among students, with experimental and experience sampling research documenting strong moment-to-moment associations between phone use and task disengagement [8,42,43]. By substantially restricting access to these behavioral alternatives, participants may have experienced a form of temptation removal analogous to ego-protective self-binding strategies described in the self-control literature [26,44]. The near-universal response to this domain (94% of participants endorsing less procrastination at post-assessment) further underscores its centrality to the intervention's psychological impact.

Sleep quality improvement ($d = 1.69$) is consistent with the substantial literature on blue-light emission and psycho-emotional arousal as mechanisms linking pre-sleep screen exposure to disrupted circadian physiology [14-16]. By removing or restricting bedtime device use, participants likely experienced earlier melatonin onset, improved sleep continuity, and enhanced slow-wave sleep architecture—changes that in turn feed back positively onto mood, stress reactivity, and cognitive performance the following day [18]. The interconnected nature of these mechanisms is empirically supported by the strong intercorrelations observed among concentration, positive affect, and stress at post-intervention, and is formally captured in the SEM pathway.

The structural model yielded an excellent fit and confirmed the hypothesized sequential mediation: screen time reduction → stress reduction and concentration improvement → productivity enhancement → life satisfaction. This architecture closely parallels pathways proposed in the attentional control and cognitive load traditions [25,37], wherein reductions in extraneous cognitive load—here operationalized as attentional fragmentation induced by digital interruptions—free working memory resources for goal-directed behavior, increasing perceived productivity and subsequently life satisfaction [24,45]. The relatively modest but significant independent contribution of stress reduction to life satisfaction ($\beta = -.21$) suggests that physiological and affective recovery from chronic low-grade digital stress represents an additional, partly separable pathway.

Moderation by baseline screen time level ($d = 0.57$ for concentration gains in heavy vs. moderate users) aligns with the principle of proportionality of benefit in behavioral medicine: individuals exhibiting the most maladaptive baseline patterns typically demonstrate the greatest short-term responsiveness to behavioral modification [46]. This finding has direct clinical implications, suggesting that targeted outreach to the heaviest digital media consumers within university populations may yield the greatest individual-level returns on intervention investment.

Limitations and future directions

Several limitations temper the interpretive scope of the present findings. First, the absence of a randomized wait-list control group precludes causal attribution and renders observed changes susceptible to natural fluctuation, regression to the mean, and non-specific demand characteristics associated with study participation [47]. The marked and behaviorally documented nature of the screen time reduction partially mitigates this concern, but future research should employ randomized controlled designs with active comparison conditions—such as a wait-list control group or an active control condition (e.g., mindfulness training)—to establish whether observed effects are specifically attributable to the digital detox intervention itself and to rule out potential confounds including demand characteristics and placebo effects. Second, the seven-day assessment interval, while sufficient to capture acute behavioral effects, does not permit conclusions regarding the durability of gains beyond the intervention period. Longitudinal follow-up assessments at four, eight, and twelve weeks would substantially strengthen ecological validity claims. Third, the student sample recruited from a single private institution limits generalizability across educational and cultural contexts. Fourth, while objective screen time data were collected via device applications, these systems do not distinguish between different content types (e.g., educational videos vs. social media scrolling) or track passive vs. active usage modes, potentially introducing measurement imprecision. Fifth, self-selection into a digital detox study likely attracted participants already motivated toward behavior change, potentially inflating effect estimates relative to less motivated community samples.

Future research should address these limitations by employing randomized controlled trial designs, comprehensive ecological momentary assessment to capture real-time behavioral and affective dynamics, neuroimaging or psychophysiological outcome measures to corroborate self-reported cognitive improvements, and longer follow-up periods. Comparative investigations examining the differential efficacy of full digital abstinence versus partial reduction protocols and qualitative studies exploring the subjective experience of digital detox—including barriers, facilitators, and the phenomenology of digital craving—would further enrich the empirical landscape.

Conclusion

The present study demonstrates that a seven-day structured digital detox intervention produces rapid, large-magnitude improvements across multiple domains of psychological functioning in university students, including concentration, procrastination, sleep quality, perceived stress, subjective productivity, social connectedness, and life satisfaction. Structural equation modeling confirms a coherent mediation pathway from behavioral digital self-regulation through stress reduction and cognitive improvement to enhanced life quality. These findings carry direct and actionable implications for university mental health services, student success programming, and digital wellness curricula. As the ubiquity of digital devices continues to expand, equipping students with evidence-based behavioral self-regulation strategies represents an increasingly critical dimension of comprehensive psychological care. A single week of intentional digital reduction appears sufficient to initiate meaningful psychological recovery—a finding that merits replication, extension, and further investigation in broader, more diverse populations to assess generalizability before translation into scalable public health programming.

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