Planning a digital detox

Findings from a randomized controlled trial to reduce smartphone usage time

Brockmeier, Lina Christin; Keller, Jan; Dingler, Tilman; Paduszynska, Natalia; Luszczynska, Aleksandra; Radtke, Theda

DOI
10.1016/j.chb.2025.108624

Publication date
2025

Document Version
Final published version

Published in
Computers in Human Behavior

Computers in Human Behavior 168 (2025) 108624

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

Planning a digital detox: Findings from a randomized controlled trial to reduce smartphone usage time

Lina Christin Brockmeier [a,b,*], Jan Keller [a], Tilman Dingler [c], Natalia Paduszynska [d], Aleksandra Luszczynska [d,e], Theda Radtke [f]

[a] Department of Education and Psychology, Division of Health Psychology, Freie Universität Berlin, Berlin, Germany
[b] School of Computing and Information Systems, University of Melbourne, Melbourne, Australia
[c] Department of Sustainable Design Engineering, Delft University of Technology, Delft, Netherlands
[d] Wroclaw Faculty of Psychology, SWPS University, Wroclaw, Poland
[e] Melbourne Centre for Behavior Change, Melbourne School of Psychological Sciences, University of Melbourne, Melbourne, Australia
[f] Department of Health Psychology and Applied Diagnostics, University of Wuppertal, Wuppertal, Germany

ARTICLE INFO

Handling Editor: Min Jou

Keywords:
Smartphone use
Health behaviour change
Self-efficacy
Social media use
Action planning
Smartphone sensing

ABSTRACT

In the recent years, studies on health consequences of smartphone usage time have increased, yet findings on the effectiveness of usage interventions remain unclear. This preregistered study investigates the effectiveness of a planning intervention to reduce total smartphone usage time. Additionally, it examines the interventions' underlying mechanisms of self-efficacy, intention, action, and coping planning. A primary analysis of a randomized controlled trial, with data collected at three measurement points was conducted. Three cohorts of university students were recruited during the period prior to the end-of-term exams. A total of $N = 787$ participants were allocated to either an intervention condition ($n = 389$) or a control condition ($n = 398$). At baseline measurement (T1) the intervention condition formed up to three actions and three coping plans. Self-reported self-efficacy, intention, action, and coping planning as well as objectively measured smartphone usage were assessed up to a three-weeks follow-up. The effectiveness of the intervention and the mediating mechanisms were evaluated using linear mixed models. The analysis revealed no significant effect on total smartphone usage time. With respect to the interventions underlying mechanisms, results show a significant indirect effect of self-efficacy at T2, on a reduction in total smartphone usage time at T3 but no evidence for intention, action, or coping planning.

1. Introduction

Smartphones have become an indispensable tool for our daily lives. They provide connectivity, immediate access to a vast amount of information and entertainment, and offer a diverse range of features that assist us with a variety of tasks (Vanden Abeele et al., 2018). However, increasing concerns about their negative impact on health, productivity, social relationships, and well-being are driving individuals desire for digital disconnection (Beisch & Koch, 2022; Vanden Abeele et al., 2024).

When displacing meaningful activities, such as face-to-face interactions with peers or sleep (Hall et al., 2019; Twenge et al., 2019), smartphone usage time has been associated with negative health outcomes. These include increased anxiety, stress, and compromised sleep quality (Thomée, 2018; Vahedi & Saiphoo, 2018). Additionally, smartphone usage can negatively impact academic and work productivity due to frequent and short interruptions (Amez & Baert, 2020). It can blur work-life boundaries, leading to social stress and role conflict (Gadeyne et al., 2018; Kao et al., 2020), and challenge well-being through exposure to negative online interactions (e.g., idealized social media portrayal) (Faelens et al., 2019, 2021). Previous research suggests that relationships between smartphone usage time and well-being may follow an inverted U-shape, where moderate use is associated with optimal well-being, and both minimal and excessive use (e.g., more than 4 h per day) is associated with negative mental health outcomes (Przybylski et al., 2020). These findings underscore the need for interventions that mitigate the maladaptive impact of smartphone usage time while maintaining its benefits.

* Corresponding author. Habelschwerdter Allee 45, 14195 Berlin, Germany.
E-mail address: lina.brockmeier@fu-berlin.de (L.C. Brockmeier).

https://doi.org/10.1016/j.chb.2025.108624
Received 20 March 2024; Received in revised form 26 February 2025; Accepted 26 February 2025
Available online 26 February 2025

1.1. Interventions to disconnect from smartphone usage

Various digital tools, including smartphone applications have been applied as timers or blockers to reduce the total usage time or frequency of smartphone usage (Grüning et al.,2023; Keller et al., 2021; Zimmermann & Sobolov, 2023). These digital tools aim to assist users in monitoring or restricting their smartphone usage time to change their smartphone-related behaviour. However, screen time monitoring and restriction alone rarely lead to an actual reduction in smartphone usage time (Zimmermann, 2021). Research on technology-based interventions such as applications to reduce smartphone usage shows mixed effects regarding intervention effectiveness and lack an examination of underlying psychological mechanisms (Purohit & Holzer, 2021; van Velthoven et al., 2018).

Interventions with a behaviour change focus mainly target digital disconnection and can be called *digital detox interventions* (Nassen et al., 2023). Digital detox refers to a period of time during which an individual abstains from using technological devices, such as smartphones (Radtke et al., 2022). To date, research on digital detox interventions promoting smartphone abstinence yields inconsistent findings (Radtke et al., 2022). While some studies report adverse effects like smartphone craving and separation anxiety (Hanley et al., 2019; Vally & D'Souza, 2019), other studies have found no negative intervention effects (e.g., Hall et al., 2021; Nguyen & Hargittai, 2023). However, further studies indicate positive effects, with a significant decrease in depression and anxiety (Lambert et al., 2022), suggesting that psychological well-being may benefit from smartphone disengagement (Brown & Kuss, 2020; Nguyen, 2021). Additionally, current research on digital detox interventions remains inconclusive on whether total abstinence or a strategic reduction in smartphone usage time is more effective (Brailovskaia et al., 2023; Plackett et al., 2023; Radtke et al., 2022).

These mixed findings highlight the need to closely examine the mechanisms within digital detox interventions (Vanden Abeele et al., 2024). Notably, interventions incorporating self-regulation, that encourages goal-oriented and effective smartphone use, have yielded positive health and well-being outcomes (Brailovskaia et al., 2023). This suggests that self-regulatory mechanisms could be crucial in targeting smartphone usage behaviour.

1.2. Self-regulatory mechanisms: Self-efficacy, action planning, and coping planning

Behaviour change theories, such as the *Health Action Process Approach* (HAPA; Schwarzer, 2008), emphasize the significance of self-regulatory processes in initiating and sustaining intended behaviour changes. Within this framework, self-efficacy and planning are key factors for translating behavioural goals into action (Schwarzer & Luszczynska, 2008).

Self-efficacy refers to an individual's belief in their capability to successfully complete a specific task, overcome difficult situations, or adopt to a novel course of action (Bandura, 1997). Moreover, self-efficacy is crucial for the successful implementation of plans to change behaviour, enhancing individuals' beliefs in their ability to overcome obstacles and adhere to their action plans, even in the face of challenges (Sniehotta et al., 2005). Ample research on behaviour change interventions has demonstrated that self-efficacy is relevant for individuals to implement and sustain behaviour change (Schwarzer & Luszczynska, 2008; Zhang et al., 2019). In the context of reducing smartphone usage time, which can potentially encompass various challenges (e.g., ignoring incoming notifications), fostering self-efficacy beliefs may be essential. For example, Keller et al. (2021) showed that self-efficacy acts as a critical mechanism within an intervention app aiming to reduce problematic smartphone use. In particular, this intervention notably enhanced self-efficacy beliefs, which was in turn associated with a significant reduction in problematic smartphone behaviour. Nonetheless, more research is needed to further explore the role of self-efficacy in the context of digital detox interventions targeting smartphone usage time.

In addition to the role of self-efficacy, action and coping planning may serve as potential predictors for the intention-behaviour relationship (Zhang et al., 2019). Action planning can be defined as a prospective self-regulator strategy that links a situational cue (e.g., 'When I study for my psychology exam, …') with a specific behavioural response (e.g., ' …, I will lock my smartphone in the kitchen drawer.') (Hagger & Luszczynska, 2014; Sniehotta et al., 2005). Action planning requires the prior forming of an intention to change a behaviour (i.e., the level of effort put into enacting a desired behaviour; Zhang et al., 2019) and is suggested to mediate the intention-behaviour relationship (Webb & Sheeran, 2006) by forming a mental association between the situational cue (when, where) and the behavioural response (how). In turn, coping planning represents the anticipation of possible barriers that might impair the intended behavioural action. It includes planning on how to overcome and manage these barriers (Zhang et al., 2019). While previous studies have explored the efficacy of planning on various health-related behaviours (e.g., physical activity, healthy nutrition, Fleig et al., 2011; Hagger & Luszczynska, 2014; Zhang et al., 2019), they have not addressed the effect of planning on the reduction of smartphone usage time (Radtke et al., 2024).

1.3. Young adults as the target group for a digital detox

Students represent a substantial proportion of 18–29-year-olds, an age group in which the prevalence of smartphone ownership is high (Pew Research Center, 2018). With a high frequency of use, that is more than 5h per day, university students' smartphone usage time often interferes with their learning and studying habits (Amez et al., 2023). Furthermore, high smartphone usage time among university students has been linked to increased levels of depression, anxiety, and sleep problems, underscoring their susceptibility to mental health challenges (Singh & Samah, 2018). These factors combined make university students a particularly relevant group for studying the effectiveness of a planning intervention targeting smartphone usage time.

1.4. Aims and hypotheses

The present study aims to examine the effects of a planning intervention (vs. a control condition) which targets the reduction of smartphone usage time among university students during their exam preparation phase. It is examined whether planning is an effective strategy to reduce daily smartphone usage time and in particular social media usage time on smartphones. Based on evidence for the effectiveness of planning interventions addressing the change of other behaviours (Zhang et al., 2019), we expect that participants in the intervention condition show lower levels of overall smartphone usage time ('H' = Hypothesis; H1a) and social media usage time (H1b) than participants in the control condition. Additionally, we propose that the effect of the planning intervention on reduced overall smartphone usage time is mediated by self-regulatory variables, including self-efficacy (H2a), intention (H2b), action planning (H2c), and coping planning (H2d).

2. Methods and materials

This study reports primary analyses from a two-condition randomized controlled trial (RCT) testing the effectiveness of a planning intervention on smartphone disconnection among university students. An existing publication by Nunez et al. (2022) has examined cohort effects of baseline variables. The RCT was conducted during exam preparation phase before the end-of-term exams, with data collected among university students during the 2020 winter term (cohort 1; between January and February 2020), the 2020 summer term (cohort 2; between May and July 2020), and the 2021 winter term (cohort 3; between

January and February 2021). The RCT preregistration can be accessed at the Clinical Trial Register at Clinicaltrials.gov (trial registration number: NCT04550286). The study was approved by the Ethics Committee at Witten/Herdecke University.

2.1. Sample and procedures

Study participants were recruited nationwide in Germany at different universities using on-campus and off-campus advertisements via social media platforms, university mailing lists, and flyers, as well as short presentations in lectures at the institution conducting the study. Eligibility criteria for participation included a minimum age of 16 years, a current enrolment as a student at a German university, regular usage of a smartphone with an Android operating system, proficient German language skills, having at least one graded exam scheduled in the consecutive semester, and not actively seeking treatment for test anxiety. Study participation was voluntary. As an incentive for full study participation, all participants were given the opportunity to partake in a lottery including various prizes consisting of adventure activity gift cards and other vouchers (worth 830 EUR in total). Additionally, psychology students of Witten/Herdecke University received course credit for full participation.

A total of $N = 787$ participants ($n = 569$ women; 72.3 %) with a mean age of 22.81 years ($SD = 3.72$, range 17–48) were assessed for eligibility and registered for the study online. They provided their e-mail address, informed consent, and completed the baseline assessment ('T' = Time; T1). Upon completion of the baseline questionnaire, all students were given general advice on how to organize their study environment and study behaviour to improve their performance during the exam preparation phase before the end-of-term exams (e.g., pauses during exam preparation, ways to organize study materials, etc.; see Appendix S1).

Using a random digit generator, participants were then assigned to either the intervention ($n = 389$) or control condition ($n = 398$). Randomization was conducted via SoSci Survey's internal randomization function, which ensures equal probability of assignment to each condition (Leiner, 2019). No stratification was applied. Participants in the intervention condition received online written instructions to generate three action and three coping plans to reduce smartphone usage time during the exam preparation phase. To ensure equivalent time duration, participants in the control condition received a survey related to their dietary habits (e.g., 'How often do you typically consume dairy products?'), which was not related to the subject of the intervention. At post-intervention, participants received online questionnaires at 7 days (T2) and 14 days (T3) following baseline (T1). Besides data analysed in this study, participants provided additional self-reported data after their first graded exam at T4 (on average 34 days after baseline) and at T5 (on average 95 days after baseline). The study design is illustrated in Fig. 1.

Moreover, all participants were asked to install a screen time application (academia.murmuras.com) on their smartphones. The mobile application assessed participants' smartphone usage time during the post-intervention period (between T1 and T3). The time of mobile usage data was logged in the background. The application did not inform participants about their smartphone behaviour. Of the eligible participants, $n = 716$ participants installed the study app, of which $n = 555$ (out of 716: 77.51%) participants had study app-measured data points on overall smartphone usage enabling behavioural data analysis. Fig. 2 provides a CONSORT flowchart.

2.2. Intervention

In the intervention condition, participants were provided with the same general advice on study behaviour and environment as those assigned to the control condition (*Behavior Change Technique Ontology*; BCIO 007051; Marques et al., 2024). Next, they were informed that the presence and use of smartphones could lead to distraction during the exam preparation phase. They were also advised to take breaks from their smartphone and other electronic devices while studying. Participants in the intervention condition were first asked to reflect on their smartphone use and create a plan for switching it off and placing it out of sight and reach during the weeks before their end-of-term exams. They were then instructed to develop three individual action plans (BCIO 007010; Marques et al., 2024). These plans needed to specify: 'when' the students would study (day of the week and time), 'where' they would study (location), and 'how long' they would put their smartphone away (duration). Example plans were provided, and participants were asked to develop three personalized plans following an 'if-then' structure (e.g. 'If I study for my biology exam on Thursday at 4 p.m., then I will turn off my smartphone and place it in my bedroom drawer until I finish reviewing two chapters'; Gollwitzer & Sheeran, 2006). Students were encouraged to ensure that their plans aligned with their study habits, could be implemented into their daily routines, and were precise and complete. They were then asked to enter each action plan into three provided blank fields within the online questionnaire. This procedure was followed by instructions to develop three individual coping plans (BCIO 007008; Marques et al., 2024), that is, the anticipation of possible barriers to engaging in the planned behaviour and how to overcome these barriers: 'If situation X appears, then I will cope with it by doing Y' (Sniehotta et al., 2006). Participants were first prompted to identify situations where it might be challenging for them to refrain from using their smartphone while studying. They were asked to develop three coping plans to address these challenges, using an if-then structure (e.g., 'If I have a question for my fellow students while studying, then I will write it on a piece of paper and ask them after my study session is completed.'; Gollwitzer & Sheeran, 2006). To support this process, example coping plans were provided. The instructions emphasized that the coping plans should be practical and align with students' study habits and their daily routines. Participants were then instructed to enter their three coping plans into designated blank fields provided in the online questionnaire. Subsequently, participants were advised to read their action and coping plans out loud, take a photo of their plans and use the photo as their smartphone background. A detailed description of the delivery and the content of the intervention and control procedure is presented in Appendices S2 and S3.

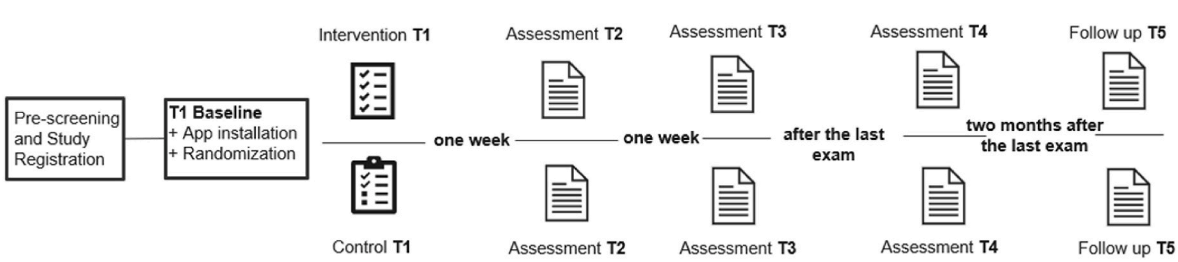

Fig. 1. Study Design with Five Measurement Points for the Control and Intervention Conditions.
Note. The present study analyses focused on the assessments between T1 and T3 which were prior to the end of term-exams.

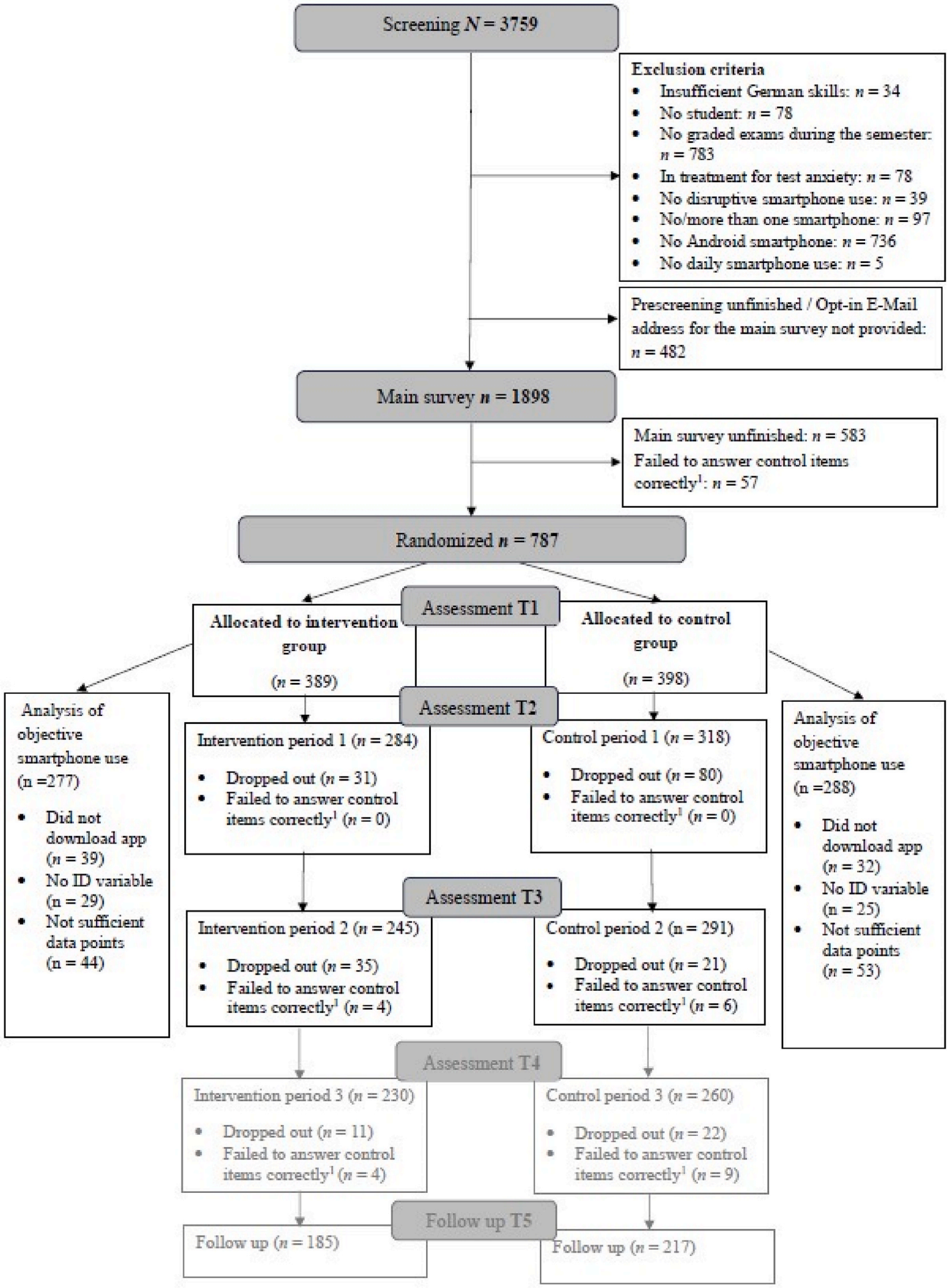

Fig. 2. Flowchart showing the Condition Allocation and Participant Dropout across the Assessment Points.
Note. 'T' = Time. The total sample consists of three independent cohorts. Cohort 1 ($n = 174$), cohort 2 ($n = 233$), cohort 3 ($n = 380$). Participants were excluded when they failed to answer the control item (i.e., those who chose the options [1] completely disagree or [2] mostly disagree when instructed to 'Please choose [4] mostly agree'). Participants were included when they chose response options close to the correct answer of the control item (i.e., [3] neither or [5] completely agree), as they did not differ from those who chose the correct control item response on the dependent variables. Data from T4 and T5 (presented in grey font) was not analysed in this study.

2.3. Measures

Except for covariates, app-usage was assessed across three time points (T1 = Day1 till Day7, T2 = Day8 till Day14 and T3 = Day15 till Day21). Self-efficacy was assessed at T1 and T2, whereas intention, action, and coping planning were self-reported at T1, T2, and T3 (each one week apart). The item examples listed below were translated from German.

2.3.1. App-measured smartphone usage data

Across 21 days following baseline, objective data on daily minutes of (1) overall smartphone usage time and (2) social media usage time were measured by a screen time application. We calculated weekly scores of average daily minutes of overall smartphone usage time and overall social media usage time. In instances of very high levels of smartphone or social media minutes per day, univariate outliers ($z \geq 3.29$) were winsorized to one unit higher than the next highest value with $z \leq 3.29$ (Tabachnick & Fidell, 2007).

2.3.2. Self-efficacy

Participants' self-efficacy to reduce smartphone usage time during study time was assessed by six self-report items with responses ranging from 'completely disagree' (1) to 'completely agree' (6). A sample item read: 'I am confident that I can switch my smartphone into airplane mode while studying'. Cronbach's alpha was $\alpha = .78$ at T1 and $\alpha = .77$ at T2.

2.3.3. Intention

Intention to decrease smartphone usage time during study periods was assessed using five items adapted from Sniehotta et al. (2005). Intention items (e.g., 'I intend to keep my smartphone out of sight and reach during study time.') were answered on a 6-point scale (1 = *completely disagree*; 6 = *completely agree*). Across measurement points and conditions, Cronbach's alpha was $\alpha = .79$ at T1, $\alpha = .77$ at T2 and $\alpha = .79$ at T3.

2.3.4. Action planning

Action planning to reduce smartphone usage time during the exam preparation phase was assessed with three items adapted from Sniehotta et al. (2005). Participants responded to items such as 'I have made detailed plans when I will switch my smartphone into airplane mode while studying' on a 6-point scale (1 = *completely disagree*; 6 = *completely agree*). Cronbach's alpha was $\alpha = .82$ at T1, $\alpha = .85$ at T2, and $\alpha = .87$ at T3.

2.3.5. Coping planning

Self-reported coping planning of reduced smartphone usage time during the exam preparation phase was measured with a 6-point scale (1 = *completely disagree*; 6 = *completely agree*). The three items used the stem 'I have made detailed plans … ' followed by statements such as 'how to deal with incoming smartphone notifications while studying'. The coping planning items were also adapted from Sniehotta et al. (2005). Cronbach's alpha was $\alpha = .73$ at T1, $\alpha = .76$ at T2 and $\alpha = .79$ at T3.

2.3.6. Covariates

The covariates included sex (not male = 0; male = 1), age, and perceptions of procrastination and self-efficacy at baseline. Procrastination was assessed using a 6-point scale (1 = *completely disagree*; 6 = *completely agree*) using items such as 'I delay the start of tasks until the last minute'. Also, two dummy-coded cohort variables (cohort 2: 1 = students from cohort 2; cohort 3: 1 = students from cohort 3) were used for the respective semester of study participation.

2.4. Data analysis

An a-priori power analysis for a repeated-measures ANOVA with G*Power v3.1 was calculated regarding the reduction of smartphone usage time compared to a control condition with a power of $1–\beta = .95$ and a p value of .05. A sample size of 116 participants would be needed to identify a small effect (Cohen's $d = .17$) (Faul et al., 2007). It has to be emphasized that the present analysis varies from the ANOVA-based power analysis by employing multilevel modelling to accommodate the nested data structure. Multilevel models offer the advantage to account for between- and within-group variability (Bolger & Laurenceau, 2013).

Data were analysed based on the intention-to-treat approach. Descriptive statistics of study variables and bivariate correlations were analysed using SPSS 28 (IBM Corp., 2021). Accommodating the nested data structure for repeated measures, Rstudio (R Core Team, 2021) and the lme4 package (Bates et al., 2015) were used to run multilevel models. A restricted estimated maximum likelihood (REML) procedure was applied to account for missing data (McNeish, 2017). For the mediation analyses, the lavaan R package was used.

An attrition analysis and a randomization check were run for baseline variables using chi-square and t-tests, which were followed by logistic regressions. Randomization to study conditions was represented by a binary outcome variable classified as 0 for the control condition or 1 for the intervention condition. Similarly, a binary attrition variable was coded for each participant, with attrition categorized as either not retained (0) or retained (1) for longitudinal analyses. It was tested whether baseline variables showed similar levels in both study conditions as well as for participants retaining or not retaining for analyses.

Univariate outliers were identified using analyses of z-scores, resulting in 67 univariate outliers for smartphone usage time and 120 univariate outliers for social media usage time, which were winsorized ($z \geq 3.29$) (Tabachnick & Fidell, 2007). Multivariate outliers were identified using analyss of Mahalanobis distance, with 35 multivariate outliers detected, based on critical chi-square values ($p < .001$). Multivariate outliers were not excluded from the analyses, as sensitivity analyses revealed similar results regardless of their inclusion.

Linear two-level models were estimated including the daily assessment of smartphone usage (within-level) nested in participants (between-level) for overall smartphone usage time and social media usage time. The models examined the interaction between experimental conditions (0 = control condition; 1 = intervention condition) and time (linear day trend) and demonstrated changes in smartphone usage time and social media usage time between the two experimental conditions across the post-intervention period. The linear mixed models were specified using a maximal random effect structure for all predictor variables (Barr et al., 2013). When models did not converge, we reduced the random effects structure until convergence was met (Bolger & Laurenceau, 2013).

In addition, we specified four mediation models, in which self-efficacy, intention, action planning and coping planning were tested as proposed mediators. To assure a temporal order of the mediators (assessed at post-intervention: T2), the overall smartphone usage time from study days 8–14 (corresponding to the week after T2) was used to compute a mean score. Baseline levels of mediators and covariates were grand-mean centred and included in the model as predictors. The mediation models were tested using bootstrapping (5000; Preacher & Hayes, 2008) and bootstrap-corrected confidence intervals were computed (CI_{bc}).

We included sex, age, procrastination, self-efficacy and cohort variables as between-person covariates. Sex (1 = male vs. 0 = not) and cohort effects of cohort 2 (1 = cohort 2 vs. 0 = not) and cohort 3 (1 = cohort 3 vs. 0 = not) were dummy-coded. Age, procrastination and self-efficacy were grand-mean centred. All covariates were used for sensitivity analysis.

3. Results

Descriptive statistics of study variables are presented in Appendix S4.

3.1. Sample characteristics, randomization check, attrition analysis, and manipulation check

The study included $N = 787$ participants ($n = 569$ women (72.3%); $n = 212$ men (26.9%) and $n = 6$ with a non-binary report (0.8%). Participants had a mean age of 22.81 years ($SD = 3.73$), ranging from 17 to 48 years old. The sample consisted of students from over >100 German universities, with $n = 577$ (73.3%) students enrolled in advanced undergraduate and graduate programs, and $n = 210$ (26.7%) students enrolled in their first year of undergraduate studies. Most students ($n =$ 611, 77.6%) were enrolled in their first-degree program, while $n = 176$ (22.4%) students were enrolled in their second-degree program (see Table 1).

The randomization check revealed no unique between-condition differences at baseline, pointing to a successful randomization. The attrition analysis revealed that compared to those who dropped out before T3 ($n = 252$) completers ($n = 536$) had higher self-efficacy (non-retainers: $M = 4.26$, $SD = .85$; retainers: $M = 4.39$, $SD = .81$; $p = .03$) and lower procrastination (non-retainers: $M = 3.08$, $SD = .36$; retainers: $M =$ 3.02, $SD = .35$; $p = .02$).

Manipulation checks revealed a significant increase in intention to reduce smartphone usage time across the measurement points in the intervention condition compared to the control condition ($b = 0.23$, $SE = 0.09$, 95% CI [0.06, 0.41], $p = .01$). Compared to the control condition, participants in the intervention condition reported higher increases in action planning ($b = 0.21$, $SE = 0.05$, $p = < .001$, 95% CI [0.11, 0.31]) and coping planning ($b = 0.45$, $SE = 0.11$, 95% CI [0.22, 0.67], $p < .001$) (see Appendix S5).

3.2. Smartphone usage over time

The first analysis aimed to test the intervention effect on objectively measured daily smartphone usage time (model 1) and social media usage time (model 2) over a 21-day post-intervention period. Using linear two-level models with assessment points nested in individuals, the intraclass correlation (ICC) of daily smartphone usage (ICC = .63) and daily social media usage time (ICC = .63) indicates that variance in smartphone and social media usage time was mainly explained by differences between participants (level 2). Regarding the time predictions, the control condition did not show statistically significant changes in smartphone usage time ($b = -1.87$, $SE = 3.55$, $p = .60$, 95% CI [−8.84, 5.09] or social media usage time ($b = 2.14$, $SE = 1.37$, $p = .12$, 95% CI [−0.55, 4.82]) across the assessment points. The Time × Group interaction did not reach statistical significance indicating that no between-condition differences in smartphone usage time ($b = 3.90$, $SE = 5.09$, $p = .45$, 95% CI [−6.08, 13.88] or social media usage time ($b = -1.65$, $SE = 1.91$, $p = .39$, 95% CI [−5.39, 2.10] could be observed. The random effects of associated intercepts were statistically significant, indicating between-participant variability in baseline levels of smartphone usage and social media usage time. The significant random slope variances imply that changes over time for these outcomes vary across participants (Bolger & Laurenceau, 2013) (see Table 2.

Table 1
Demographic Information about the Total Sample and per Condition.

Demographic information	Total sample (N = 787)	Intervention condition (n = 389)	Control condition (n = 398)
Gender, *n (%)*			
Women	569 (72.3)	281 (72.3)	288 (72.4)
Men	212 (26.9)	107 (27.4)	105 (26.4)
Non-binary	6 (.8)	1 (.3)	5 (1.3)
Age in years: *M* (*SD*)	22.81 (3.73)	22.80 (3.85)	22.80 (3.62)
Number of exams: *M* (*SD*)	4.38 (1.91)	4.37 (1.98)	4.38 (1.84)
Semester information, *n (%)*			
First study program	611 (77.6)	301 (77.4)	310 (77.9)
Second study program	176 (22.4)	88 (22.6)	88 (22.1)
First year undergraduate students	210 (2.76)	112 (28.8)	98 (24.6)
Advanced undergraduate and graduate students	577 (73.3)	277 (71.2)	300 (75.4)

3.3. Effects of the intervention condition on changes in smartphone usage time mediated by self-efficacy, intention, and planning

In the model with self-efficacy as the mediator, an increase at T2 ($b = 0.16$, $SE = 0.08$, 95% CI_{bc} [0.01, 0.32]) was observed for the intervention (vs. control condition), which was associated with a decrease in smartphone usage time during the following seven days ($b = -21.37$, $SE = 7.16$, 95% CI_{bc} [−35.00, −7.65]) (see Fig. 3). The bootstrap-corrected confidence interval values indicated an indirect effect ($b = -3.43$, $SE =$ 2.14, 95% CI_{bc} [−8.45, −0.03]).

In the model with intention as the mediator, the intervention (vs. control) condition was positively associated with increases in intention at T2 ($b = 0.23$, $SE = 0.12$, 95% CI_{bc} [0.05, 0.41]), which was associated with reduced smartphone usage time during the following seven days ($b = -13.37$, $SE = 5.51$, 95% CI_{bc} [−24.35, −2.77]). The bootstrap-corrected confidence interval reflected a negative indirect effect ($b =$ −3.06, $SE = 1.96$, 95% CI_{bc} [−7.81, −0.19]).

The mediation model with action planning as the mediator showed that the intervention (vs. control condition) was positively related to increases in action planning at T2 ($b = 0.48$, $SE = .12$, 95% CI_{bc} [0.25, 0.72]) which, in turn, was associated with non-substantial reductions in smartphone usage time during the following seven days ($b = -5.42$, $SE = 4.45$, 95% CI_{bc} [−14.13, 3.28]. For coping planning as the mediator, increases in T2 coping planning ($b = 0.53$, $SE = 0.10$), CI_{bc} 95% [0.34, 0.73]) were observed for the intervention (vs. control) condition, which showed no substantial changes in smartphone usage time during seven days after T2 ($b = -3.26$, $SE = 4.32$, 95% CI_{bc} [−12.13, 5.16]).

Sensitivity analyses across all models revealed that the patterns of results remained similar when covariates were added, except for a non-substantial indirect effect for intention as mediator. Models from sensitivity analyses are listed in Appendix S6.

4. Discussion

This study examined the effects of a planning intervention to reduce smartphone usage time and the underlying self-regulatory mechanisms of such an intervention. Contrary to our initial hypotheses, the planning condition (vs. the control condition), did not show a direct effect on an overall reduction in smartphone usage time or social media usage time (not supporting H1a and H1b). Notably, while the intervention had an influence on self-efficacy and indirectly on reduced smartphone usage time (supporting H2a), the indirect effects of intention, action, and coping planning on a reduction of smartphone usage time were non-significant (not supporting H2b, H2c and H2d).

4.1. Effects of planning on smartphone disconnection

Our findings are somewhat surprising as planning has been identified as an effective strategy across diverse health behaviour change domains (Zhang et al., 2019). However, the effectiveness of planning mechanisms might vary for behaviour change within the context of digital disconnection (Vanden Abeele et al., 2024). There are several reasons that could explain a lack of direct effects of the planning intervention.

One key consideration is the fragmented nature of smartphone usage time. Fragmentation, that is, usage sessions being dispersed in numerous brief sessions throughout the day rather than occurring in a few prolonged periods, is notably evident in the context of social media applications, where push notifications and spontaneous 'checking' behaviours are common (Deng et al., 2019; große Deters & Schoedel, 2024; Hendrickson et al., 2019). Users often find themselves instinctively checking their smartphones for new messages or updates in social media apps, even in the absence of explicit prompts (Fitz et al., 2019; Klimmt et al., 2017; Kushlev & Leitao, 2020; Montag et al., 2015). Our study focused on total daily usage during study periods, which may have overlooked a more nuanced view of smartphone usage patterns and changes, such as reductions during specific times. Future studies could

Table 2
Estimates of Two-level Model Predictions of Smartphone and Social Media Usage Time, with Covariates and using the Control Condition as the Reference Group.

	Model 1a: Smartphone usage time			Model 2a: Social media usage time		
Fixed Effects	Est *(SE)*	*p*	95% CI	Est *(SE)*	*p*	95% CI
Intercept at baseline	264.27 (13.19)	<.001	238.55, 289.98	54.97 (5.05)	<.001	45.13, 64.81
Time	−1.87 (3.55)	.60	−8.84, 5.09	2.14 (1.37)	.12	−0.55, 4.82
Group	−8.30 (10.96)	.45	−29.68, 13.08	−.10 (4.12)	.98	−8.12, 7.92
Group by time	3.90 (5.09)	.44	−6.08, 13.88	−1.65 (1.91)	.39	−5.39, 2.10
Age	−1.44 (1.34)	.28	−4.05, 1.18	−1.01 (.53)	.05	−2.03, 0.02
Sex[a]	−20.09 (11.51)	.08	−42.52, 2.34	−10.36 (4.51)	.02	−19.44, −1.81
Procrastination	42.42 (14.00)	<.001	15.13, 69.71	−2.51 (5.36)	.64	−12.96, 7.93
Self-efficacy	−22.35 (6.03)	<.001	−34.11, −10.57	−2.90 (2.31)	.21	−7.40, 1.62
Cohort 2[b]	−11.50 (14.88)	.44	−40.52, 17.51	.58 (5.73)	.91	−10.58, 11.74
Cohort 3[c]	20.27 (13.55)	.14	−6.14, 46.68	11.36 (5.21)	.03	1.20, 21.50
Random Effects (variances)	Estimate		95% CI	Estimate		95% CI
Intercept	122.34		113.92, 129.81	42.99		39.75, 45.79
Time	43.10		38.18, 47.95	14.11		12.18, 15.99
Residual variance	93.17		91.89, 94.49	33.16		32.66, 33.68
ICC	.63			.63		
Pseudo-R^2	.63			.63		

Note. Est = Estimate; CI = Confidence interval; ICC = Intraclass correlation; CI = Confidence interval. Models are based on data from $497 \leq n \leq 555$ participants and $3878 \leq n \leq 10{,}498$ observations due to missing values. Coefficients smaller than .005 were rounded to .01.
[a] Sex coded as 0 = *not male*, 1 = *male*.
[b] Cohort 2 coded as 1 = *cohort 2*.
[c] Cohort 3 coded as 1 = cohort 3.

integrate Ecological Momentary Assessment methods (Stieger & Lewetz, 2018) and additionally examine the frequency of usage or app pick-ups to provide a more nuanced understanding of the dynamics of smartphone usage time.

Another consideration is the potential for compensatory behaviour outside planned time intervals of smartphone non-use. This phenomenon resonates with the concept of 'craving' or increased desire following a period of restriction, where a rebound in behaviour occurs after a period of suppression (Erskine & Georgiou, 2010; Sayers & Sayette, 2013). This aligns with findings from digital detox research, which found symptoms associated with craving, withdrawal, and potential overuse during and after phases of abstinence from smartphone or social media usage time (Eide et al.,2018; Stieger & Lewetz, 2018; Wilcockson et al., 2019).

4.2. The role of self-regulatory mechanisms on a reduction of smartphone usage time

A pivotal factor in the behaviour change process grounded in the theoretical framework of the HAPA model is self-efficacy (Schwarzer, 2008). Consistent with our assumptions, the present planning intervention enhanced self-efficacy beliefs, which, in turn, was associated with a decrease in smartphone usage time. Our findings align with existing research by Keller et al. (2021) and suggest that when individuals engage in planning to reduce smartphone usage time, it enhances their confidence to do so.

Self-efficacy might have served as a psychological resource when facing obstacles or resisting temptations associated with smartphone usage time (Bandura, 1997). By fostering beliefs in participants' capabilities to reduce smartphone usage time, the present findings underscore the importance of enabling individuals to self-regulate time spent with one's smartphone. Furthermore, these results highlight the potential for self-efficacy to not only facilitate initial behaviour change but also sustain those changes over time, providing a resource against relapse. Therefore, future studies should enhance self-efficacy by interventions targeting digital disconnection and thereby supporting more self-regulated smartphone usage time.

Moreover, we found that the planning intervention significantly increased intention to spend less time with one's smartphone, which in turn, led to reduced overall smartphone usage time. However, this effect diminished when covariates were added in sensitivity analyses. Furthermore, contrary to our hypotheses, neither self-reported action planning nor coping planning were significant mediators in reducing smartphone usage time.

The lack of mediating effects of intention and self-reported planning on a reduction of smartphone usage time may indicate that the impact of the planning intervention was not sufficiently intensive to result in a regular formation of action and coping plans. This may be due to the procedure relying on a single episode of action and coping planning. While one-time planning has been shown to be beneficial for health-related behaviours (Zhang et al., 2019), there is also evidence that booster sessions may be crucial to realize sustainable behaviour change, translating intentions into actions (Hagger & Luszczynska, 2014). For instance, Wicaksono et al. (2019) showed that adding plan reminders to the intervention led to better compliance and recall of the action plan. In addition, implementing booster planning sessions can help prevent relapses and prompt knowledge and skills related to the new behaviour (Fleig et al., 2013; Hagger & Luszczynska, 2014).

Another explanation for the lack of indirect effects of self-reported planning is that participants potentially encountered situations that made it difficult to integrate their initial plans into their daily routines such as changing study environment. The lack of opportunity to modify plans in response to changing circumstances or unexpected obstacles can significantly hinder the success of behaviour change efforts (Hagger & Luszczynska, 2014). Providing instructions on adjusting plans by for instance, giving participants the opportunity to specify situational cues that fit better in the daily routine (e.g., 'If I study for my diagnostics exam on Tuesday from 9 to 12 a.m. at home, I will switch off my smartphone and place it in the kitchen drawer.') can increase adaptability.

Furthermore, as our primary intervention focus, our study utilised 'If-then' plans solely. While action and coping planning offer a valuable approach, our findings suggest that their effectiveness might be enhanced when combined with other *behaviour change techniques* (BCTs). Existing literature indicates that integrating additional BCTs, such as goal setting, self-monitoring, and feedback can enhance the effectiveness of planning interventions (de Vries et al.,2013; Harkin et al., 2016; Marques et al., 2024). In the context of a reduction of smartphone usage time, researchers and practitioners have the opportunity to combine planning interventions with *digital self-control tools* (DSCTs), which are software applications or digital features designed to help individuals regulate their digital behaviours, offering a more dynamic and responsive framework for behaviour modification (Schwartz et al., 2021).

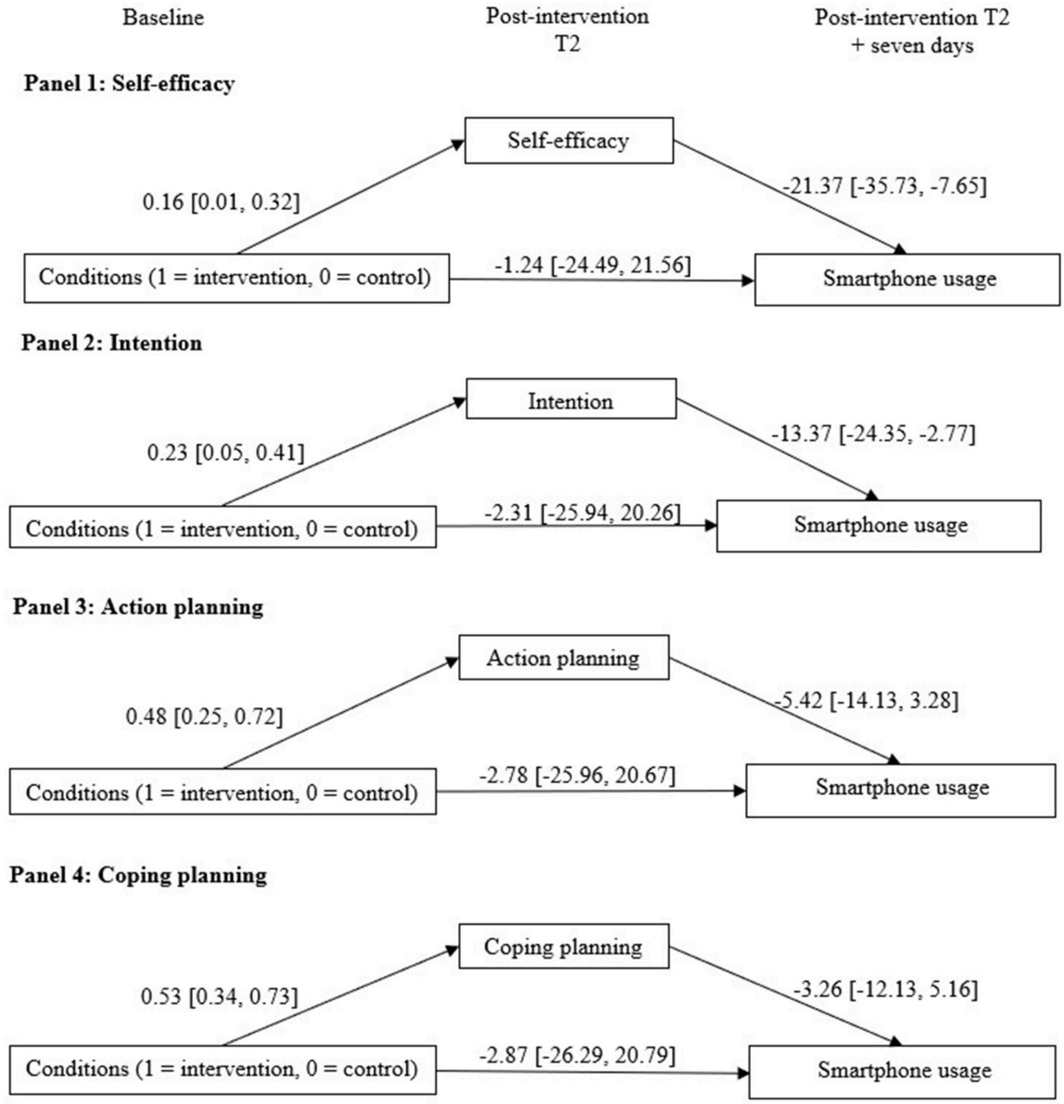

Fig. 3. Self-efficacy, Intention, Action Planning, and Coping Planning as Separate Mediators between Conditions and Smartphone Usage Time.
Note. Bootstrapping-corrected intervals are shown for path analyses.

4.3. Strengths, limitations, and future directions

With a randomized controlled trial, an intensive-longitudinal design, a device-based measurement of smartphone usage time and a large sample, the present study adds to our knowledge of planning interventions in the field of digital disconnection. Additionally, the study provides insights into smartphone-related outcomes and the role of self-regulatory factors such as self-efficacy and planning.

Some limitations must be acknowledged. First, the primary outcome (i.e., smartphone usage time) was assessed over the post-interventional phase using total usage time per day. Future studies could additionally include a baseline measurement of smartphone usage time and capture fragmentation of usage patterns throughout the day. This may provide a more nuanced understanding of the temporal dynamics of the intervention mechanisms and the specific reduction of smartphone or social media usage during targeted periods (Hendrickson et al., 2019). Second, social media apps were categorized based on the classifications provided by the Google Play Store (Google Play, 2023). These categories are primarily driven by marketing considerations and may not adequately reflect the psychological or behavioural dimensions of app use (Sust et al., 2023). Future studies should consider classifying apps based on psychological theoretical frameworks, such as those proposed by Schoedel et al. (2022), to provide a more nuanced understanding of how disconnecting from different app features influences users' psychological well-being (Schenkel et al., 2024). Third, our study did not account for the potential use of other digital tools, such as monitoring or device-locking apps, to manage smartphone usage time while studying. Future studies should identify the use of other digital tools by either adding this as an exclusion criterion or as a control variable. Fourth, while increased planning was reported in the intervention condition during the post-intervention phase, this did not translate into significant changes in smartphone usage time. Drawing on recommendations from Hagger & Luszczynska, 2014, adding booster sessions or planning reminders can enhance the effectiveness of planning interventions. Additionally, allowing participants to modify their plans, if initially found ineffective, may improve the translation from plans into action (Hagger & Luszczynska, 2014). Fifth, monitoring of participants' plan adherence as well as continuous support for plan adherence should be implemented as additional intervention components after participants formed their plans. This could be applied using a smartphone application with features like self-monitoring, feedback on plan pursuit, and opportunities for plan adjustment (Michie et al., 2009; Schwartz et al., 2021). This could help individuals stick to their plans by minimizing distractions and managing time effectively.

5. Conclusion

Present findings emphasize the potential of planning interventions for fostering self-efficacy, a crucial psychological resource for self-regulated smartphone usage time. However, the non-significant reduction of total overall smartphone and social media usage time in the intervention condition, along with the outlined limitations highlight the need for further refinement of these interventions. Future studies should focus on enhancing planning interventions with additional elements that support and strengthen plan enactment, thereby improving their long-term effectiveness.

CRediT authorship contribution statement

Lina Christin Brockmeier: Writing – review & editing, Writing – original draft, Project administration, Investigation, Formal analysis, Data curation. **Jan Keller:** Writing – review & editing, Validation, Supervision, Formal analysis. **Tilman Dingler:** Writing – review & editing. **Natalia Paduszynska:** Writing – review & editing. **Aleksandra Luszczynska:** Writing – review & editing, Validation. **Theda Radtke:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors are grateful for the administrative support of Tania Nunez as well as Alexandra Pongs and Christopher Grolla for their assistance during the recruiting phase of this study.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2025.108624.

Data availability

For privacy reasons, datasets with aggregated variables are available; raw data cannot be shared. The dataset is available via: https://osf.io/kd26v/?view_only=ca229d82523c48119251c34887f87fda.

References

Amez, S., & Baert, S. (2020). Smartphone use and academic performance: A literature review. *International Journal of Educational Research, 103*, 101618. https://doi.org/10.1016/j.ijer.2020.10161.

Amez, S., Vujić, S., De Marez, L., & Baert, S. (2023). Smartphone use and academic performance: First evidence from longitudinal data. *New Media & Society, 25*(3), 584–608. https://doi.org/10.1177/14614448211012374.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. New York, NY: Freeman.

Barr, D. J., Levy, R., Scheepers, C., & Tily, H. J. (2013). Random effects structure for confirmatory hypothesis testing: Keep it maximal. *Journal of Memory and Language, 68*(3), 255–278. https://doi.org/10.1016/j.jml.2012.11.001.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software, 67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01.

Beisch, N., & Koch, W. (2022). *ARD/ZDF-Onlinestudie: Vier von fünf Personen in Deutschland nutzen täglich das Internet* (Vol. 10, pp. 460–470), 2022.

Bolger, N., & Laurenceau, J.-P. (2013). *Intensive longitudinal methods: An introduction to diary and experience sampling research*. Guilford press.

Brailovskaia, J., Delveaux, J., John, J., Wicker, V., Noveski, A., Kim, S., & Margraf, J. (2023). Finding the "sweet spot" of smartphone use: Reduction or abstinence to increase well-being and healthy lifestyle?! An experimental intervention study. *Journal of Experimental Psychology: Applied, 29*(1), 149–161. https://doi.org/10.1037/xap0000430.

Brown, L., & Kuss, D. J. (2020). Fear of missing out, mental wellbeing, and social connectedness: A seven-day social media abstinence trial. *International Journal of Environmental Research and Public Health, 17*(12), 4566. https://www.mdpi.com/1660-4601/17/12/4566.

de Vries, H., Eggers, S. M., & Bolman, C. (2013). The role of action planning and plan enactment for smoking cessation. *BMC Public Health, 13*(1), 393. https://doi.org/10.1186/1471-2458-13-393.

Deng, T., Kanthawala, S., Meng, J., Peng, W., Kononova, A., Hao, Q., & David, P. (2019). Measuring smartphone usage and task switching with log tracking and self-reports. *Mobile Media & Communication, 7*(1), 3–23. https://doi.org/10.1177/2050157918761491.

Eide, T. A., Aarestad, S. H., Andreassen, C. S., Bilder, R. M., & Pallesen, S. (2018). Smartphone restriction and its effect on subjective withdrawal related scores [Original Research]. *Frontiers in Psychology, 9*. https://doi.org/10.3389/fpsyg.2018.01444.

Erskine, J. A. K., & Georgiou, G. J. (2010). Effects of thought suppression on eating behaviour in restrained and non-restrained eaters. *Appetite, 54*(3), 499–503. https://doi.org/10.1016/j.appet.2010.02.001.

Faelens, L., Hoorelbeke, K., Cambier, R., van Put, J., Van de Putte, E., De Raedt, R., & Koster, E. H. W. (2021). The relationship between instagram use and indicators of mental health: A systematic review. *Computers in Human Behavior, 4*, 100121. https://doi.org/10.1016/j.chbr.2021.100121.

Faelens, L., Hoorelbeke, K., Fried, E., De Raedt, R., & Koster, E. H. W. (2019). Negative influences of Facebook use through the lens of network analysis. *Computers in Human Behavior, 96*, 13–22. https://doi.org/10.1016/j.chb.2019.02.002.

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods, 39*(2), 175–191. https://doi.org/10.3758/BF03193146.

Fitz, N., Kushlev, K., Jagannathan, R., Lewis, T., Paliwal, D., & Ariely, D. (2019). Batching smartphone notifications can improve well-being. *Computers in Human Behavior, 101*, 84–94. https://doi.org/10.1016/j.chb.2019.07.016.

Fleig, L., Lippke, S., Pomp, S., & Schwarzer, R. (2011). Intervention effects of exercise self-regulation on physical exercise and eating fruits and vegetables: A longitudinal study in orthopedic and cardiac rehabilitation. *Preventive Medicine, 53*(3), 182–187. https://doi.org/10.1016/j.ypmed.2011.06.019.

Fleig, L., Pomp, S., Schwarzer, R., & Lippke, S. (2013). Promoting exercise maintenance: How interventions with booster sessions improve long-term rehabilitation outcomes. *Rehabilitation Psychology, 58*(4), 323–333. https://doi.org/10.1037/a0033885.

Gadeyne, N., Verbruggen, M., Delanoeije, J., & De Cooman, R. (2018). All wired, all tired? Work-Related ICT-use outside work hours and work-to-home conflict: The role of integration preference, integration norms and work demands. *Journal of Vocational Behavior, 107*, 86–99. https://doi.org/10.1016/j.jvb.2018.03.008.

Google Play. 2023. Google Play. https://play.google.com/store/apps?hl=de_CH (22.05.2023).

Gollwitzer, P. M., & Sheeran, P. (2006). In M. P. Zanna (Ed.), *Advances in experimental social psychology, 38* pp. 69–119). Elsevier Academic Press. https://doi.org/10.1016/S0065-2601(06)38002-1.

große Deters, F., & Schoedel, R. (2024). Keep on scrolling? Using intensive longitudinal smartphone sensing data to assess how everyday smartphone usage behaviors are related to well-being. *Computers in Human Behavior, 150*, Article 107977.

Grüning, D. J., Riedel, F., & Lorenz-Spreen, P. (2023). Directing smartphone use through the self-nudge app one sec. *Proceedings of the National Academy of Sciences, 120*(8), Article e2213114120. https://doi.org/10.1073/pnas.2213114120.

Hagger, M. S., & Luszczynska, A. (2014). Implementation intention and action planning interventions in health contexts: State of the research and proposals for the way forward. *Applied Psychology Health Well Being, 6*(1), 1–47. https://doi.org/10.1111/aphw.12017.

Hall, J. A., Johnson, R. M., & Ross, E. M. (2019). Where does the time go? An experimental test of what social media displaces and displaced activities' associations with affective well-being and quality of day. *New Media & Society, 21*(3), 674–692. https://doi.org/10.1177/1461444818804775.

Hall, J. A., Xing, C., Ross, E. M., & Johnson, R. M. (2021). Experimentally manipulating social media abstinence: Results of a four-week diary study. *Media Psychology, 24*(2), 259–275. https://doi.org/10.1080/15213269.2019.1688171.

Hanley, S. M., Watt, S. E., & Coventry, W. (2019). Taking a break: The effect of taking a vacation from Facebook and Instagram on subjective well-being. *PLoS One, 14*(6), Article e0217743. https://doi.org/10.1371/journal.pone.0217743.

Harkin, B., Webb, T. L., Chang, B. P. I., Prestwich, A., Conner, M., Kellar, I., … Sheeran, P. (2016). Does monitoring goal progress promote goal attainment? A meta-analysis of the experimental evidence. *Psychological Bulletin, 142*(2), 198–229. https://doi.org/10.1037/bul0000025.

Hendrickson, A., De Marez, L., Martens, M., Muller, G., Ponnet, K., Schweitzer, C., & Vanden Abeele, M. (2019). How do people use their smartphone? A data scientific approach to describe and identify user-related, system-related and context-related patterns in use. *In the 69th annual conference of the international communication association 2019*. Washington, United States.

IBM Corp. (2021). *IBM SPSS Statistics for windows (version 28.0)*. Armonk, NY: IBM Corp [Computer Software].

Kao, K.-Y., Chi, N.-W., Thomas, C. L., Lee, H.-T., & Wang, Y.-F. (2020). Linking ICT availability demands to burnout and work-family conflict: The roles of workplace telepressure and dispositional self-regulation. *Journal of Psychology, 154*(5), 325–345. https://doi.org/10.1080/00223980.2020.1745137.

Keller, J., Roitzheim, C., Radtke, T., Schenkel, K., & Schwarzer, R. (2021). A mobile intervention for self-efficacious and goal-directed smartphone use in the general population: Randomized controlled trial. *JMIR mHealth and uHealth, 9*(11), Article e26397. https://doi.org/10.2196/26397.

Klimmt, C., Hefner, D., Reinecke, L., Rieger, D., & Vorderer, P. (2017). The permanently online and permanently connected mind: Mapping the cognitive structures behind mobile internet use. In *Permanently online, permanently connected. Living and communication in a POPC world* (pp. 18–28). Routledge.
Kushlev, K., & Leitao, M. R. (2020). The effects of smartphones on well-being: Theoretical integration and research agenda. *Current Opinion in Psychology, 36*, 77–82. https://doi.org/10.1016/j.copsyc.2020.05.001.
Lambert, J. B., George, M. E., Cooper, J., & McEwan, D. (2022). Taking a one-week break from social media improves well-being, depression, and anxiety: A randomized controlled trial. *Cyberpsychology, Behavior, and Social Networking, 25*(5), 287–293. https://doi.org/10.1089/cyber.2021.0324.
Leiner, D. J. (2019). SoSci survey (Version 3.2.00) [Computer Software]. Retrieved from https://www.soscisurvey.de.
Marques, M. M., Wright, A. J., Corker, E., Johnston, M., West, R., Hastings, J., … Michie, S. (2024). The behaviour change technique ontology: Transforming the behaviour change technique taxonomy v1. *Wellcome Open Research, 8*, 308. https://doi.org/10.12688/wellcomeopenres.19363.1.
McNeish, D. (2017). Small sample methods for multilevel modeling: A colloquial elucidation of REML and the kenward-roger correction. *Multivariate Behavioral Research, 52*(5), 661–670. https://doi.org/10.1080/00273171.2017.1344538.
Michie, S., Abraham, C., Whittington, C., McAteer, J., & Gupta, S. (2009). Effective techniques in healthy eating and physical activity interventions: A meta-regression. *Health Psychology, 28*(6), 690–701. https://doi.org/10.1037/a0016136.
Montag, C., Kannen, C., Lachmann, B., Sariyska, R., Duke, É., Reuter, M., & Markowetz, A. (2015). The importance of analogue zeitgebers to reduce digital addictive tendencies in the 21st century. *Addictive Behaviors Reports, 2*, 23–27. https://doi.org/10.1016/j.abrep.2015.04.002.
Nassen, L.-M., Vandebosch, H., Poels, K., & Karsay, K. (2023). Opt-out, abstain, unplug. A systematic review of the voluntary digital disconnection literature. *Telematics and Informatics, 81*, 101980. https://doi.org/10.1016/j.tele.2023.101980.
Nguyen, M. H. (2021). Managing social media use in an "Always-On" society: Exploring digital wellbeing strategies that people use to disconnect. *Mass Communication & Society, 24*(6), 795–817. https://doi.org/10.1080/15205436.2021.1979045.
Nguyen, M. H., & Hargittai, E. (2023). Digital disconnection, digital inequality, and subjective well-being: A mobile experience sampling study. *Journal of Computer-Mediated Communication, 29*(1). https://doi.org/10.1093/jcmc/zmad044.
Nuñez, T. R., Pallasch, N., & Radtke, T. (2022). Students' emotional well-being and academic functioning before, during, and after lockdown in Germany: Cohort study. *JMIR Formative Research, 6*(11), Article e34388. https://doi.org/10.2196/34388.
Pew Research Center. (2018). Mobile fact sheet. Retrieved December, 2023, from http://www.pewinternet.org/fact-sheet/mobile/.
Plackett, R., Blyth, A., & Schartau, P. (2023). The impact of social media use interventions on Mental well-being: Systematic review. *Journal of Medical Internet Research, 25*, Article e44922. https://doi.org/10.2196/44922.
Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods, 40*(3), 879–891. https://doi.org/10.3758/BRM.40.3.879.
Przybylski, A. K., Orben, A., & Weinstein, N. (2020). How much is too much? Examining the relationship between digital screen engagement and psychosocial functioning in a confirmatory cohort study. *Journal of the American Academy of Child & Adolescent Psychiatry, 59*(9), 1080–1088. https://doi.org/10.1016/j.jaac.2019.06.017.
Purohit, A. K., & Holzer, A. (2021). Unhooked by design: Scrolling mindfully on social media by automating digital nudges. In *Proceeding of the 27th americas conference on information systems, (AMCIS 2021)* (pp. 1–10). Association for Information Systems (AIS).
Radtke, T., Apel, T., Schenkel, K., Keller, J., & von Lindern, E. (2022). Digital detox: An effective solution in the smartphone era? A systematic literature review. *Mobile Media & Communication, 10*(2), 190–215. https://doi.org/10.1177/20501579211028647.
Radtke, T., Diering, M., Alfermann, L., Luszczynska, A., Kuźmińska, J., & Nuñez, T. R. (2024). *Absent presence – results of a randomized controlled trial to reduce phubbing in couples and enhance individual well-being, 31*. Hogrefe Publishing. https://doi.org/10.1027/2512-8442/a000158.
R Core Team, R. (2021). R: A language and environment for statistical computing [computer programm]. In Radtke, T., Apel, T., Schenkel, K., Keller, J., & von Lindern, E. (Eds.), Digital detox: An effective solution in the smartphone era? A systematic literature review. Mobile media & communication: Vol. 10 (pp. 190–215). https://doi.org/10.1177/20501579211028647. 2022.
Sayers, W. M., & Sayette, M. A. (2013). Suppression on your own terms: Internally generated displays of craving suppression predict rebound effects. *Psychological Science, 24*(9), 1740–1746. https://doi.org/10.1177/0956797613479977.
Schenkel, K., Nussbeck, F. W., Kerkhoff, D., Scholz, U., Keller, J., & Radtke, T. (2024). Digital generation: The association between daily smartphone app use and well-being. *Behaviour & Information Technology*, 1–18. https://doi.org/10.1080/0144929X.2024.2406255.
Schoedel, R., Oldemeier, M., Bonauer, L., & Sust, L. (2022). Systematic categorisation of 3,091 smartphone applications from a large-scale smartphone sensing dataset. *Journal of Open Psychology Data, 10*(1). https://doi.org/10.5334/jopd.59.
Schwartz, R. X., Roffarello, A. M., Russis, L. D., & Apostolellis, P.. Reducing risk in digital self-control tools: Design patterns and prototype. Extended abstracts of the 2021 CHI conference on human factors in computing systems. https://doi.org/10.1145/3411763.3451843.
Schwarzer, R. (2008). Modeling health behavior change: How to predict and modify the adoption and maintenance of health behaviors. *Applied Psychology, 57*(1), 1–29. https://doi.org/10.1111/j.1464-0597.2007.00325.x.
Schwarzer, R., & Luszczynska, A. (2008). How to overcome health-compromising behaviors: The health action process approach. *European Psychologist, 13*(2), 141–151. https://doi.org/10.1027/1016-9040.13.2.141.
Singh, M., & Samah, N. A. (2018). Impact of smartphone: A review on positive and negative effects on students. *Asian Social Science*. https://doi.org/10.5539/ASS.V14N11P83.
Sniehotta, F. F., Scholz, U., & Schwarzer, R. (2005). Bridging the intention–behaviour gap: Planning, self-efficacy, and action control in the adoption and maintenance of physical exercise. *Psychology and Health, 20*(2), 143–160. https://doi.org/10.1080/08870440512331317670.
Sniehotta, F. F., Scholz, U., & Schwarzer, R. (2006). Action plans and coping plans for physical exercise: A longitudinal intervention study in cardiac rehabilitation. *British Journal of Health Psychology, 11*(1), 23–37. https://doi.org/10.1348/135910705X43804.
Stieger, S., & Lewetz, D. (2018). A week without using social media: Results from an ecological momentary intervention study using smartphones. *Cyberpsychology, Behavior, and Social Networking, 21*(10), 618–624. https://doi.org/10.1089/cyber.2018.0070.
Sust, L., Talaifar, S., & Stachl, C. (2023). Mobile application usage in psychological research. *Mobile Sensing in Psychology: Methods and Applications, 184*, 184–214.
Tabachnick, B. G., & Fidell, L. S. (2007). *Using multivaraite statistics* (5th ed.). Allyn & Beacon/Pearson Education.
Thomée, S. (2018). Mobile phone use and mental health. A review of the research that takes a psychological perspective on exposure. *International Journal of Environmental Research and Public Health, 15*(12), 2692. https://www.mdpi.com/1660-4601/15/12/2692.
Twenge, J. M., Spitzberg, B. H., & Campbell, W. K. (2019). Less in-person social interaction with peers among U.S. adolescents in the 21st century and links to loneliness. *Journal of Social and Personal Relationships, 36*(6), 1892–1913. https://doi.org/10.1177/0265407519836170.
Vahedi, Z., & Saiphoo, A. (2018). The association between smartphone use, stress, and anxiety: A meta-analytic review. *Stress and Health, 34*(3), 347–358. https://doi.org/10.1002/smi.2805.
Vally, Z., & D'Souza, C. G. (2019). Abstinence from social media use, subjective well-being, stress, and loneliness. *Perspectives in Psychiatric Care, 55*(4), 752–759. https://doi.org/10.1111/ppc.12431.
van Velthoven, Powell, J., & Powell, G. (2018). *Problematic smartphone use: Digital approaches to an emerging public health problem. Digital Health* (p. 4). https://doi.org/10.1177/2055207618759167.
Vanden Abeele, M., De Wolf, R., & Ling, R. (2018). Mobile media and social space: How anytime, anyplace connectivity structures everyday life. *Media and Communication, 6* (2), 5–14. https://doi.org/10.17645/mac.v6i2.1399.
Vanden Abeele, Vandebosch, H., Koster, E. H. W., De Leyn, T., Van Gaeveren, K., … Baillien, E. (2024). Why, how, when, and for whom does digital disconnection work? A process-based framework of digital disconnection. *Communication Theory, 34*(1), 3–17. https://doi.org/10.1093/ct/qtad016.
Webb, T. L., & Sheeran, P. (2006). Does changing behavioral intentions engender behavior change? A meta-analysis of the experimental evidence. *Psychological Bulletin, 132*(2), 249–268. https://doi.org/10.1037/0033-2909.132.2.249.
Wicaksono, A., Hendley, R., & Beale, R. (2019). Investigating the impact of adding plan reminders on implementation intentions to support behaviour change. Interacting with. *Computers, 31*(2), 177–191. https://doi.org/10.1093/iwc/iwz012.
Wilcockson, T. D. W., Osborne, A. M., & Ellis, D. A. (2019). Digital detox: The effect of smartphone abstinence on mood, anxiety, and craving. *Addictive Behaviors, 99*, 106013. https://doi.org/10.1016/j.addbeh.2019.06.002.
Zhang, C.-Q., Zhang, R., Schwarzer, R., & Hagger, M. S. (2019). A meta-analysis of the health action process approach. *Health Psychology, 38*(7), 623–637. https://doi.org/10.1037/hea0000728.
Zimmermann, L. (2021). Your screen-time app is keeping track": Consumers are happy to monitor but unlikely to reduce smartphone usage. *Journal of the Association for Consumer Research, 6*(3), 377–382. https://doi.org/10.1086/714365.
Zimmermann, L. S., & Sobolov M. (2023). Digital strategies for screen time reduction: A randomized field experiment. *Cyberpsychology, Behavior, and Social Networking, 26* (1), 42–49. https://doi.org/10.1089/cyber.2022.0027.