Evaluating the Effectiveness of Apps Designed to Reduce Mobile Phone Use and Prevent Maladaptive Mobile Phone Use
Multimethod Study

Rahmillah, Fety Ilma; Tariq, Amina; King, Mark; Oviedo-Trespalacios, Oscar

Important note
To cite this publication, please use the final published version (if applicable).
Please check the document version above.

<u>Original Paper</u>

Evaluating the Effectiveness of Apps Designed to Reduce Mobile Phone Use and Prevent Maladaptive Mobile Phone Use: Multimethod Study

Fety Ilma Rahmillah[1], MSci; Amina Tariq[1], PhD; Mark King[1], PhD; Oscar Oviedo-Trespalacios[1,2], PhD

[1]Faculty of Health, Queensland University of Technology, Brisbane, Australia
[2]Faculty of Technology, Policy and Management, Delft University of Technology, Delft, Netherlands

Corresponding Author:
Oscar Oviedo-Trespalacios, PhD
Faculty of Technology, Policy and Management
Delft University of Technology
Jaffalaan 5
Delft, 2628 BX
Netherlands
Phone: 31 15 2783887
Email: O.OviedoTrespalacios@tudelft.nl

Abstract

Background: Mobile apps are a popular strategy for reducing mobile phone use and preventing maladaptive mobile phone use (MMPU). Previous research efforts have been made to understand the features of apps that have the potential to reduce mobile phone use and MMPU. However, there has been a lack of a comprehensive examination of the effectiveness of such apps and their features.

Objective: This paper investigated existing apps designed to reduce mobile phone use and prevent MMPU and examined the evidence of their effectiveness. The research aimed to provide a comprehensive analysis of app features that can reduce mobile phone use and MMPU, while also assessing their effectiveness. In addition, we explored users' perceptions of these apps and the various features the apps offer to understand potential adoption issues and identify opportunities.

Methods: This study used 3 methods: a review of scientific evidence, content analysis, and sentiment analysis.

Results: Our study comprehensively examine the common features of 13 apps designed to reduce mobile phone use. We extracted and classified the features into 7 types: self-tracking, social tracking, goal setting, blocking, gamification, simplification, and assessment. The effectiveness of these apps in reducing mobile phone use and MMPU varied from weak to strong. On the basis of content analysis, self-tracking and goal setting were the most frequently used features, whereas gamification and assessment were used the least frequently. The intervention strategies that effectively reduce mobile phone use and MMPU included using grayscale mode, app limit features, and mixed interventions. Overall, users tended to accept these apps, as indicated by sentiment scores ranging from 61 to 86 out of 100.

Conclusions: This study demonstrates that app-based management has the potential to reduce mobile phone use and MMPU. However, further research is required to evaluate the effectiveness of app-based interventions. Collaborations among researchers, app developers, mobile phone manufacturers, and policy makers could enhance the process of delivering, evaluating, and optimizing apps aimed at reducing mobile phone use and MMPU.

Introduction

Background

Mobile phones are beneficial in many aspects of our lives, such as working and staying connected with our family and friends regardless of distance as well as helping to organize day-to-day activities. People generally have favorable perceptions regarding their mobile phones and their impact. However, an individual's level of mobile phone use can also lead to adverse outcomes. Excessive mobile phone use is often referred to as maladaptive mobile phone use (MMPU), which occurs when use negatively interferes with individuals' work and social interactions [1,2]. MMPU encompasses various related concepts, including problematic mobile phone use, smartphone addiction, fear of missing out (FoMO; a persistent desire to share others' gratifying experiences), nomophobia (the fear of being without a mobile phone), mobile phone involvement, compulsive mobile phone checking, texting dependency, texting automaticity (texting without thinking or intending to do it), and mobile phone dependency [2]. An example of how MMPU can result in adverse outcomes is the association between MMPU and risky mobile phone use behaviors, such as falling, slipping, bumps or collisions, moving violations, road traffic injuries, and motor vehicle crashes [2,3]. The higher the MMPU score, the more likely road users are to engage with their mobile phones in risky situations, such as while driving, riding a motorcycle, cycling, or crossing the road [2]. Other issues linked to MMPU include decreased academic performance (measured in terms of grade point average) [4,5], increased anxiety [4], increased stress [4-6], and irregular sleep patterns [6]. The negative consequences of MMPU and its growing prevalence worldwide [1] highlight the need to identify effective strategies to manage and reduce MMPU.

One strategy to manage and reduce MMPU is to use apps designed specifically for reducing and regulating mobile phone use [7]; for instance, apps such as *AppDetox* can regulate information flow by setting rules, *RescueTime* can establish goals, and *Forest* uses gamification [8]. These apps can assist in reducing mobile phone use and MMPU. Evidence suggests that such apps can effectively limit overall mobile phone use and decrease perceived distractions [9]. Empirical studies have demonstrated that avoiding persuasive functions (resulting in a reduction of up to 37%) or disabling certain persuasive functions (resulting in a reduction of up to 16.72%) can effectively decrease mobile phone use [10]. As for built-in functions, enabling grayscale mode can reduce the desire to use the mobile phone because the interface becomes visually less appealing [11]. The blue light emitted from the colorful screen of the mobile phone can attract the human brain and trigger the release of cortisol, a hormone that promotes wakefulness [12]. Switching the mobile phone interface to grayscale mode eliminates positive reinforcements and can diminish the urge to stay engaged in social media [12]. However, apps that aim to manage and reduce mobile phone use and MMPU have faced criticism for not effectively changing habits and not being restrictive enough. As a result, doubts persist regarding the

effectiveness of such apps in altering mobile phone use behavior [13]. A critical gap in the existing literature concerns understanding the effectiveness of such apps and their features in managing and reducing mobile phone use and MMPU.

There have been some previous attempts to understand the features of apps that have the potential to reduce mobile phone use and MMPU [8], such as through blocking [14,15], mobile phone vibration [16], tracking [14,17], goal advancement [14,17], group-based intervention [9,18], and gamification [19]. Such categorization of app features is essential because each feature could support different cognitive processes [20]. A classification of apps and browser extensions for digital self-control resulted in 4 features based on functionality: block or removal, self-tracking, goal advancement, and reward or punishment [21]. A recent review of Google's *Digital Wellbeing* apps delineated 2 main categories of features: self-monitoring and interventions [13].

Objectives

This paper examined current apps designed to reduce mobile phone use and prevent MMPU. It investigated the features of these apps and evaluated the extent to which the benefits of these features are supported by evidence of their effectiveness in reducing MMPU. The approach taken involved developing a comprehensive map of the app features that have been assessed in the scientific literature, along with the corresponding evidence for their effectiveness. In addition, this study explored users' perceptions of the apps and the various features these apps offer, aiming to understand potential acceptance issues. The following research questions (RQs) were addressed:

RQ1: Which apps have been scientifically evaluated?

RQ2: What features are offered by current apps to reduce mobile phone use and MMPU?

RQ3: What is the efficacy of these apps?

RQ4: How have users responded to these apps and their features in terms of popularity and reviews?

Methods

Overview

A multimethod approach was used to thoroughly address the aforementioned RQs, as depicted in Figure 1. The study encompassed 2 distinct phases. In the first phase, extensive web-based searches were conducted to identify a representative set of apps. The objective was to ensure a comprehensive selection of apps for further analysis. Subsequently, the second phase involved an analytical approach, encompassing a comprehensive examination of the effectiveness of the apps and their respective features in reducing mobile phone use and MMPU. This examination was achieved through a combination of literature review, content analysis, and sentiment analysis. Each of these steps will be elaborated upon in the subsequent sections of this paper, providing a detailed account of the methodology used in this study.

Figure 1. Methodology of the study. MMPU: maladaptive mobile phone use.
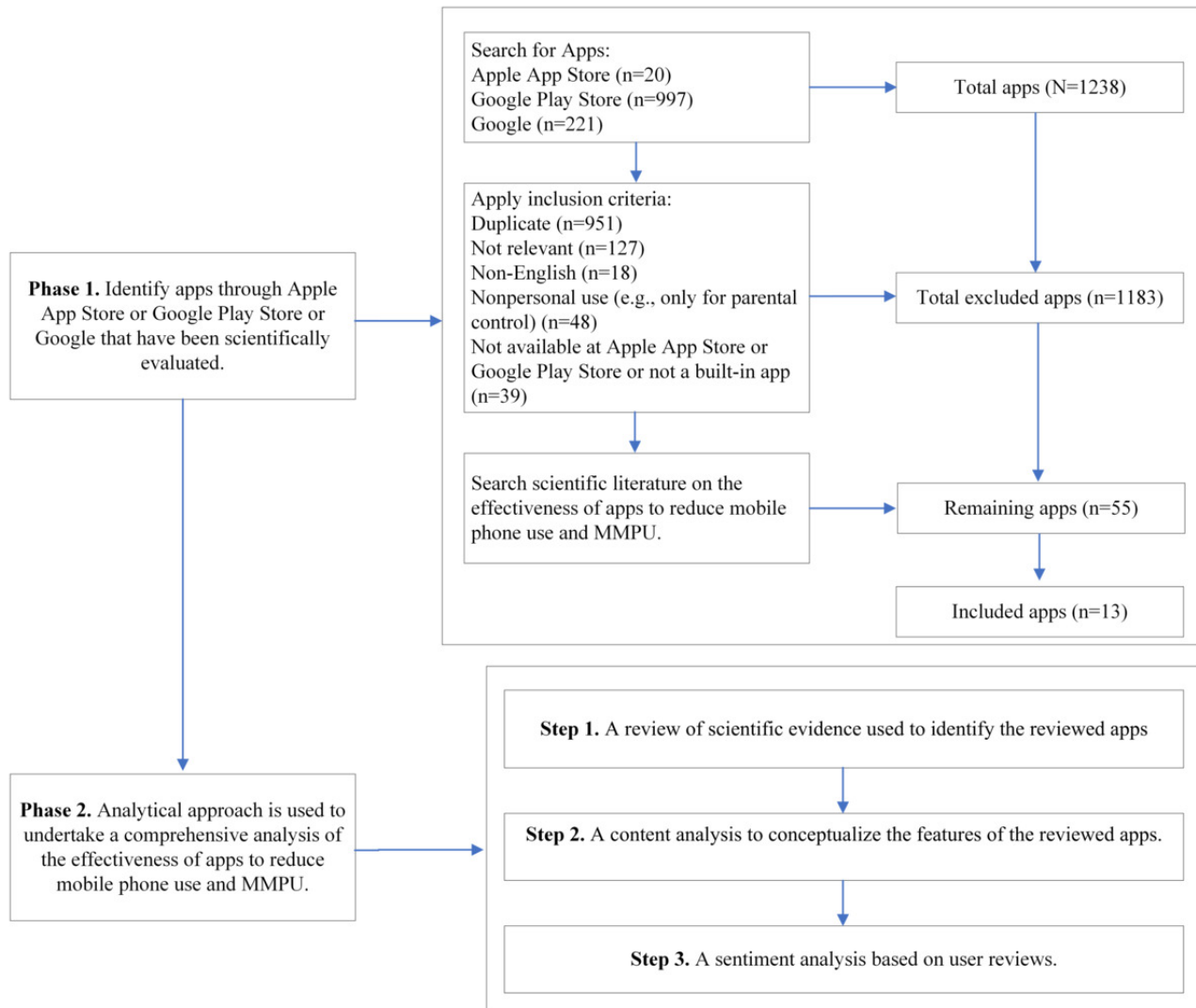
Ethical Considerations

Before commencing the research, ethics approval for using secondary data was sought, and the study was deemed exempt by the human research ethics committee at Queensland University of Technology.

Procedure to Identify Apps That Reduce Mobile Phone Use and MMPU

A web-based search was conducted to identify a representative set of apps that reduce mobile phone use and MMPU to be reviewed through the Google Play Store, the Apple App Store, and a Google search. A search through the first page of the Google search engine was needed to identify popular apps to be reviewed and to obtain comprehensive data regarding their aims and features as what has been done by [22]. The term "apps" was used as a generic reference encompassing functionalities offered by both built-in apps (eg, *Screen Time* [iOS] within Settings app, *Digital Wellbeing* [within Android]) and third-party apps downloaded from Apple App Store or Google Play Store, encompassing all software programs designed for reducing mobile phone use and MMPU on mobile phones. We used the following keywords: (("[name of the potential app]" AND "app") AND ("reduce" OR "limit") AND

("screen time" OR "phone use")). The original total number of apps was 1238. Next, the following exclusion criteria were applied: duplicate, not relevant (designed for computer or website, not mobile phone), non-English, nonpersonal use (eg, only for parental control), not available in the Google Play Store or Apple App Store, or not a built-in app. Of the 1238 apps, 55 (4.44%) were selected for further consideration after the application of the screening process based on the exclusion criteria. The next step involved identifying apps that have been evaluated in the scientific literature in terms of their effectiveness in supporting the reduction of mobile phone use and MMPU. To achieve this, each of the apps (n=55) was searched on Google Scholar, PubMed, and Scopus. Evidence of the efficacy of 13 (24%) of the 55 apps in 19 papers was identified through this process. Basic information about these apps is available in Multimedia Appendix 1.

Analytical Approach

This section summarizes the analytical approach, including the research methods adopted to review scientific evidence on the effectiveness of the reviewed apps in reducing mobile phone use and MMPU, content analysis to extract app features, and sentiment analysis to examine users' perceptions.

A Review of the Evidence Concerning the Effectiveness of Apps to Reduce Mobile Phone Use and MMPU

This paper reviewed peer-reviewed literature concerning the evidence of apps to reduce mobile phone use and MMPU. The research papers concerning the original identified apps (n=55) were identified using Scopus, PubMed, and Google Scholar. As explained earlier, there was evidence about 13 (24%) of the 55 apps in 19 papers (refer to the *Results* section). Refer to Multimedia Appendix 2 for the details of the search strategy used in these databases. Time restrictions were not implemented, but only papers published before April 10, 2023, were considered. The inclusion criteria were as follows: (1) papers that provide information related to the effectiveness of apps and features in reducing mobile phone use and MMPU; (2) peer-reviewed scientific articles, including conference papers; and (3) papers published in English. The study was designed using preestablished criteria based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses)

protocol (See Multimedia Appendix 3 for details) [23]. Papers were selected from the 3 aforementioned databases (Figure 2). A total of 611 papers were identified. Microsoft Excel was used for data extraction, and duplicates were removed manually by a team member (FIR). One team member (FIR) conducted the screening, which was verified by another team member (OO-T). Once the screening was completed, other team members (OO-T, AT, and MK) reviewed and confirmed the included and excluded studies. Any disagreement was discussed and resolved among all 4 team members at any of these stages. The following data were extracted from 19 (3.1%) of the 611 articles: country, study design, sample size, authors, year of publication, age, sex of the sample, type of MMPU scales, intervention, effect in reducing mobile phone use and MMPU, and key findings. This review used the Quality Assessment Tool for Quantitative Studies developed by the Effective Public Health Practice Project (EPHPP) to evaluate the methodological quality of the eligible studies [24]. Given the small number of papers and the diversity of the apps, a meta-analysis could not be conducted.

Figure 2. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowchart. MMPU: maladaptive mobile phone use.
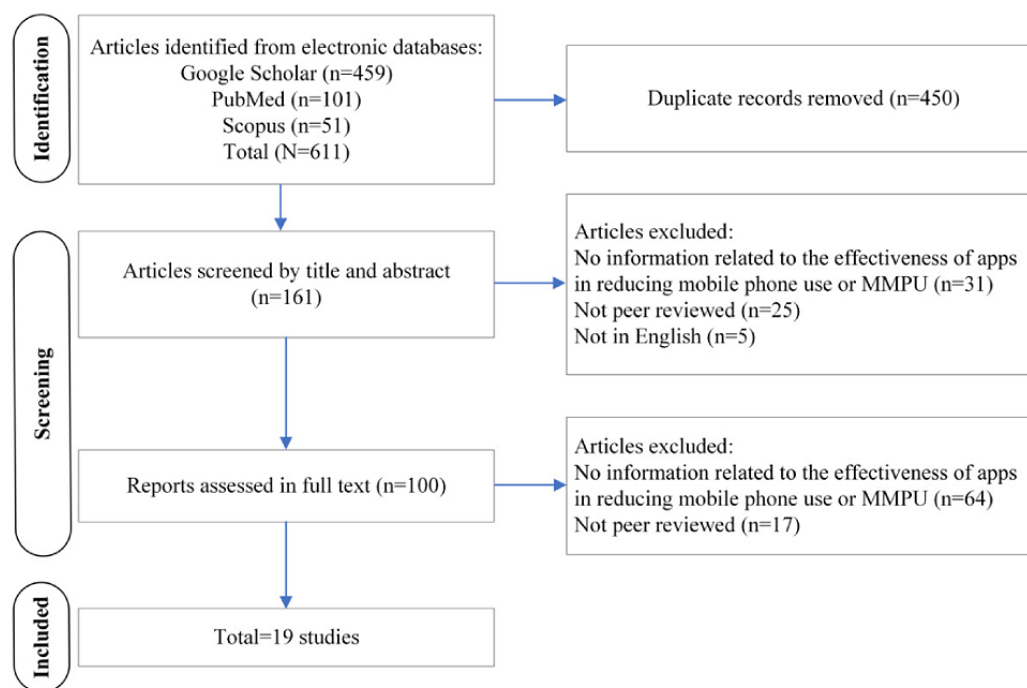
Content Analysis

Content analysis was used to identify the features of the mobile phone apps (n=13)—designed to reduce mobile phone use and prevent MMPU—that were included in the study. Content analysis is a method used to draw inferences from qualitative data by systematically characterizing themes. This method has frequently been used to analyze apps aimed at reducing mobile phone use while driving [22], minimizing alcohol and illicit substance use [25], aiding smoking cessation [26], monitoring alcohol use [27], and treating depression [28]. The content analysis process comprised two steps: (1) identifying and (2) analyzing features that contribute to reducing mobile phone use and preventing MMPU.

A coding process, based on previous research on similar apps [13,21], was developed to extract key features from the apps.

This study adapted the app clustering strategy framework developed in previous literature [13,21] because the initial approaches were found to be incomplete and included distractions related to other devices such as laptop computers as well as the internet. In addition, the aim of the study was to identify how categorization evolved over time based on the reviewed apps, resulting in the creation of new categories. The classification framework used to characterize the key features is presented in Table 1. The first author extracted data from full descriptions, screenshots, videos on the Google Play Store, Apple App Store, app website, and previous review studies. Moreover, the first author also installed each app and examined its functionality for a minimum duration of 30 minutes. Subsequently, the last author checked the data extracted to reach a consensus.

Table 1. The classification framework of app features.

Category and feature	Definition	Source of definition
Self-tracking		
Use history and visualization	Provides a summary of mobile phone use history and a visualization (ie, mobile phone use history, notification, most used app, and unlocked count) daily, weekly, or monthly	Monge Roffarello and de Russis [13], Lyngs et al [21], and the authors of this paper
Social tracking		
Social sharing of mobile phone use	Shares progress	Lyngs et al [21]
Global comparison	Provides information about the global use average and compares it with the user's mobile phone use	The authors of this paper
Goal setting		
Set goal or group goal	Allows users to set limits on mobile phone use or desired focus time. In addition, users can create groups within the app to set use limits for specific apps, such as social media apps	Lyngs et al [21] and the authors of this paper
Set activity or interest goal	Allows users to set goals for hobbies or activities	Lyngs et al [21]
Goal warning	Sends use alert (a reminder when the set limit is approaching)	The authors of this paper
Blocking		
Spontaneous	Allows users to lock the mobile phone quickly (duration can be chosen), lock the mobile phone (until the user chooses to unlock it), or immediately disconnect via 1-click access to the widget	The authors of this paper
Scheduled	Schedules or sets rules to silence notifications, alerts, and calls; schedules blocklist; schedules off time; disconnects from distracting apps; automatically enters "do not disturb" mode; and automatically locks apps (a password or PIN[a] must be entered to continue accessing apps, modify the active app block profile, or uninstall the app used to reduce mobile phone use and MMPU[b])	The authors of this paper
Gamification		
Gain or loss points	Incorporates engaging features to motivate users to reduce mobile phone use. One such feature is the points system, where users can earn rewards by staying focused and lose points for excessive mobile phone use	Lyngs et al [21]
Real-world reward	Plants trees (ie, *Forest* app)	Lyngs et al [21]
Simplification	Changes the interface display from color to black and white to make for a less engaging screen (ie, grayscale mode); other authors call it minimization [21]	The authors of this paper
Assessment	Assesses the level of addiction to help users understand their current situation	The authors of this paper

[a]PIN: personal identification number.

[b]MMPU: maladaptive mobile phone use.

User Reviews

User reviews of 12 (92%) of the 13 apps (the *Screen Time* [iOS] app was excluded because it did not have user reviews) were analyzed using the Appbot platform, which is designed to analyze all reviews for apps [29] and it has been used by Kaur and Chakravarty [30] and Bano et al [31]. User reviews posted in Google Play Store or Apple App Store in English from July 2008 to December 2022 were used to examine users' perceptions and sentiments regarding the various features of the identified apps. To enhance the depth of the analysis, it was further broken down based on the app features and several custom topics. In this study, sentiment analysis of reviews refers to extracting magnitude (eg, positive, negative, neutral, or mixed) and subjectivity from the text review. Sentiment scores and the cutoff created by Appbot range from 0 to 100, based on the volume of reviews for the period; the trend in review volume (whether it is trending up or down); the trend in the star rating; the ratio of positive, neutral, and negative reviews; and the trend in the percentage of positive, neutral, and negative reviews. More information on calculating the score is available on the Appbot website [29]. The process of extracting the user reviews through the custom topics automatically tracks reviews containing keywords and phrases developed using a Boolean strategy. The results provide insights into how satisfied or dissatisfied users are with a particular feature. All user reviews that contain text from app stores were used to examine users' perceptions and sentiments regarding the various features of the identified apps. We followed procedures similar to those used sentiment score to assess the satisfaction level of mobile apps for library use [30] and to evaluate the mobile pedagogical affordances of apps [31].

Results

Effectiveness of Apps

A total of 19 studies in the literature have evaluated the effectiveness of 13 apps in reducing mobile phone use and MMPU (See Multimedia Appendix 4 for more details). These studies used various types of research designs, including randomized controlled trials (5/19, 26%) [32-36], experimental designs (6/19, 32%) [37-42], interviews (4/19, 21%) [37,40,43,44], cross-sectional designs (8/19, 34%) [11,38,39,44-48], longitudinal studies (3/19, 16%) [34,38,42], and observational research-secondary data [49]. Some of the studies (5/19, 26%) used a combination of different designs [11,37,39,40,44]. The duration of app use in most studies ranged from 3 days to 16 weeks. However, because of the heterogeneity across the studies, including differences in intervention strategies, durations of interventions, methodologies, scales, and study designs, a direct comparison of the 19 studies was not feasible.

To assess the quality of the quantitative studies, the EPHPP guideline was used [24]. The EPHPP guideline consists of 8 criteria: study design, selection bias, dropouts, blinding, intervention integrity (if applicable), data collection, analysis, and confounding. The findings revealed that, of the 19 studies, 1 (5%) was of methodologically strong quality [34], 6 (32%) were of moderate quality [32,33,35,36,39,40], and the remaining 11 (58%) were of weak quality [11,37,38,41,42,44-49]. Meta-analyses of the quantitative data could not be conducted owing to the heterogeneity of the data and the quality of the included studies. Therefore, the effectiveness of app features in reducing mobile phone use and MMPU were summarized narratively, and caution should be exercised when interpreting the findings.

The study findings revealed that 4 (31%) of the 13 apps can effectively reduce mobile phone use. Specifically, *Screen Time* (iOS) [11,32-34,39,40], *Forest* and *Screen Time* [43], and *AntiSocial* [36] were found to be effective in reducing mobile phone use. Various intervention strategies were also found to be effective in reducing mobile phone use, including the use of grayscale mode [11,32,33,39,40], app limit feature [34]; and mixed interventions [11,36]. The use of grayscale mode was found to be particularly effective in reducing mobile phone use, with average reductions of up to 37.90 minutes per day (preintervention: mean 255.34, SD 100.46; postintervention: mean 217.44, SD 94.90; $P \leq .001$) [33,39]. Mixed interventions have been shown to be effective; for instance, a study successfully reduced mobile phone use by combining interventions such as self-monitoring mobile phone use (*AntiSocial* app), mindfulness (*Headspace* app), and mood tracking (*Pacifica* app; preintervention: mean 4.515, SD 2.28; postintervention: mean 3.51, SD 1.88; $P<.001$) [36]. Some studies used the evaluated apps without explicitly mentioning their features. An app limit intervention strategy was found to significantly decrease mobile phone use by 6.2% per day ($P<.05$)

and Facebook use by 33.2% in the short term ($P<.01$) [34]. In the long term, this strategy can significantly decrease Facebook use by 36.8% ($P<.001$) and Instagram use by 33.9% ($P<.01$) but not substantially reduce mobile phone use [34]. However, although *Forest* and *Screen Time* were found to be effective in reducing mobile phone use [43], the small sample size of the study (n=26) limits the conclusiveness of the results.

Of the 19 papers, 6 (32%) investigated the effect of using apps on MMPU [32,35,36,39-41]. The scales used to measure MMPU were the Mobile Phone Problematic Usage Scale developed by Bianchi and Phillips [50] and used by Ochs and Sauer [32]; Mobile Phone Problem Use Scale developed by Foerster et al [51] and used by Keller et al [35]; Smartphone Addiction Scale Short Version developed by Kwon et al [52] and used by Holte et al [39], Olson et al [40], and Loid et al [41]; Fear of Missing Out Scale developed by Przybylski et al [53] and used by Throuvala et al [36], Nomophobia Questionnaire developed by Yildirim and Correia [54] and used by Throuvala et al [36]; and 4 questions based on the study by Roberts et al [55] and used by Schmuck [47]. The findings were mixed: of the 19 studies, 3 (16%) suggested that apps can decrease MMPU [36,39,40], 3 (16%) suggested that apps do not affect MMPU [35,36,41], and 1 (5%) suggested that apps can even increase MMPU [32]. According to a study, participants who initially scored 35.29 (SD 8.84) on the Smartphone Addiction Scale achieved a lower score of 28.08 (SD 9) after receiving a nudge intervention for 2 to 8 weeks ($P<.001$) [40]. In another study, participants were able to reduce their MMPU score from 27.6 (SD 6.12) to 25 (SD 7.1; $P<.001$) by changing their mobile phone display to grayscale mode for a minimum of 2 weeks [39]. A further study found a significant decrease in mobile phone use per day and in terms of FoMO (preintervention: mean 77.17, SD 2.40; postintervention: mean 78.03, SD 2.72; $P<.001$), but no significant results were observed in terms of nomophobia [36].

Features of Apps Used to Reduce Mobile Phone Use and MMPU

Features of the 13 apps with scientific evidence about their effectiveness were extracted and categorized (Table 2). The most common features are self-tracking and goal setting, available in all included apps to reduce mobile phone use and MMPU. Social tracking features such as inviting friends or family to join off time together (ie, *Offtime* and *Flipd*), inviting friends or family to share focus mode, tree planting together (ie, *Forest*), or creating a group to share progress and feel accountable to the group (ie, *Space*) are only offered by 4 (31%) of the 13 apps. The assessment feature could help users to understand their mobile phone use and MMPU (ie, *Space*). The only app that provides a gamification method is *Forest,* where, if users stay focused on the task, a digital seed will grow into a tree, and it can be substituted for a real tree in the real world. The simplification offered by 2 (15%) of the 13 apps is a grayscale feature enabled by using the *Screen Time* (iOS) feature within the Settings app and part of the wind down (previously called bedtime mode) in *Digital Wellbeing*.

Table 2. Distribution of features.

Name of the app	Self-tracking	Goal setting			Blocking		Gamification		Social tracking		Simplification	Assessment
	Use history and visualization	Set goal or group goal	Set activity or interest goal	Goal warning	Spontaneous	Scheduled	Gain or loss points or grow tree	Real-world reward	Social sharing of mobile phone use	Global comparison		
AntiSocial	✓	✓	✓	✓	✓	✓				✓		
AppDetox	✓	✓	✓	✓								
App Usage	✓	✓		✓								
Detox: Procrastination Blocker	✓	✓			✓							
Digital Wellbeing	✓	✓		✓		✓					✓	
Flipd	✓	✓	✓	✓					✓	✓		
Forest	✓	✓					✓	✓	✓	✓		
Screen Time (iOS)	✓	✓		✓	✓	✓					✓	
Offtime	✓	✓	✓		✓	✓						
QualityTime	✓	✓	✓	✓	✓	✓						
RescueTime	✓	✓	✓	✓	✓	✓						
Screen Time	✓	✓										
Space	✓	✓							✓	✓		✓

User Reviews and Sentiment Analysis

The apps included for in-depth review had 353,043 reviews in all languages, of which 145,454 (41.2%) were in English. *Forest* was the most reviewed app (72,499/145,454, 49.84%) and had the highest positive sentiment (53,649/72,499, 74%), whereas the least reviewed app and the one with the lowest positive sentiment was *RescueTime*. The majority of the user reviews had given 5 stars (87,272/145,454, 60%) to this group of 12 apps (the *Screen Time* [iOS] was excluded because it did not have user reviews), whereas the rest were given 4 stars (17,454/145,454, 12%), 3 stars (10,181/145,454, 7%), 2 stars (5818/145,454, 4%), and 1 star (24,727/145,454, 17%). The sentiment scores ranged from 61 to 86 out of 100, meaning that users tended to express a positive sentiment toward all apps. For details, refer to Table 3 for overall sentiment breakdown of the apps and Table 4 for sentiment breakdown of the app features.

In-depth analyses were conducted on critical themes of the reviews. Table 4 shows the sentiment breakdown of app features.

We developed initial relevant search terms through custom topics (Multimedia Appendix 5), whereas machine learning developed by the Appbot software provided the rest. Overall, 21.81% (31,729/145,454) of the reviews reported reduced mobile phone use, 63% (19,989/31,729) of the users had a positive sentiment, and 48% (5505/11,468) users had a positive sentiment toward gamification offered by *Forest*. Users also thought that customer support was helpful (3118/4585, 68%). In addition, users used the apps to help them in some use cases (ie, studying, 3823/4498, 84.99% positive sentiment in reviews; working, 3535/6669, 53.01% positive sentiment in reviews; and sleeping, 120/236, 50.8% positive sentiment in reviews). The first review of a grayscale feature that *Digital Wellbeing* launched appeared in September 2018. Among the reviews about this feature, 56% (200/357) had negative sentiments. Users felt dissatisfied (gave more negative comments) in terms of bugs (7297/32,274, 22.61%), updates (2837/32,274, 8.79%), performance (1415/32,274, 4.38%), notifications and alerts (1350/32,274, 4.18%), too many advertisements (211/32,274, 0.65%), payment (718/32,274, 2.22%), privacy (428/32,274, 1.33%), and battery drain issue (132/32,274, 0.41%).

Table 3. Overall sentiment breakdown of apps (N=145,454 reviews). Percentage values correspond to the total number of the reviews for each app.

Name of the app	Sentiment score	Reviews, n	Average rating	Star breakdown					Sentiment breakdown			
				5, n (%)	4, n (%)	3, n (%)	2, n (%)	1, n (%)	Positive, n (%)	Neutral, n (%)	Mixed, n (%)	Negative, n (%)
Forest	86	72,499	4.4	49,227 (67.9)	10,418 (14.37)	4596 (6.34)	2762 (3.81)	5495 (7.58)	53,649 (74)	4349 (6)	4349 (6)	10,149 (14)
Detox: Procrastination Blocker	83	1362	4.1	870 (63.88)	171 (12.56)	108 (7.93)	58 (4.25)	155 (11.38)	885 (65)	109 (8)	123 (8)	245 (18)
App Usage	82	1995	4.1	1251 (62.71)	270 (13.53)	150 (7.52)	91 (4.56)	233 (11.68)	1137 (57)	239 (12)	239 (12)	379 (19)
Space	79	4262	4.1	2062 (48.38)	1065 (24.99)	431 (10.11)	302 (7.09)	402 (9.43)	2515 (59)	469 (11)	384 (9)	895 (21)
Screen Time	78	1868	3.8	1097 (58.73)	230 (12.31)	123 (6.58)	79 (4.23)	339 (18.15)	1233 (66)	112 (6)	112 (6)	411 (22)
AntiSocial	73	1236	3.7	550 (44.53)	200 (16.2)	179 (14.5)	116 (9.4)	190 (15.37)	593 (48)	111 (9)	99 (8)	433 (35)
Digital Wellbeing	71	50,895	3.3	27,493 (54.02)	3985 (7.83)	2591 (5.09)	1598 (3.14)	15,228 (29.92)	28,501 (56)	3563 (7)	3563 (7)	15,269 (30)
AppDetox	70	1303	3.5	448 (34.37)	278 (21.34)	225 (17.27)	149 (11.44)	203 (15.58)	469 (36)	182 (14)	156 (12)	495 (38)
Offtime	69	3780	3.4	1568 (41.48)	575 (15.21)	420 (11.11)	353 (9.34)	864 (22.86)	1550 (41)	378 (10)	378 (10)	1474 (39)
QualityTime	69	3469	3.5	1400 (40.36)	575 (16.58)	436 (12.57)	363 (10.46)	695 (20.03)	1457 (42)	347 (10)	347 (10)	1318 (38)
Flipd	65	2192	3.3	830 (37.85)	318 (14.5)	247 (11.27)	203 (9.28)	594 (27.10)	921 (42)	197 (9)	153 (7)	921 (42)
RescueTime	61	593	3.1	180 (30.35)	85 (14.33)	105 (17.71)	75 (12.65)	148 (24.96)	196 (33)	59 (10)	53 (9)	285 (48)

Table 4. Sentiment breakdown of app features. Percentage values correspond to the total number of the reviews for each app.

Custom topic	Total reviews (N=145,454)	Sentiment breakdown			
	Reviews, n (%)	Positive, n (%)	Neutral, n (%)	Mixed, n (%)	Negative, n (%)
Analysis provided by the authors					
Reduce mobile phone use and MMPU[a]	31,729 (21.81)	19,989 (63)	2856 (9)	2221 (7)	6663 (22)
Gamification (only in *Forest*)	11,468 (7.88)	5505 (48)	1606 (14)	1147 (10)	3211 (28)
Grayscale mode (part of wind down feature in *Digital Wellbeing*)	357 (0.25)	68 (19)	46 (13)	43 (12)	200 (56)
Blocking	9710 (6.68)	5923 (60)	971 (10)	680 (7)	2136 (22)
Goal setting	7546 (5.19)	5735 (75)	679 (9)	302 (4)	830 (11)
Tracking	7819 (5.38)	2815 (35)	1056 (13)	938 (12)	3049 (39)
Analysis provided by the software					
Design and UX[b]	15,565 (10.7)	8872 (57)	1557 (10)	1090 (7)	4047 (26)
Use cases	9914 (6.82)	6940 (71)	991 (10)	496 (5)	1487 (15)
Customer support	4585 (3.15)	2613 (58)	459 (10)	459 (10)	1055 (23)
Feature request	6708 (4.61)	2616 (39)	1207 (18)	805 (12)	2079 (31)
Notification and alerts	2878 (1.98)	432 (16)	403 (14)	489 (17)	1554 (54)
Advertising	1517 (1.04)	349 (23)	152 (10)	228 (15)	789 (52)
Privacy	631 (0.43)	38 (6)	38 (6)	44 (7)	511 (81)
Battery	231 (0.16)	39 (16)	16 (7)	23 (10)	152 (66)

[a]MMPU: maladaptive mobile phone use.

[b]UX: user experience.

Discussion

Principal Findings

Previous research has indicated that there is a lack of scientific evidence regarding the efficacy and effectiveness of apps in delivering health interventions, including apps aimed at reducing mobile phone use [8,56]. As a result, this study aimed to examine the evidence supporting the effectiveness of apps in reducing mobile phone use and addressing MMPU. To the best of our knowledge, no previous study has evaluated such apps and their relationship to different types of MMPU. The findings of this study revealed that various types of MMPU were addressed in 6 (32%) of the 19 papers [32,35,36,39-41], which included the use of the Mobile Phone Problematic Usage Scale developed by Bianchi and Phillips [50] and used by Ochs and Sauer [32]; Mobile Phone Problem Use Scale developed by Foerster et al [51] and used by Keller et al [35]; Smartphone Addiction Scale Short Version developed by Kwon et al [52] and used by Holte et al [39], Olson et al [40], and Loid et al [41]; Fear of Missing Out Scale developed by Przybylski et al [53] and used by Throuvala et al [36]; Nomophobia Questionnaire developed by Yildirim et al [54] and used by Throuvala et al [36]; and an adapted set of 4 questions based on the study of Roberts et al [55] and used by Schmuck [47].

As per existing primary evidence, the apps that have shown effectiveness in reducing mobile phone use and MMPU include *Screen Time* (iOS; with moderate to strong evidence)

[11,32-34,39,40], *AntiSocial* (strong evidence) [36], and *Forest* and *Screen Time* (with weak evidence) [43]. However, it is important to note that 2 (11%) of the 19 studies included a mixed intervention (where using apps was just one of them) to reduce mobile phone use and MMPU [11,36]. Specifically, the grayscale feature offered by *Screen Time* (iOS) has been shown to be effective in reducing mobile phone use [11,32,33,36,39,40]. Some of the studies (6/19, 32%) directly assessed the impact of apps on MMPU. Among the 6 studies that examined MMPU, 3 (50%) demonstrated that the grayscale feature could lower MMPU [36,39,40], whereas 3 (50%) found that apps as an intervention did not reduce MMPU [35,36,41]. Finally, 1 (17%) of these 6 studies yielded contrasting results, indicating an increase in users' MMPU [32]. A study by [36] showed that mixed intervention could lower FoMO, but not for Nomophobia.

Regarding the features of the apps, we identified 7 categories: self-tracking, social tracking, goal setting, blocking, gamification, simplification, and assessment. The most popular features were self-tracking and goal setting, whereas gamification and assessment were less commonly observed. The most comprehensive apps in terms of features were *AntiSocial*, with *Forest* being the only one offering gamification. *Space* provided an assessment of MMPU by asking users a few short questions, helping them to understand their mobile phone use and MMPU. However, the effectiveness of gamification and assessment in reducing mobile phone use has not been thoroughly examined in the literature. Social tracking features,

XSL•FO

RenderX

such as inviting friends and family to join off time together (eg, *Offtime* and *Flipd*), inviting them to share focus mode and tree planting together (eg, *Forest*), or creating a group to share progress and foster accountability (eg, *Space*), were only offered by 4 (31%) of the 13 apps.

The sentiment scores ranged from 61 to 86 out of 100, indicating that users tend to accept apps that address mobile phone use reduction. The highest score was obtained by *Forest*, thanks to its gamification feature that helps users to focus more on their activities. Of note, adoption and sentiment information for *Screen Time* (iOS) were not available because this is a built-in app in the iPhone. Thus, it remains unclear how it has been adopted and received by the public. Analyzing sentiment around features in all apps, we found that users had a negative sentiment associated with the grayscale in *Digital Wellbeing* (200/357, 56%) as part of the wind down feature. This low acceptance suggests that users do not prefer using it, and there might be less adoption of this feature. Future research should explore ways to enhance the acceptability of this feature because some studies have concluded that grayscale mode enabled by using the *Screen Time* feature within the Settings app (iOS) effectively reduces mobile phone use [11,32,33,39,40] and MMPU [39,40].

Reducing mobile phone use and MMPU involves limiting meaningless use and supporting meaningful use [57]. The uses and gratifications theory can be applied to examine how user motivation (specific intention or general habit) and the type of use (eg, information seeking or communication) affect the meaning derived from mobile phone use [58]. At times, mobile phone users may feel a lack of autonomy and meaning, leading them to seek gratification by escaping from the situation [57]. On the basis of an autoethnographic study and functionality review, most apps primarily focus on limiting screen time by creating obstacles to restrict use, promoting awareness of reaching set limits, supporting focused attention, and encouraging motivation to limit use [59]. However, further work is needed to define strategies that provide gratification from limiting mobile phone use.

Although some apps are effective in helping to reduce mobile phone use, without user motivation and commitment, they are likely to fail [36]. Personal characteristics of users, such as an awareness of the relationship between mobile phone use behavior and well-being as well as the motivation to achieve goals, will influence the results [44,60]. Therefore, app developers should allow users to maintain their freedom of choice and provide content that promotes motivation and commitment to facilitate the adoption of new habits and engagement in long-term behavior change [60,61]. Some recommendations from consumers' point of view include ensuring that the app is enjoyable to use, meets their needs, supports existing habits, allows for goal creation and modification, and provides rewards and opportunities to share progress within a social community. Currently, few apps include reinforcing factors such as social sharing of mobile phone use, which is considered important for long-term adoption of behavior change [61].

In future research, it is important to address certain limitations. First, the samples in the literature reviews included in this study exhibited cultural and social similarities in terms of research locations, age groups, and educational backgrounds. However, for a more comprehensive understanding of our diverse world, it is crucial to incorporate a heterogeneous sample that encompasses a broader range of cultural, social, and demographic characteristics. Different age groups may exhibit varying texting and mobile phone etiquette norms [62], and mobile phone use tends to decline linearly with age, whereas MMPU remains relatively stable throughout adulthood before declining rapidly around the age of 40 years [63]. In addition, the samples in the included studies predominantly consisted of individuals with a high level of education, which can influence technology perceptions and use patterns. It is worth noting that users in these studies may have been more familiar with technology than the general population. Previous research has indicated that young people with higher education, excellent health, and higher income tend to be the primary users of health apps [64]. Second, it is possible that we missed certain apps that were being trialed and had not yet been published because we only included active apps that had undergone scientific evaluation. Third, it is important to acknowledge that user reviews are not the sole method for conducting sentiment analysis. Alternative approaches should also be considered. Fourth, future research should not only explore reduction in mobile phone use but also focus on meaningful use as a better approach to addressing and decreasing MMPU. Fifth and last, the heterogeneity of intervention strategies, duration, scale, and methods used in the included studies prevented us from conducting a meta-analysis. Future research should consider these limitations and strive to address them effectively.

Conclusions

This paper investigated existing apps designed to reduce mobile phone use and prevent MMPU and examines the evidence of their effectiveness. To the best of our knowledge, no previous study has conducted a comprehensive review and sentiment analysis of apps aimed at reducing mobile phone use and MMPU. Although our study demonstrates the effectiveness of app-based management as a strategy for reducing mobile phone use and MMPU, further research is necessary to evaluate the efficacy of app-based interventions. According to the scientific literature, *Screen Time* (iOS) and *AntiSocial* showed moderate to strong evidence, whereas *Forest* and *Screen Time* exhibited a weak level of evidence, in reducing mobile phone use and MMPU. Effective intervention strategies for reducing mobile phone use and MMPU included using grayscale mode, app limit features, and mixed interventions. In addition, self-tracking and goal setting were found to be the most popular features, whereas gamification and assessment were less frequently used. Users generally displayed positive sentiment toward these apps, with sentiment scores ranging from 61 to 86 out of 100. Notably, *Forest* received the highest score owing to its gamification feature, which aids users in enhancing focus on their activities. This study holds significance because the public's use of apps to reduce mobile phone use and MMPU is likely to increase. Therefore, users should be better informed about the factors that make an app appealing and successful in facilitating behavior change. Collaboration among researchers, app developers, mobile phone manufacturers, and policy makers

can contribute to the delivery and evaluation of apps aimed at   reducing mobile phone use and MMPU.

Data Availability

The data set used to conduct sentiment analysis is publicly available and can be accessed over the internet [65].

Conflicts of Interest

None declared.

Multimedia Appendix 1

Characteristics of the reviewed apps.
[DOCX File , 26 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Search strategy.
[DOCX File , 28 KB-Multimedia Appendix 2]

Multimedia Appendix 3

PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) checklist.
[DOCX File , 27 KB-Multimedia Appendix 3]

Multimedia Appendix 4

Summary of published literature evaluating the effectiveness of apps.
[DOCX File , 38 KB-Multimedia Appendix 4]

Multimedia Appendix 5

Search terms in the custom topics for user reviews.
[DOCX File , 14 KB-Multimedia Appendix 5]

References

1. Oviedo-Trespalacios O, Nandavar S, Newton JD, Demant D, Phillips JG. Problematic use of mobile phones in Australia…is it getting worse? Front Psychiatry 2019;10:105 [FREE Full text] [doi: 10.3389/fpsyt.2019.00105] [Medline: 30914975]
2. Rahmillah FI, Tariq A, King M, Oviedo-Trespalacios O. Is distraction on the road associated with maladaptive mobile phone use? A systematic review. Accid Anal Prev 2023 Mar;181:106900 [FREE Full text] [doi: 10.1016/j.aap.2022.106900] [Medline: 36580764]
3. Oviedo-Trespalacios O, Truelove V, King M. "It is frustrating to not have control even though I know it's not legal!": a mixed-methods investigation on applications to prevent mobile phone use while driving. Accid Anal Prev 2020 Mar;137:105412 [doi: 10.1016/j.aap.2019.105412] [Medline: 32006729]
4. Lepp A, Barkley JE, Karpinski AC. The relationship between cell phone use, academic performance, anxiety, and satisfaction with life in college students. Comput Hum Behav 2014 Feb;31:343-350 [doi: 10.1016/j.chb.2013.10.049]
5. Samaha M, Hawi NS. Relationships among smartphone addiction, stress, academic performance, and satisfaction with life. Comput Hum Behav 2016 Apr;57:321-325 [doi: 10.1016/j.chb.2015.12.045]
6. Thomée S, Härenstam A, Hagberg M. Mobile phone use and stress, sleep disturbances, and symptoms of depression among young adults--a prospective cohort study. BMC Public Health 2011 Jan 31;11:66 [FREE Full text] [doi: 10.1186/1471-2458-11-66] [Medline: 21281471]
7. Aboujaoude E, Vera Cruz G, Rochat L, Courtois R, Ben Brahim F, Khan R, et al. Assessment of the popularity and perceived effectiveness of smartphone tools that track and limit smartphone use: survey study and machine learning analysis. J Med Internet Res 2022 Oct 20;24(10):e38963 [FREE Full text] [doi: 10.2196/38963] [Medline: 36264627]
8. van Velthoven MH, Powell J, Powell G. Problematic smartphone use: digital approaches to an emerging public health problem. Digit Health 2018 Mar 05;4:2055207618759167 [FREE Full text] [doi: 10.1177/2055207618759167] [Medline: 31463071]

9. Ko M, Choi S, Yatani K, Lee U. Lock n' LoL: group-based limiting assistance app to mitigate smartphone distractions in group activities. In: Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems. 2016 Presented at: CHI'16: CHI Conference on Human Factors in Computing Systems; May 7-12, 2016; San Jose California USA [doi: 10.1145/2858036.2858568]

10. Chen X. Does persuasive technology make smartphones more addictive? An empirical study of Chinese University students. KTH Royal Institute of Technology School of Electrical Engineering and Computer Science. 2021. URL: https://www.diva-portal.org/smash/get/diva2:1586507/FULLTEXT01.pdf [accessed 2023-06-30]

11. Myers E, Drees ET, Cain J. An intervention utilizing the salience principle to reduce pharmacy students' psychological attraction to smartphones. Am J Pharm Educ 2022 Apr;86(4):8717 [FREE Full text] [doi: 10.5688/ajpe8717] [Medline: 34507959]

12. Alter A. Irresistible The Rise of Addictive Technology and the Business of Keeping Us Hooked. Westminster, UK: Penguin Press; 2017.

13. Monge Roffarello A, de Russis L. The race towards digital wellbeing: issues and opportunities. In: Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems. 2019 Presented at: CHI '19: CHI Conference on Human Factors in Computing Systems; May 4-9, 2019; Glasgow, UK [doi: 10.1145/3290605.3300616]

14. Hiniker A, Hong S, Kohno T, Kientz JA. MyTime: designing and evaluating an intervention for smartphone non-use. In: Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems. 2016 Presented at: CHI'16: CHI Conference on Human Factors in Computing Systems; May 7-12, 2016; San Jose, CA [doi: 10.1145/2858036.2858403]

15. Kim J, Park J, Lee H, Ko M, Lee U. LocknType: lockout task intervention for discouraging smartphone app use. In: Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems. 2019 Presented at: CHI '19: CHI Conference on Human Factors in Computing Systems; May 4-9, 2019; Glasgow, UK [doi: 10.1145/3290605.3300927]

16. Okeke F, Sobolev M, Dell N, Estrin D. Good vibrations: can a digital nudge reduce digital overload? In: Proceedings of the 20th International Conference on Human-Computer Interaction with Mobile Devices and Services. 2018 Presented at: MobileHCI '18: 20th International Conference on Human-Computer Interaction with Mobile Devices and Services; September 3-6, 2018; Barcelona, Spain [doi: 10.1145/3229434.3229463]

17. Foulonneau A, Calvary G, Villain E. Stop procrastinating: TILT, time is life time, a persuasive application. In: Proceedings of the 28th Australian Conference on Computer-Human Interaction. 2016 Presented at: OzCHI '16: The 28th Australian Conference on Human-Computer Interaction; November 29-December 2, 2016; Launceston, Australia [doi: 10.1145/3010915.3010947]

18. Ko M, Yang S, Lee J, Heizmann C, Jeong J, Lee U, et al. NUGU: a group-based intervention app for improving self-regulation of limiting smartphone use. In: Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing. 2015 Presented at: CSCW '15: Computer Supported Cooperative Work and Social Computing; March 14-18, 2015; Vancouver, BC [doi: 10.1145/2675133.2675244]

19. Goel M, Dixit T, Bajpai A, Singh A. Using gamification to rationalize excessive use of mobile devices among children and adolescents. In: Proceedings of the International Conference on COMmunication Systems & NETworkS (COMSNETS). 2021 Presented at: International Conference on COMmunication Systems & NETworkS (COMSNETS); January 05-09, 2021; Bangalore, India [doi: 10.1109/comsnets51098.2021.9352888]

20. Stawarz K, Cox AL, Blandford A. Beyond self-tracking and reminders: designing smartphone apps that support habit formation. In: Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems. 2015 Presented at: CHI '15: CHI Conference on Human Factors in Computing Systems; April 18-23, 2015; Seoul, Republic of Korea [doi: 10.1145/2702123.2702230]

21. Lyngs U, Lukoff K, Slovak P, Binns R, Slack A, Inzlicht M, et al. Self-control in cyberspace: applying dual systems theory to a review of digital self-control tools. In: Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems. 2019 Presented at: CHI '19: CHI Conference on Human Factors in Computing Systems; May 4-9, 2019; Glasgow, UK [doi: 10.1145/3290605.3300361]

22. Oviedo-Trespalacios O, King M, Vaezipour A, Truelove V. Can our phones keep us safe? A content analysis of smartphone applications to prevent mobile phone distracted driving. Transp Res Part F Traffic Psychol Behav 2019 Jan;60:657-668 [doi: 10.1016/j.trf.2018.11.017]

23. Shamseer L, Moher D, Clarke M, Ghersi D, Liberati A, Petticrew M, PRISMA-P Group. Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015: elaboration and explanation. BMJ 2015 Jan 02;350:g7647 [FREE Full text] [doi: 10.1136/bmj.g7647] [Medline: 25555855]

24. Thomas BH, Ciliska D, Dobbins M, Micucci S. A process for systematically reviewing the literature: providing the research evidence for public health nursing interventions. Worldviews Evid Based Nurs 2004 Jun 23;1(3):176-184 [doi: 10.1111/j.1524-475x.2004.04006.x]

25. Tofighi B, Chemi C, Ruiz-Valcarcel J, Hein P, Hu L. Smartphone apps targeting alcohol and illicit substance use: systematic search in in commercial app stores and critical content analysis. JMIR Mhealth Uhealth 2019 Apr 22;7(4):e11831 [FREE Full text] [doi: 10.2196/11831] [Medline: 31008713]

26. Abroms LC, Lee Westmaas J, Bontemps-Jones J, Ramani R, Mellerson J. A content analysis of popular smartphone apps for smoking cessation. Am J Prev Med 2013 Dec;45(6):732-736 [FREE Full text] [doi: 10.1016/j.amepre.2013.07.008] [Medline: 24237915]

27. Hoeppner BB, Schick MR, Kelly LM, Hoeppner SS, Bergman B, Kelly JF. There is an app for that - or is there? A content analysis of publicly available smartphone apps for managing alcohol use. J Subst Abuse Treat 2017 Nov;82:67-73 [doi: 10.1016/j.jsat.2017.09.006] [Medline: 29021117]

28. Bowie-DaBreo D, Sünram-Lea SI, Sas C, Iles-Smith H. Evaluation of treatment descriptions and alignment with clinical guidance of apps for depression on app stores: systematic search and content analysis. JMIR Form Res 2020 Nov 13;4(11):e14988 [FREE Full text] [doi: 10.2196/14988] [Medline: 33185566]

29. appbot homepage. appbot. URL: https://appbot.co/ [accessed 2023-06-30]

30. Kaur S, Chakravarty R. Analytics for measuring library use and satisfaction of mobile apps. Libr Hi Tech News 2021 Jun 28;38(4):10-12 [FREE Full text] [doi: 10.1108/lhtn-04-2021-0014]

31. Bano M, Zowghi D, Kearney M. Feature based sentiment analysis for evaluating the mobile pedagogical affordances of apps. In: Tatnall A, Webb M, editors. Tomorrow's Learning: Involving Everyone. Cham: Springer; 2017.

32. Ochs C, Sauer J. Curtailing smartphone use: a field experiment evaluating two interventions. Behav Inf Technol 2021 Dec 04;41(16):3598-3616 [doi: 10.1080/0144929x.2021.2007284]

33. Holte AJ, Ferraro FR. True colors: grayscale setting reduces screen time in college students. Soc Sci J 2020 Apr 03;60(2):274-290 [doi: 10.1080/03623319.2020.1737461]

34. Hoong R. Self control and smartphone use: an experimental study of soft commitment devices. Eur Econ Rev 2021 Nov;140:103924 [doi: 10.1016/j.euroecorev.2021.103924]

35. Keller J, Roitzheim C, Radtke T, Schenkel K, Schwarzer R. A mobile intervention for self-efficacious and goal-directed smartphone use in the general population: randomized controlled trial. JMIR Mhealth Uhealth 2021 Nov 23;9(11):e26397 [FREE Full text] [doi: 10.2196/26397] [Medline: 34817388]

36. Throuvala MA, Griffiths MD, Rennoldson M, Kuss DJ. Mind over matter: testing the efficacy of an online randomized controlled trial to reduce distraction from smartphone use. Int J Environ Res Public Health 2020 Jul 05;17(13):4842 [FREE Full text] [doi: 10.3390/ijerph17134842] [Medline: 32635650]

37. Collins EI, Cox AL, Bird J, Cornish-Tresstail C. Barriers to engagement with a personal informatics productivity tool. In: Proceedings of the 26th Australian Computer-Human Interaction Conference on Designing Futures: the Future of Design. 2014 Presented at: OzCHI '14: Proceedings of the 26th Australian Computer-Human Interaction Conference on Designing Futures: the Future of Design; Dec 2-5, 2014; Sydney, New South Wales, Australia [doi: 10.1145/2686612.2686668]

38. Zimmermann L. "Your screen-time app is keeping track": consumers are happy to monitor but unlikely to reduce smartphone usage. J Assoc Consum Res 2021 Jul 01;6(3):377-382 [doi: 10.1086/714365]

39. Holte AJ, Giesen DT, Ferraro FR. Color me calm: grayscale phone setting reduces anxiety and problematic smartphone use. Curr Psychol 2021 Jun 26;42(8):6778-6790 [doi: 10.1007/s12144-021-02020-y]

40. Olson JA, Sandra DA, Chmoulevitch D, Raz A, Veissière SP. A nudge-based intervention to reduce problematic smartphone use: randomised controlled trial. Int J Ment Health Addict 2022 May 17:1-23 [FREE Full text] [doi: 10.1007/s11469-022-00826-w] [Medline: 35600564]

41. Loid K, Täht K, Rozgonjuk D. Do pop-up notifications regarding smartphone use decrease screen time, phone checking behavior, and self-reported problematic smartphone use? Evidence from a two-month experimental study. Comput Hum Behav 2020 Jan;102:22-30 [doi: 10.1016/j.chb.2019.08.007]

42. Neuwirth LS. Flipd app reduces cellular phone distractions in the traditional college classroom: implications for enriched discussions and student retention. J Coll Stud Ret Res Theory Pract 2020 May 04;24(2):386-420 [doi: 10.1177/1521025120921348]

43. Dai C, Tai Z, Ni S. Smartphone use and psychological well-being among college students in China: a qualitative assessment. Front Psychol 2021;12:708970 [FREE Full text] [doi: 10.3389/fpsyg.2021.708970] [Medline: 34566786]

44. Parry DA, le Roux DB, Morton J, Pons R, Pretorius R, Schoeman A. Digital wellbeing applications: adoption, use and perceived effects. Comput Hum Behav 2023 Feb;139:107542 [doi: 10.1016/j.chb.2022.107542]

45. Prasad A, Quinones A. Digital overload warnings - "the right amount of shame"? In: Kurosu M, editor. Human-Computer Interaction. Cham: Springer; 2020.

46. Oeldorf-Hirsch A, Chen Y. Mobile mindfulness: predictors of mobile screen time tracking. Comput Hum Behav 2022 Apr;129:107170 [doi: 10.1016/j.chb.2021.107170]

47. Schmuck D. Does digital detox work? Exploring the role of digital detox applications for problematic smartphone use and well-being of young adults using multigroup analysis. Cyberpsychol Behav Soc Netw 2020 Aug;23(8):526-532 [doi: 10.1089/cyber.2019.0578] [Medline: 32354288]

48. Zhou Y, Bird J, Cox AL, Brumby D. Estimating usage can reduce the stress of social networking. In: Proceedings of the Personal Informatics in the Wild: Hacking Habits for Health & Happiness — CHI 2013 Workshop. 2013 Presented at: Personal Informatics in the Wild: Hacking Habits for Health & Happiness — CHI 2013 Workshop; Apr 27-May 2, 2013; Paris, France URL: https://discovery.ucl.ac.uk/id/eprint/1412160

49. Löchtefeld M, Böhmer M, Ganev L. AppDetox: helping users with mobile app addiction. In: Proceedings of the 12th International Conference on Mobile and Ubiquitous Multimedia. 2013 Presented at: MUM '13: 12th International Conference on Mobile and Ubiquitous Multimedia; Dec 2-5, 2013; Luleå, Sweden [doi: 10.1145/2541831.2541870]

50. Bianchi A, Phillips JG. Psychological predictors of problem mobile phone use. Cyberpsychol Behav 2005 Mar;8(1):39-51 [FREE Full text] [doi: 10.1089/cpb.2005.8.39] [Medline: 15738692]

51. Foerster M, Roser K, Schoeni A, Röösli M. Problematic mobile phone use in adolescents: derivation of a short scale MPPUS-10. Int J Public Health 2015 Mar;60(2):277-286 [FREE Full text] [doi: 10.1007/s00038-015-0660-4] [Medline: 25645102]

52. Kwon M, Kim DJ, Cho H, Yang S. The smartphone addiction scale: development and validation of a short version for adolescents. PLoS One 2013;8(12):e83558 [FREE Full text] [doi: 10.1371/journal.pone.0083558] [Medline: 24391787]

53. Przybylski AK, Murayama K, DeHaan CR, Gladwell V. Motivational, emotional, and behavioral correlates of fear of missing out. Comput Hum Behav 2013 Jul;29(4):1841-1848 [doi: 10.1016/j.chb.2013.02.014]

54. Yildirim C, Correia AP. Exploring the dimensions of nomophobia: development and validation of a self-reported questionnaire. Comput Hum Behav 2015 Aug;49:130-137 [doi: 10.1016/j.chb.2015.02.059]

55. Roberts JA, Pullig C, Manolis C. I need my smartphone: a hierarchical model of personality and cell-phone addiction. Pers Individ Differ 2015 Jun;79:13-19 [FREE Full text] [doi: 10.1016/j.paid.2015.01.049]

56. Zhao J, Freeman B, Li M. Can mobile phone apps influence people's health behavior change? An evidence review. J Med Internet Res 2016 Oct 31;18(11):e287 [FREE Full text] [doi: 10.2196/jmir.5692] [Medline: 27806926]

57. Lukoff K, Yu C, Kientz J, Hiniker A. What makes smartphone use meaningful or meaningless? Proc ACM Interact Mob Wearable Ubiquitous Technol 2018 Mar 26;2(1):1-26 [FREE Full text] [doi: 10.1145/3191754]

58. Cho H, Choi D, Kim D, Kang WJ, Choe EK, Lee SJ. Reflect, not regret: understanding regretful smartphone use with app feature-level analysis. Proc ACM Hum Comput Interact 2021 Oct 18;5(CSCW2):1-36 [FREE Full text] [doi: 10.1145/3479600]

59. Almoallim S, Sas C. Toward research-informed design implications for interventions limiting smartphone use: functionalities review of digital well-being apps. JMIR Form Res 2022 Apr 19;6(4):e31730 [FREE Full text] [doi: 10.2196/31730] [Medline: 35188897]

60. Dennison L, Morrison L, Conway G, Yardley L. Opportunities and challenges for smartphone applications in supporting health behavior change: qualitative study. J Med Internet Res 2013 Apr 18;15(4):e86 [FREE Full text] [doi: 10.2196/jmir.2583] [Medline: 23598614]

61. Fitzgerald M, McClelland T. What makes a mobile app successful in supporting health behaviour change? Health Educ J 2016 Dec 27;76(3):373-381 [FREE Full text] [doi: 10.1177/0017896916681179]

62. Forgays DK, Hyman I, Schreiber J. Texting everywhere for everything: gender and age differences in cell phone etiquette and use. Comput Hum Behav 2014 Feb;31:314-321 [doi: 10.1016/j.chb.2013.10.053]

63. Horwood S, Anglim J, Mallawaarachchi SR. Problematic smartphone use in a large nationally representative sample: age, reporting biases, and technology concerns. Comput Hum Behav 2021 Sep;122:106848 [doi: 10.1016/j.chb.2021.106848]

64. Carroll JK, Moorhead A, Bond R, LeBlanc WG, Petrella RJ, Fiscella K. Who uses mobile phone health apps and does use matter? A secondary data analytics approach. J Med Internet Res 2017 Apr 19;19(4):e125 [FREE Full text] [doi: 10.2196/jmir.5604] [Medline: 28428170]

65. Appbot. URL: https://appbot.co/ [accessed 2023-08-07]

Abbreviations

EPHPP: Effective Public Health Practice Project
FoMO: fear of missing out
MMPU: maladaptive mobile phone use
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RQ: research question

XSL•FO

RenderX