

# Facing Up to Nomophobia: A Systematic Review of Mobile Phone Apps that Reduce Smartphone Usage



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**Abstract** Excessive smartphone use has been linked to adverse health outcomes including distracted driving, sleep disorders, and depression. Responding to this growing trend, apps have been developed to support users in overcoming their dependency on smartphones. In that vein, our investigation explored the “big data” available on these types of apps to gain insights about them. We narrowed our search of apps, then reviewed content and functionality of 125 Android and iOS apps that purport to reduce device usage in the United States and elsewhere. This sample was curated based on popularity through the market research tool, *App Annie* (which indicates revenue and downloads per category of app and by country). The apps fell into 13 broad categories, each of which contained several different features related to filters, usage controls, and monitoring programs. Findings suggest that social media technologies, including smartphone apps, are being attempted for use for health behavior change. We discuss methods of sorting through “big data” generated by apps that purport to curb smartphone addiction. Finally, we propose data-driven features, such as social facilitation and gamification, that developers might use to enhance the effectiveness of these apps.

**Keywords** Smartphone • Phantom vibration syndrome • Social cognitive theory • Cognitive behavioral therapy

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## 1 Introduction

The proliferation of smartphones and access to wireless and data networks has enabled people to learn, connect, and navigate worldwide. Despite the clear advantages of these “smart” devices, their near-constant use has given rise to negative social and health consequences such as smartphone addiction, lowered sleep quality [15], and decreased road safety [18].

This is not surprising, given a 2013 Harris poll which revealed that 72% of United States (US) adults claimed they were so dependent on their smartphones that they kept them within 5 feet of their bodies the majority of the time. In fact, some respondents noted they kept their smartphone nearby while showering, during sexual intercourse, and/or attending religious services [19]. Findings like these have given rise to a new term, “nomophobia.” The fear of being without one’s phone is so pervasive that it not only has a name, it was recently proposed for inclusion into the *DSM-V* [4, 12]. Symptoms of excessive smartphone use and nomophobia include compulsive text messaging and phantom vibration syndrome, wherein a user feels the sensation of a device’s vibration even when it is not in use [17, 20].

Fortunately, these symptoms may be resolved through behavioral interventions, as the technology itself may be a useful tool for that very behavior therapy. For example, public health announcements have been conveyed by television and radio advertisements, text messages, and mobile apps [24].

More precisely, behavior change techniques include gaining end-user acceptance and commitment (“commitment”) [5], goal-setting and promotion of standards (“setting standards”) [21], offering tools for self-awareness and monitoring (“self-tracking”) [22], customization of feedback based on the audience and situation (“tailoring messages”) [11], encouraging the end user to strengthen relationships with family, friends, and peers (“social facilitation”) [2, 7, 23, 26, 27] and implementation of rewards, competition, or other game elements (“gamification”) [8, 16]. Therefore, although smartphones may be associated with addiction, they may also serve as a platform that enables positive behavior change [9].

We provide a review of the “big data” from these types of apps based on data from the data aggregator, *App Annie*. This review aimed at: (i) illustrating the content and functionality of the new generation of apps that serve to mitigate the problems associated with smartphone addiction and excessive device usage; and (ii) exploring (indirectly) ideas on how to enhance the effectiveness of these “detox apps”.

## 2 Methods

### 2.1 Keyword Search Terms

Prior to initiating the review process, we conducted research via *Google Trends* to identify relevant keyword terms related to mobile phone “over-usage.” First, we entered the expression “smartphone addiction” into *Google Trends* on September 1, 2016. Three related search terms were returned, all of which were relevant, namely: “smartphone addiction test,” “smartphone addiction scale,” and “phone addiction.” Entering the term “phone addiction” yielded a total of 11 results, of which 3 were relevant, i.e. “cell phone addiction,” “internet addiction,” and “social media addiction.” Entering “smartphone addiction scale” and “smartphone addiction test” did not generate additional results.

### 2.2 App Selection Process

*Google Play* and *iTunes App Store* were used to conduct a systematic review of apps on September 1, 2016. Our inclusion criteria were composed of the noted search terms. Exclusion criteria were: (i) the app description did not feature content related to excessive device usage, (ii) the app was a duplicate, or slight adaptation, of another app already under investigation, (iii) the app had no English-language user interfaces, (iv) the app claimed to increase device usage, or (v) the app could harm (even judge) the end user.

### 2.3 Ranking

Popularity was assessed using *App Annie* [1]. [AppAnnie.com](http://AppAnnie.com) is a market research website that collects aggregate data from its clients (comprised of approximately 94% of the top smartphone app publishers), and then extrapolates rankings for all apps [6]. Given that neither *Google* nor *Apple* provide precise data about the total revenue or downloads achieved by an app, *App Annie*'s estimates are a valuable resource for contextualizing and interpreting the data provided on these platforms. Furthermore, *App Annie*'s data have high credibility, in that it has been successfully applied in other research studies for evaluating the market visibility of health apps [3, 25].

## 2.4 Statistical Analysis

Data were expressed as percentages for categorical variables and as median (interquartile range [IQR]) for ordinal/continuous variables. Comparisons between groups were performed by Chi-squared or Fisher's exact tests for categorical variables, and by the Mann-Whitney test or Kruskal-Wallis with Dunn's post hoc test for continuous variables.

A logistic regression model was built so that we could explore the relationship between ranking and the characteristics of the selected apps (e.g. platform and features). Because the ranking did not have a normal distribution, the variable was included in the model as a dichotomous variable (i.e. ranking less than or greater than 500). The independent variables were chosen based on an exploratory analysis and a hierarchical backward approach was then used to determine which variables to keep or drop from the model [13]. A generalized variance inflation-factor (VIF) greater than 5 served to identify multicollinearity. Following this, the Durbin Watson test was applied to evaluate the model's validity. From this foundation, statistical analysis was performed using STATA-10. A  $p$  value  $<0.05$  was considered significant.

## 3 Results

The *Google Play* and *iTunes* filtering search resulted in 125 apps that were available on Android ( $n = 67$ ), iOS ( $n = 37$ ) or both platforms ( $n = 21$ ). While the search term "smartphone addiction" returned the greatest number of results across both operating systems, the *iTunes* search engine provided, on average, 56.0% more relevant results to our queries than *Google Play*. The flow chart of the selection process is shown in Fig. 1.

### 3.1 Content and Functionality of Selected Apps in the US and the Rest of the World

The selected apps fell into the following categories: productivity (52.0%), tools (12.0%), lifestyle (9.6%), and health and fitness (8.8%). The remaining 17.6% is represented by business, communication, education, medical, parenting, personalization, photography, social networking, and utilities apps. Each app had at least one of the following features: blocking, parental control, tracking, rewards, reminders, coaching, and/or social media. As demonstrated in Table 1, reminders and tracking were the most represented (90.4% and 82.4%, respectively). Half of the categories included at least 3 features and there were no significant differences among app categories in terms of average number of features (KW = 7.75,  $p = 0.101$ ).

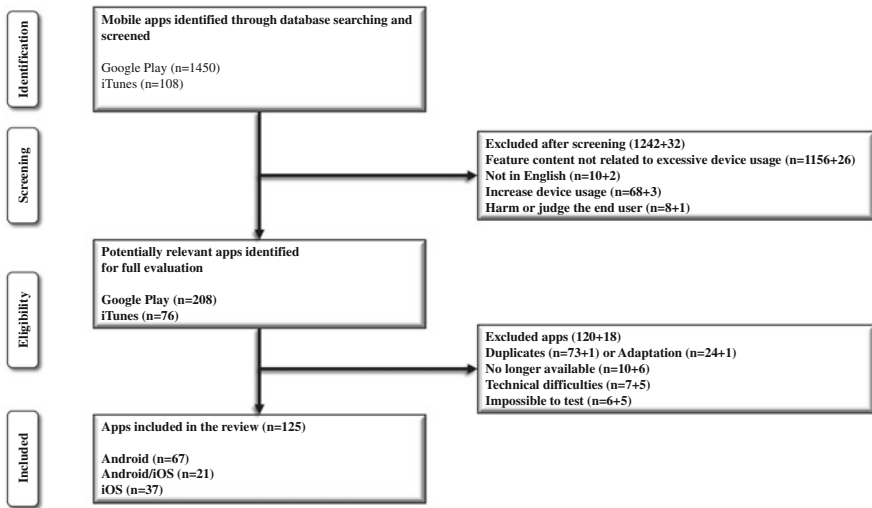


Fig. 1 Flow chart of the app selection process

Since roughly half of the data (56.7%) originated in the US, we focused our analysis on the possible differences in app preferences and usage between countries. Specifically, Android and iOS platforms showed a different distribution between the US and the rest of the world. In the US, the prevalence of iOS users (40.3%) was comparable to the prevalence of Android users (41.7%), while in the rest of the world the choice of the platform was polarized ( $\chi^2 = 11.2, p = 0.004$ ) toward Android (69.8%) rather than iOS (15.1%). Tracking and reminder features were the most represented, at 80.0% (Table 1).

Because sample size was not always representative when stratified by category, the least numerically relevant categories were grouped in “other” (e.g. business, communication, education, medical, parenting, personalization, photography, social networking, and utility). Android and iOS showed a statistically significant difference in apps related to productivity ( $\chi^2 = 7.94, p = 0.019$ ) and tools ( $p < 0.001$ ). These categories were the least and most represented on the Android platform, respectively (Table 2).

### 3.2 Popularity of Apps in the US and the Rest of the World

Ranking was available for 91 out of 125 of the apps. On average, *Annie’s* rank was significantly higher (KW = 22.50, adjusted  $p < 0.001$ ) on the iOS platform (917; 577.3–1310.0) than on Android (477.5; 332.3–526.5). The lowest ranked 25% of iOS apps were still better ranked than Android’s top 25% (Fig. 2). Within app

**Table 1** Prevalence distribution of the 125 selected apps into the seven different features

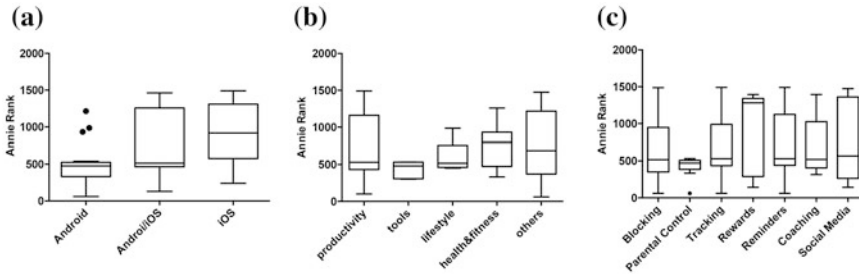
Feature	Apps among platforms %(N)			Apps between country blocks %(N)		Overall apps %(N)
	Android (n = 67)	Android/iOS (n = 21)	iOS (n = 37)	US (n = 72)	Rest of the world (n = 53)	
Blocking	55.2 (37)	33.3 (7)	18.9 (7)	37.5 (27)	45.3 (24)	40.8 (50)
Parental control	13.4 (9)	14.3 (3)	0.0 (0)	9.7 (7)	9.4 (5)	9.6 (12)
Tracking	80.6 (54)	90.5 (19)	81.1 (30)	80.6 (58)	84.9 (45)	82.4 (103)
Rewards	3.0 (2)	14.3 (3)	8.1 (3)	5.6 (4)	7.5 (4)	6.4 (8)
Reminders	86.6 (58)	95.2 (20)	94.6 (35)	87.5 (63)	94.3 (50)	90.4 (113)
Coaching	13.4 (9)	9.5 (2)	24.3 (9)	13.9 (10)	18.9 (10)	16.0 (20)
Social media	7.5 (5)	4.8 (1)	13.5 (5)	8.3 (6)	9.4 (5)	8.8 (11)

*Note* The data refer to the total number of apps and to the apps stratified among platform and country blocks; the prevalence is expressed as percentage and absolute frequency (N) in brackets

**Table 2** Prevalence distribution of the 125 selected apps into the 13 different categories

Category	Apps among platforms %(N)			Apps between country blocks %(N)		Overall apps %(N)
	Android (n = 67)	Android/iOS (n = 21)	iOS (n = 37)	US (n = 72)	Rest of the World (n = 53)	
Productivity	40.3 (27)	66.7 (14)	64.9 (24)	62.5 (45)	37.7 (20)	52.0 (65)
Tools	22.4 (15)	0.0 (0)	0.0 (0)	12.5 (9)	11.3 (6)	12.0 (15)
Lifestyle	14.9 (10)	4.8 (1)	2.7 (1)	5.5 (4)	15.1 (8)	9.6 (12)
Health and fitness	7.5 (5)	4.8 (1)	13.5 (5)	8.3 (6)	9.4 (5)	8.8 (11)
Business	0.0 (0)	4.8 (1)	0.0 (0)	0.0 (0)	1.9 (1)	0.8 (1)
Communication	4.5 (3)	0.0 (0)	0.0 (0)	2.8 (2)	1.9 (1)	2.4 (3)
Education	1.5 (1)	0.0 (0)	5.4 (2)	0.0 (0)	5.7 (3)	2.4 (3)
Medical	0.0 (0)	0.0 (0)	5.4 (2)	1.4 (1)	1.9 (1)	1.6 (2)
Parenting	1.5 (1)	0.0 (0)	0.0 (0)	1.4 (1)	0.0 (0)	0.8 (1)
Personalization	4.5 (3)	0.0 (0)	0.0 (0)	1.4 (1)	3.8 (2)	2.4 (3)
Photography	0.0 (0)	0.0 (0)	2.7 (1)	1.4 (1)	0.0 (0)	0.8 (1)
Social networking	2.9 (2)	4.8 (1)	2.7 (1)	1.4 (1)	5.7 (3)	3.2 (4)
Utilities	0.0 (0)	14.3 (3)	2.7 (1)	1.4 (1)	5.7 (3)	3.2 (4)

*Note* The data refer to the total number of apps and to the apps stratified among platform and country blocks; the prevalence is expressed as percentage and absolute frequency (N) in brackets



**Fig. 2** Boxplot showing *App Annie* rank of apps developed in the three groups of platforms, Android, iOS and the shared one’s (a), stratified by category (b) or by feature (c). Whiskers were drawn based on Tukey method

categories and features, ranking did not show any statistical difference (KW = 3.09, p = 0.543 and KW = 5.54, p = 0.476, respectively).

Based on the results attained in the explorative phase, we built a logistic regression model of *Annie*’s rank on platforms as a significant, independent variable ( $\beta = 1.46$ , standard error = 0.535; p = 0.006). Note, “parental features” was included as a covariate, since it was differently distributed within the three platform groups. Our model suggested that of the apps available for iOS, the opportunity to have a medium/high rank (>500) was approximately four times greater than apps available for Android.

### 3.3 Review of Three Randomly Selected Smartphone Apps

We randomly selected three apps with a broad range of features. The apps *BreakFree* and *Unplug* were downloaded to an iPhone 5S, and *QualityTime* to a Samsung Galaxy S5. *Breakfree* included 3 features and presented an average rank (Annie rank = 491), *Unplug* included the greatest number of features (n = 5) and presented a high rank (Annie rank = 1394) and, finally, *QualityTime* included 2 features and presented a low rank (Annie rank = 316). Then, we explored whether the apps implemented any of the 6 behavior change methods that were noted in the introduction, that is: commitment, setting standards, self-tracking, tailoring, social-facilitation, and/or gamification.

Based on our assessments, we highlight features and functions in what follows, with the expectation that it may address outstanding issues for end users seeking to reduce their device usage.

*QualityTime*, *BreakFree*, and *Unplug* include key features consistent with at least 4 behavior change principles. Two apps—*BreakFree* and *Unplug*—contain key features consistent with gamification (i.e. “achievement titles” and “last high score”). The only app to provide key features consistent with social facilitation

(i.e. “parental notification” and “family time”) is *BreakFree*. This is also the only app of the group to require the use of GPS to deliver a key feature, while *Unplug* is the only app to integrate the “Airplane Mode” feature of iOS as one of its key functions.

*QualityTime* provides several features that require users to commit to behavior change, such as auto-blocking inbound calls and sending an auto-reply to inbound text messages. It also features self-tracking, in the form of summaries that report usage and standard settings in the form of a configurable screen and app auto-locks. Still, *QualityTime* does support tailoring, insofar as it enables the user to tune auto-locks, auto-replies, and restriction periods (with exceptions).

*Unplug* immediately, repeatedly, and colorfully prompts the user to set their phone to “Airplane Mode” and to put the phone down until the user complies. It is important to note that *Unplug* also blocks graphics and alerts. It is perhaps best described as a nomophobia version of the “cold turkey” method.

*BreakFree* embraces gamification by using a points-and-title system. Unlike *Unplug* and *QualityTime*, *BreakFree* features an animated character, “Sato” that notifies the user to “slow down” after an hour of phone usage. Moreover, users can schedule “family time” hours in advance, during which the Internet and sound are disabled on the device. This app also comes with parental control settings that enable users to monitor their children’s usage. The latter feature differentiates *BreakFree* from the other apps investigated, as supporting “social facilitation.”

## 4 Discussion

To our knowledge from this analysis, there are no apps for nomophobia that rely on evidence-based research. In fact, the most promising evidence-informed apps, such as *PTSD Coach*—an app used to mitigate acute distress in veterans who experience post-traumatic stress disorder—has no long-term data regarding its effectiveness [14]. Nevertheless, the Veterans Administration has successfully used *PTSD Coach* to generate “big data” related to patient satisfaction and VA mental health outreach services on the order of 130,000 downloads (as of 2013). On the clinical side, several smartphone apps have been effective in studies for managing depression and anxiety, though their examination is outside the scope of this paper [10]. Generally speaking, these apps help users commit to new behaviors; learn about and set quantifiable goals and standards; self-monitor and track trends; receive tailored messages from professional counselors; enjoy elements of games; and they bring users closer to friends and family.

Given that we were unable to directly explore associations between the use of behavior change techniques and changes in health behavior, or other health-related outcomes, we posit some key observations in app features and usage patterns between the US and other countries. Foremost, there were no significant differences



in app categories as a function of their average number of features, or the most used types of apps in the US as compared to other countries. Platforms, however, are used differently across countries. For instance, apps showed, in some cases, a different distribution among platforms in terms of feature and category. Of note, the platform seems to play a crucial role in defining the popularity of an app, insofar as iOS ranks significantly better than Android.

#### ***4.1 Recommendations for Developers to Use Big Data from Apps***

Big data from apps, such as aggregate data from *App Annie*, can be used to inform developers about new features they can use to improve apps, such as apps to address nomophobia. Smartphone app developers interested in addressing the challenges of nomophobia might focus on features that address the key principles of behavior change that are underrepresented in the apps featured in this review, namely: commitment, setting standards, self-tracking, tailoring, gamification, and social facilitation. “Big Data” from nomophobia apps can also inform app publishers whether their users find these apps acceptable. They can evaluate this, for example, by analyzing data on device usage provided by Google and Apple, daily information from *App Annie*, potential data from in-app advertisers, as well as data that end users may choose to volunteer on their experiences with features.

#### ***4.2 Limitations***

One of the feasibility and time-challenges of this review was that individual apps in *Google Play* and *iTunes* had to be opened to determine whether they were intended to reduce smartphone usage. To minimize the harm to end users who are using devices while searching for apps that address nomophobia, developers can create logos that clarify the app’s key features and/or behavior change techniques.

A further limitation is that *App Annie* could not be used for the purposes of an academic research article to unlock raw or “premium” content, such as estimated downloads and lifetime advertising dollars earned by each app. To date, there is no more timely way to conduct a systematic review of nomophobia apps without using the leading provider of such data.

Finally, it was not possible to directly determine the effectiveness of “detox apps” against a range of processes and health-related outcomes. Additional well-designed studies are needed to explore associations between the use of these behavior change techniques and smartphone addiction recovery.

## 5 Conclusion

Big data from apps can be used to study the usability and acceptability of apps. This information can be incorporated into analyses to determine how apps are being used, and for example, in the case of nomophobia apps, whether they are based on scientific research on how to reduce nomophobia. *QualityTime*, *BreakFree*, and *Unplug* are nomophobia-focused apps that are marketed to smartphone users seeking to reduce their usage. Each of these apps has achieved notable success among non-nomophobia users within the “productivity” app store category, as validated by *App Annie*. Of the 3 apps, *BreakFree* includes the most features consistent with the principles of behavior change. However, this review using data found no evidence-based smartphone apps to thoroughly address nomophobia, and so recommends further research efforts devoted to this area. Future research using smartphone data can help to guide the integration of scientific research findings into nomophobia apps to help address nomophobia.

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