Beyond Smartphone Overuse: Identifying Addictive Mobile Apps

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Abstract
Current research on smartphone addiction has mainly focused on addiction at the device level. This motivated us to explore more specifically on app addiction. We investigate smartphone usage for college students using surveys, logged data, and interviews. The analysis of our data shows that social and communication apps are the top 2 most addictive categories among participants. Female and male participants show no significant difference in terms of smartphone addiction. However, female participants tend to report that they are addicted to more apps. The psychological factors associated with app addiction are different between app categories. For example, compared to communication apps, participants report that it is easier to withdraw from social apps, but more difficult to control time spent on them. Correlation analysis between app usage features and app addictiveness scores reveals that compulsive open times, usage duration, and regularity of usage are good indicators of app addiction, though response time to notifications has limited predictive power.

Author Keywords
Smartphone Overuse; Mobile App Addiction; Mobile Apps.

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous

Introduction

In recent years excessive use of smartphones has become prevalent [14, 15, 11], which often has negative impact on social interaction [12] and mental health [10, 4, 13]. Young adults, who as a group have high smartphone adoption rates [1] and are vulnerable to technology overuse [8], are at higher risk of suffering negative impact.

Researchers have been working on how to identify problematic phone use based on self-reported questionnaires and device measurements. Recently, Shin et al. [15, 11] proposed to automatically classify problematic smartphone use by modeling features derived directly from device usage, which is more objective and less prone to recall errors [16]. However, research on device overuse still leaves much unexplained. For example, people who were classified as non-problematic using existing assessment tools were also concerned about smartphone overuse during certain daily activities [15]. Therefore, understanding the smartphone overuse problem by focusing more specifically on mobile apps is necessary to obtain deeper insights of the problematic smartphone use.

In this paper, we explore the problem of mobile app addiction. We collected actual smartphone usage data from 26 college students and conducted data analysis with an app addiction psychometric scale adapted from an established smartphone addiction psychometric instrument [9]. Specifically, we aim to understand the following questions:

- What kind of smartphone apps do college students feel addictive to?
- Are there any differences between male and female students in terms of Smartphone Addiction and App Addiction?
- In what psychological aspect do college students feel addicted to apps?
- What app usage features are good indicators of App Addiction?

Related Work

The term “addiction” used by general public does not have the same rigorous meaning as defined in psychiatry for ailments such as drug addictions. Often technology-related addictions (non-chemical) have been classified as behavioral addictions [17] as interactive devices induce and reinforce features that may promote addictive tendencies [5]. In particular, Internet Addiction was well studied in the scientific community. Young [19] concluded that although the Internet itself is not addictive, specific applications appear to play a role in the development of pathological Internet use. Young’s conclusion is consistent with Kandell’s observation that role-playing games, internet relay chat and chat rooms are the primary Internet activities that lead to addictive behavior [8].

However, research on smartphone addiction has not yet focused on individual apps. Problematic mobile phone use was usually identified through self-reported questionnaires [3, 6, 7]. Only recently researchers have been working on detecting problematic smartphone use computationally. Shin and Dey [15] propose to automatically classify problematic smartphone use by modeling device-level usage features derived directly from the device. In their interviews with participants, some pointed out they were using specific apps too much such as games and SMS. Similarly, Lee et al. [11] constructed predictive models to classify at-risk users to smartphone overuse and compared the app usage patterns between at-risk and non-risk groups. Their interviews with participants showed greater degree of interference by instant messaging and less structured content consumption in the at-risk group. Motivated by these results, this work focuses on understanding addictive behaviors to individual apps.

Study Design

Our study consists of three phases. In the first phase, we administered surveys to acquire demographic data and measure the level of Smartphone Addiction. In the second phase, we deployed an Android *logger* app to participants' smartphones to collect their app usage and contexts (such as location) during usage. In the final phase, we screened top-used apps for each participant and administered a survey to measure his/her level of addiction to these apps. We also performed interviews to better understand participants' app usage behaviors.

Participants
We selected college students for this study because of the high smartphone adoption rate among young adults and their vulnerability to technology overuse. 26 out of 32 participants completed 4 weeks of study during the spring semester of 2015 and were compensated with a $20 gift card. The 26 participants come from 8 majors with an average age of 21.9 years (SD 2.4); 18 are male and 8 are female; 10 are graduate students and 16 are undergraduate students.

Smartphone Usage Logging
We developed an Android *logger* app which collected participants' app usage events (screen on/off/unlock, which app and how long it was used, touch, scroll and click events, notification events and Call/SMS Log). It also collected location context throughout the day using WiFi signatures to identify individual places [20]. On average, the logger consumed less than 10% of the battery throughout a day. In the exit interview, no one reported that their app usage was impacted by the logger when asked.

Our logger is based on *funf* [2] framework. The implementation details of location tracking component can be found in [20].

F1	My school grades(or work productivity) dropped due to excessive smartphone use. *My smartphone does not distract me from my studies.
F2	Using a smartphone is more enjoyable than spending time with my family or friends When I cannot use a smartphone, I feel like I have lost the entire world.
F3	It would be painful if I am not allowed to use a smartphone. *I am not anxious even when I am without a smartphone.
F4	I try cutting my smartphone usage time, but I fail. *I can not control my smartphone usage time.

Table 1: Sample Questions of Smartphone Addiction Proneness Scale (its factors include F1: Interference, F2: Virtual World, F3: Withdrawal, and F4: Tolerance). * are reversed coded items.

Initial and Exit Interview
In the first phase, we adopted the *Smartphone Addiction Proneness Scale for Adults* (SAPSA) [9] to measure participants' level of smartphone overuse. This established scale consists of 15 four-point Likert-scale questions measuring four psychological factors associated with addictive behaviors. Table 1 lists some sample questions for each factor.

In the final phase, we screened potential addictive apps for each participant by usage score [18] calculated from both usage frequency and duration. We adapted the SAPSA scale, converting device-level questions to app-level questions (e.g. "My school grades dropped due to excessive smartphone usage" was changed to "My school grades dropped due to excessive usage of app X"). Using the adapted assessment instrument, we derived an "addiction score" for each of the top apps using the number of ques-

App Category	#
Social	46
Communication	37
Media&Video	12
Browser	12
Games	6
Music&Audio	5
News&Magazines	4
Tools	3
Shopping	3
Productivity	3
Entertainment	2
Travel&Local	1
Sports	1
Photography	1
Lifestyle	1
Book&Reference	1

Table 2: Number of rated instances for each app category

App Category	#
Social	22
Communication	20
Browser	12
Media&Video	11
Games	6

Table 3: Number of Participants who rated the app category. Here we only show categories rated by at least 5 participants

tions with "Yes" answers ("No" for reverse-coded items). Thus the addictive score for each app ranges from 0 to 15.

Results

We calculated usage scores (considering usage duration and frequency) for participants' apps. For each participant, we screened his/her top 10 used apps as potentially addictive and asked him/her to rate his/her level of addiction to these apps using our adapted scale. The score for each app ranges from 0 to 15, measured by four factors associated with addictive behaviors. We collected 138 rated app instances (addictive score >= 0) from 26 participants. Table 2 shows the number of rated app instances for each category.

Categories of Addictive Apps
Table 3 shows the number of unique users who consider an app category addictive. Social and communication apps are commonly considered as addictive. 22 out of 26 participants consider themselves addicted to social apps to some level, and 20 report they are addicted to communication apps. The top 3 rated social apps are Facebook, Instagram and Snapchat, considered as addictive by 20, 9 and 5 participants, respectively. The top 3 rated communication apps are MMS, Whatsapp, and Email, considered as addictive by 9, 6 and 5 participants, respectively.

Table 3 shows that 12 participants consider web browser apps as addictive. Unlike social and communication apps, browser apps do not push any content to users, and users use them proactively. The addiction to browser apps reflects their addiction to the content they access. In the exit interview, most participants said they used their web browser to access various news portals. 3 participants said they accessed social websites more often using mobile browsers than directly using social apps because they were concerned about these social apps collecting private information in the background. For these 3 participants, the addiction to browser apps reflects their addiction to social medias, similar to the addiction to social apps.

Gender Differences in Smartphone/App Addiction
A theme of interest for many researchers relates to gender differences in smartphone addiction. However, there is no agreement on which gender group is at the higher risk of addiction.

We performed unpaired t-tests(two-tailed) of the level of smartphone overuse collected in initial interviews between female and male participants. Female participants are slightly more prone to smartphone addiction (32.9, SD:3.9 vs 28.7, SD:6.3, p=0.09). However the difference is not statistically significant. Also unpaired t-tests(two-tailed) of daily usage duration between female and male groups show no significant difference (154 min, SD:86 vs 128 min, SD:50, p=0.34).

However, there are significant differences between female and male participants in the number of apps they think are addictive and reported levels of addiction to the apps. Unpaired t-tests(two-tailed) show female participants have more apps they think are addictive than male participants (7.4, SD:2.4 vs 4.4, SD:2.1, p=0.04). Unpaired t-tests(two-tailed) also show female participants tend to think they are more addicted to apps than male participants, in terms of addictive score ratings of the apps (4.7, SD:2.26 vs 2.8, SD:1.63, p=0.03).

Psychological Factors of App Addiction
Table 4 shows the average scores of four psychological factors associated with addiction for different app categories. For each factor, we also performed unpaired t-tests(two-tailed) between different app categories.

App Category	No. of Rated Apps	Interference[0-5]	Virtual[0-2]	Withdrawal[0-4]	Tolerance[0-4]
Social	46	1.65 [1.27, 2.03]	0.30 [0.14, 0.46]	0.57 [0.24,0.88]	1.90 [1.37,2.41]
Communication	37	0.97 [0.5,1.44]	0.35 [0.19,0.51]	1.20 [0.84,1.53]	0.90 [0.49,1.29]
Browser	12	0.92 [0.04,1.79]	0.42 [-0.008,0.84]	1.08 [0.25,1.91]	1.17 [0.51,1.82]
Media & Video	12	0.58 [0.16,1]	0.08 [-0.1,0.2]	0.67 [-0.015,1.34]	0.67 [0.1,1.23]
Games	6	1.83 [-0.2,3.8]	0.00 [0,0]	0.50 [-0.08,1.07]	2.00 [0.24,3.75]

Table 4: The average scores for each factor associated with addiction for different categories (including 95% confidence interval)

For the factor of interference, the average scores of social apps and games were higher than other app categories. However, the *t*-tests results only show significant difference between social and two other app categories (communication, p=0.02 and Media & Video, p=0.007). Lee et al. [11] discussed frequent interference from instant messaging apps. Here our data shows that, compared with communication apps, participants feel that social apps interfered with them more.

From the aspect of withdrawal, the statistically significant difference between social and communication categories (p=0.01) suggests that, although social apps are more interesting in terms of content provided, participants are not as psychologically attached to them as to communication apps.

For tolerance factor, significant difference was also found between social and communication apps. Although from the factor of withdrawal, we found that psychologically participants did not feel withdrawal from social apps to be as difficult as withdrawal from communication apps, they report it is more difficult for them to control time spent on social apps.

Predictive Features of App Addiction

To investigate whether addiction to apps is reflected by apps' actual usage, we extracted four types of usage features for each app: basic usage features (e.g. use time, open times, etc), active behavior features (e.g. compulsive open times, notification response rate, etc), spatial behavior features (e.g. number of places the app was used), and irregularity features (e.g. open times irregularity, use time irregularity, etc). Here the irregularity is calculated using coefficient variation. We considered 25 features in total (not listed due to space limitation).

We chose these features based on our following intuitive assumptions:

1. The longer he/she uses the app, the more addicted he/she is to the app.
2. The more frequently he/she compulsively opens the app, instead of responding to notifications, the more addicted he/she is to the app.
3. The more he/she is triggered by external notification to use the app, the more addicted he/she is to the app.
4. The more regularly he/she uses the app every day, the more addicted he/she is to the app.

Features	Avg. Corr. Coeff.	#P
Daily No. of compulsive open times	0.66	11
Daily Usage duration	0.65	9
DI of compulsive open times	-0.62	9
DI of [6pm-12am] usage duration	-0.68	9
DI of compulsive usage duration	-0.63	8
*Daily Open times per day	0.51	7
DI of [6pm-12am] open times	-0.67	7
*No. of visited places	0.47	7

Table 5: Usage features showing strong correlation over 7 or more participants. Features showing both positive and negative correlations are marked with * ,#P stands for the number of participants and DI stands for Daily Irregularity.

5. The more places where he/she use the app, the more addicted he/she is to the app.

For each participant, we conducted *Spearman* correlation analysis between the usage features and addiction score for his/her top 10 used apps. We extracted usage features strongly correlated (coefficient > 0.5) with addictiveness score and with statistical significance($p<0.05$). We show features that have strong correlation among several participants(>=7) in Table 5.

From Table 5, three of our assumptions can be validated through correlation of several usage features to the addictive score. Assumption 1 and 2 are reflected by basic app usage features (e.g. daily usage duration) and active behavior features (daily no. of compulsive open times). Assumption 4 can be validated by irregularity features (daily irregularity of compulsive open times, daily irregularity of [6pm-12am] usage duration and daily irregularity of [6pm-12am] open times). Two of these irregularity features within the evening time slot demonstrate the special characteristics of the student group. They take classes during the day which makes daytime smartphone usage somewhat irregular. In the evening, however, regular use of addictive apps can be observed in many participants. From the spatial feature No. of places, we find Assumption 5 does not generalize to a large group. Assumption 3 was observed in several students, though we did not find this generalizable to a large group so response behavior to the notifications is not a good indicator of app addiction.

Conclusion

We presented the analysis of app addiction among 26 college students using surveys, logged data and interviews. Our analysis shows that social and communication apps are more addictive among participants. There is no significant difference between female and male participants in terms of smartphone addiction. However female participants have more addictive apps. Compared to communication apps, participants report it is easier to withdraw from social apps but more difficult to control time spent on them. Correlation analysis between app usage features and app addiction scores reveals that compulsive open times and usage time are good indicators of app addiction and usage of addictive apps is more regular over time. However, response time to notifications does not correlate well with app addiction scores. We plan to extend this work and construct classification models using machine learning algorithms.

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