Determining typical smartphone usage: What data do we need?

Abstract

Problematic smartphone use is an emerging issue in behavioural addiction research. At the same time, measuring smartphone use with mobile apps has become increasingly common. However, understanding how much data is necessary requires careful consideration if the field is to move forward. Here, we examine how much time should be spent measuring mobile phone operation in order to reliably infer general patterns of usage and repetitive checking behaviours. In a second analysis, we consider whether a self-report measure of problematic smartphone use is associated with real-time patterns of use. Results suggest that smartphone usage collected for a minimum of five days will reflect typical weekly usage (in hours), but habitual checking behaviours (uses lasting less than 15 seconds) can be reliably inferred within two days. These measurements did not reliably correlate with a self-reported measure. We conclude that patterns of smartphone use are repetitive and our results suggest that checking behaviour is a particularly consistent and efficient measure when quantifying typical and problematic smartphone usage.

Keywords

Smartphones; digital traces; addiction; behavioural addiction;

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Introduction

Problematic mobile phone usage reportedly shares characteristics that are traditionally associated with other addictive behaviours including tolerance, craving, withdrawal, and functional impairment[1]. Thus, measures of smartphone usage should be considered to examine this emerging addictive behaviour. Numerous research projects have aimed to measure mobile phone usage (e.g., [2, 3]). Some of this research involves self-report estimates of usage or questionnaires which may not be entirely reliable [4]. Comparatively few studies have used mobile apps, which can measure usage behaviour directly [5]. With studies increasingly reliant upon such measures, the development of norms regarding the type and volume of data required in order to make reliable inferences about day-to-day behaviour is paramount. For example, the duration of data capture in recent projects varies considerably with usage being measured from one week to one month [3,6,7].

In order to determine what a suitable time frame for data collection might look like, one must first establish how stable individual smartphone usage is over time. In theory, researchers could continuously collect smartphone usage data, but this would become ethically problematic long before hitting a computational wall. Nevertheless, collecting fewer data points would enable procedural advantages and increase participant retention. Therefore, in this study we aim to answer this question by conducting some additional analysis on an existing data set that previously quantified smartphone usage over a period of two weeks.

Materials and Methods

The data obtained for this study has previously been described in [6]. However, a secondary analysis reported here aims to determine the volume of data required to reliably infer typical smartphone usage patterns. This is distinct from what the original paper aimed to explore (for a more detailed account of the original methodology see [6]).

Participants

Data was collected from 27 students and staff from the University of Lincoln (17 females, mean age = 22.52, range = 18–33). Our sample comprised of clerical, technical and academic university staff, and students who were studying a range of subjects including psychology, computer science, zoology, and media production. This sample size was deemed adequate for our analyses as vast amounts of usage data was collected for each participant over the duration of the study. All participants provided informed consent and were able to view example data in advance.

Data collection

We developed an Android smartphone app using the Funf in a Box framework [8]. This resulted in a small app that recorded a timestamp when smartphone use started and ended. Data is encrypted and uploaded to a server over Wi-Fi (for more details see [8]). The app provided a timestamp when the phone became active, and a second when this activity stopped and the phone was inactive. This was primarily anything that involved screen use, but also included processor intensive activities (e.g., calls and playing music). Two behavioural measures were generated at the end of each day:

total hours of usage and frequency of use. Total hours of usage was determined by the amount of time that the phone was active. Frequency of use (or checking) was measured in terms of number of smart phone checks, which were defined by [6] as any usage lasting less than 15 seconds. Checks are included within the present analysis because we believe this is more informative for future problematic smartphone use research. In addition, the number of times someone checks their phone each day does not correlate with total hours of use [all *p's* >.1] [6]. In other words, these are two completely separate behavioural measures (Figure 1).

Data was collected for 14 days, however, due to between-participant time differences when the app was installed, we removed data collected between application installation and midnight of day one. This left 13 complete days of data for analysis. Week one contained a full weekend and four week days for all participants. Week two contained a full weekend and five week days for all participants. The majority of participants installed the application on a Thursday (n=14) or Friday (n=12) with a single installation occurring on a Wednesday.

A self-report measure was also administered (Cronbach's alpha = .89) in order to test if this was also predictive of behaviour. The Mobile Phone Problem Use Scale (MPPUS) consists of 27 items, which have previously demonstrated positive correlations with self-reported mobile phone use [9]. Items include “I feel lost without my mobile phone” and “I can never spend enough time on my mobile phone”.

Results

We observe remarkable consistency when data points from all 13 days are clustered for each participant (Figure 1). This is particularly noticeable regarding checking behaviour with hours of usage per day being generally more variable. Our subsequent analysis initially considers weekday and daily comparisons before assessing the predictive ability of self-reported smartphone usage.

[insert Figure 1 about here]

Weekly Comparisons

Participant total hours of use and checks were calculated for each week independently. We observed that smartphone behaviours measured during the first 6 days of data collection when collapsed across all participants were highly predictive of total usage [r (25) = .81; p <.0001] and checks [r (25) =.96; p <.0001] observed in week two (7 days). This implies that just under one week of data collection is already sufficient to determine typical usage and checking behaviours for the following week. We also observed that average usage and checking patterns were remarkably similar between weekends and weekdays with no significant differences observed between average number of weekday hours (M = 4.95, SD = 2.96) and average weekend hours (M = 5.25, SD = 3.13), [t (26) = -0.80, p = 0.43]. Similarly, no significant differences were observed when comparing the average number of checks during weekdays or (M = 41.00, SD = 35.00) weekends (M = 39.31, SD = 40.64), [t (26) = 0.41, p = 0.68].

Daily Comparisons

A further analysis considered if reliable behaviour for an entire week could be inferred from single or multiple days. Each individual 24-hour usage period from the first six days was compared with total hours use and checks from week two. These 6 correlation coefficients were averaged to provide an indication of how well a 24-hour period represented a typical weeks use. This resulted in an average of [r = .61, range = .41 - .74] for usage and [r = .82, range = .64 - .89] for checks.

To illustrate the minimum number of days required to reliably infer patterns of smartphone behaviour for an entire week, we aggregated the means from several days' data from week one and again compared this with totals from week two. Days included in a running mean increased cumulatively, i.e., average of day 1 & 2 correlated with week 2 total, then average of day 1, 2, & 3 correlated with week 2 total etc. Based on the strength of pervious correlations between weeks one and two, we predicted that the number of days required to reach a *priori* target of r >.8 would be small. As expected, hours of usage fluctuate more between subsequent days as the correlation coefficient reaches its zenith after about five days. On the other hand, predicting future checking behaviour requires very little data before an equally strong relationship is observed (Figure 2). This result holds regardless of when a participant installed the application on their phone.

[insert Figure 2 about here]

Selecting a random combination of any 2 days from the first 6 will always result in a correlation > .7 when compared to the following week. Similarly, a random combination of any 5 days usage will result in a correlation > .7 when compared to the following week. These results are therefore robust and even a single day can often remain predictive of any other day with average correlations for usage [r = .44, SD = .20] and checks [r = .72 SD=.13] remaining high.

Self-Report Analysis

To further understand the value of self-report and its relation to real-world smartphone behaviour, a measure of problematic phone use (the MPPUS) was also analysed. Self-reported mobile phone behaviour when using the MPPUS was previously found not to correlate (using Pearson's) with either of the two mobile phone usage measures over the duration of the original study (two weeks) [6]. This suggests that self-reporting problematic use may not be an accurate measure of actual behaviour. However, self-report measures such as this are not always consistent as small differences between self-reported items are interpreted as being meaningful by Pearson's correlations. Instead, it is conceptually plausible to rank-order participants from least to most self-reported usage. Therefore, using the Spearman rank-order correlation coefficient (nonparametric measure) may allow us to retrieve an additional indication of the strength and direction of association that exists between two variables without any extreme self-reported scores affecting the analysis. However, ranked MPPUS scores were unable to predict total use or number of checks across the entire 13-day period [p's > .07]. Following our previous analysis protocol, we observed that the MPPUS was inconsistent when predicting usage or checks from an individual week or day.

Discussion

The type and duration of data required for smartphone usage and addiction studies lacks direction. These analyses will hopefully enable researchers to consider adopting standardised methods when collecting and quantifying such data. In addition, relatively little behavioural data is required to quantify typical usage over longer periods of time. Within these analyses, it was observed that data collection over a period of a week is probably unnecessary. Participants in our sample appear to use their phone in a very similar pattern over a single 24-hour period. Similar to other digital traces, (e.g., location tracking[10]) these results confirm that smartphone interactions are a repetitive and consistent individual marker of behaviour. Therefore, in order to obtain a measure relating to hours of usage for a week, it would appear that an average of about five days is required. For comparable checking behaviour, only 48 hours of data are required. These results imply that measuring checking behaviour may have procedural advantages over hours used. By requiring less data in order to reliably infer typical smartphone phone, research can become more efficient and attract greater numbers of participants who are more likely to install non-invasive applications onto their smartphones.

One may question why phone checking frequency provides a more efficient measure of usage? It is possible that this variable is a better measure of preoccupation with mobile phones. Multiple checks could indicate an absent-minded use of mobile phones, which may not necessarily be goal-directed. Therefore, checking frequency may represent more habitual usage. It could also be due to habitual behaviour becoming more automatic and indicative of an unconscious problem (cf. [11]). This is in contrast to a measure of hour's use which may be more at risk of being affected by general use varying from one day to the next.

Self-reported problematic mobile phone use was unreliable when predicting subsequent behaviour (see [4]). This may be because the cognitive processes associated with compulsive use would conceivably be automatic (e.g. [12]) and as such, could not be captured adequately through self-reports which may only measure deliberate, conscious behaviours.

There are some limitations to the current study. The first 24 hours after the app is installed could be an even more useful measure for researchers. In this analysis the first full day of data collection was taken from midnight following installation of the mobile application and so we were unable to explore if even a few hours of data are sufficient to reliably infer typical behaviour. Beyond checking for weekend effects, we have not considered potential weekday effects, but a more complete analysis would have required many more participants to commence data collection on different days. The original study design attempted to control for this with almost every participant installing the application on a Thursday or Friday. However, we acknowledge that our youthful sample may demonstrate smartphone usage patterns that are markedly different from other groups. For example, older age groups who use their smartphone less frequently may require an extended period of data collection. Alternatively, data collection could be even shorter as their behaviour patterns may be relatively stable. It is worth noting that participants with reduced usage overall demonstrated less variability when compared with those who use or check their smartphone more often.

In conclusion, these analyses indicate that it is not necessary to collect smartphone data for weeks or months at a time to infer typical patterns of usage, particularly when it comes to shorter instances of use or checking behaviours. These short, but frequent behaviours are likely to be a more valuable measure of phone usage because they are procedurally easier to measure and are more likely to be associated with problematic phone usage behaviour. This simple measure of behaviour alone may prove to be more suitable for addiction-related smartphone studies in the future[4].

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[Figure 1. Distributions of total usage (a) and checks (b) by day for every participant over a 13-day period. Participants are ordered by median value, indicated by a solid line across each measure. This ordering illustrates that hours of usage and checking are unrelated.]

[Figure 2. Pearson's correlation coefficients between single and combined averages from week one and the average derived from week two. The black line indicates the value of r demonstrating that: (a) an average usage calculated from 5 days is highly predictive of future behaviour and (b) an average derived based on the number of checks over 2 days in week one is also predictive of similar behaviour the following week. The dotted line highlights where $r > .8$.]