Pers Ubiquit Comput (2012) 16:105–114
DOI 10.1007/s00779-011-0412-2

ORIGINAL ARTICLE

Habits make smartphone use more pervasive

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Received: 22 September 2010 / Accepted: 10 May 2011 / Published online: 16 June 2011

Abstract Examining several sources of data on smartphone use, this paper presents evidence for the popular conjecture that mobile devices are "habit-forming." The form of habits we identified is called a *checking habit*: brief, repetitive inspection of dynamic content quickly accessible on the device. We describe findings on kinds and frequencies of checking behaviors in three studies. We found that checking habits occasionally spur users to do other things with the device and may increase usage overall. Data from a controlled field experiment show that checking behaviors emerge and are reinforced by informational "rewards" that are very quickly accessible. Qualitative data suggest that although repetitive habitual use is frequent, it is experienced more as an annoyance than an addiction. We conclude that supporting habit-formation is an opportunity for making smartphones more "personal" and "pervasive."

Keywords Smartphones · Habits · Logging data · Diary studies

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1 Introduction

The impact of portable computing devices is undergoing a heated debate in the popular media.[1] It is evident that users' practices are changing—they socialize in new ways; they do tasks in new ways, often interleaving and cross-pollinating between activities; they share and gather information in new ways. A concern expressed repeatedly centers around the notion of *habit*—that is, how new technologies, like mobile phones in the 1990s and laptops and smartphones in the 2000s, spur unforeseen consequences the fabric of everyday life. While many appreciate the ubiquitous and continuous access to social networks, there are concerns about invasion into private domains [8], and it has been observed that gains achieved in productivity do not automatically generate free time but complicate work–life balance [9]. Indeed, sociologists have reported Westerners' time-use becoming more irregular, fragmented, overlapped, and shifting to new places [13, 18].

Smartphones—handheld personal computers—represent the most recent step in the evolution of portable information and communication technology (see Fig. 1). Smartphones—equipped with persistent network connectivity and supporting the installation of new applications—have the potential to produce new habits related to Internet use. Their exact impact on the formation of new habits is not well understood, however. Our preliminary logging studies indicated that smartphones could be used as much as 2.7 h

[1] http://www.nytimes.com/2010/06/07/technology/07brain.html
http://www.nytimes.com/2010/06/10/garden/10childtech.html
http://www.techdirt.com/articles/20100607/0224269710.shtml
http://www.nytimes.com/2010/06/11/opinion/11Pinker.html.

Fig. 1 Three smartphones investigated in the studies (from *left* to *right*): Android G1 (launched to market in 2008), Nokia 6600 (2003), and Nokia N97 (2009)

per day and typically longer than traditional forms of computing.[2] However, it was left open *what* the new habits are, qualitatively speaking, and what their role in the fabric of everyday use is.

The goal of the present paper is to investigate the habit-forming nature of smartphones in more detail and with a specific view to what habits are and what their role is in human–computer interaction. As our scientific approach, we build on a recent theory in cognitive psychology that defines habit as *an automatic behavior triggered by situational cues*, such as places, people, and preceding actions [10, 21]. The study of habits in this context is the study of two interrelated things: (1) automatized behaviors relating to smartphone use and (2) the cues that trigger these behaviors. If we accept that habits are a cognitively "inexpensive" element of behavior, due to automatic and "ballistic" execution, understanding them is essential in the pursuit of making computing devices natural, "invisible," and pervasively used. At the other extreme, habits that are repetitively triggered by external cues reduce the intrinsic locus of control of an individual. Smartphones are a potential source of addictions, and understanding them is essential in preventing them (see Sect. 1.1).

Contrary to the persuasive computing enterprise [3], the theory of habits as automatized behaviors [21] does not deal as much with changing or understanding how *new* behaviors emerge—rather the purpose is understand what habits are. The most popular model in persuasive computing, the Behavior Change Model [2], suggests that behavior changes when a person is motivated to achieve something novel, has some ability to achieve it, and is triggered (or cued) by an external or internal event. The model does not discuss at length how behavior and its cognitive underpinnings change when it automatizes after repeated execution. In this way, the two approaches to user behavior complement each other: the one discusses the birth of new behaviors and the other the status of "old behaviors."

We address three broad and interrelated questions:

1. How prominent a factor, if at all, are habits in smartphone use?
2. How do users experience habits?
3. What design factors promote habit-formation?

We approach these questions by examining data from three longitudinal studies of smartphone use conducted between 2005 and 2010:

1. A logging study comparing usage patterns of smartphone users ($N = 136$) to those of laptop users ($N = 160$), with a focus on the prevalence of habit-driven behavior and associated factors;
2. An intervention study where awareness cues (real-time location information) were added to the address book to three user groups ($N = 5 + 4 + 6$);
3. A diary study of smartphone users' ($N = 12$) experiences during first 2 weeks of use.

The typical method to examine users' "habits" and "practices" from quantitative data is to look at *frequent* behaviors across all users or within an individual; for example, logging studies of mobile phone use (e.g., [19]) and time-use studies (e.g., [14]) typically compare averages of behaviors or application uses. However, habits and frequent behaviors should not be confused; the former is a subset of the latter. Our starting point is to look for behaviors that are *consistently associated* with an explicit cue (other recorded event) or implicit cue (an event that logically precedes an action). Therefore, our unit of analysis is *a usage session* (henceforth: a session): all user actions recorded between two events: (1) the user activating the device from the idle or screensaver mode and (2) the next time the phone is idle or locked again. Sessions are quantitatively characterized by a number of properties,

[2] http://www2.berkeley.intel-research.net/~tlratten/public_usage_data/.

such as total duration (in seconds), the applications launched, frequency and order of individual applications launched, average duration for each application, etc. To identify habits from logging data, we looked for sessions or part thereof that fulfill three criteria: (1) sessions that are extremely rapidly executed, with the idea that *non*-habitual behavior is slower due to decision-making and problem-solving, etc., (2) sessions that are repeated in very similar fashion time after time, and thus more likely to represent automated actions, (3) sessions that are consistently associated with the same trigger (cue): whenever the cue appears, so should the associated behavior. After several analyses of the available data, where we tried to mine for frequent sequences of interactions on the phone, we converged to a very simple type of habit: checking habit.

To recap the main finding, the data provides evidence for habit-formation in smartphones use, mainly attributable to their capacity of providing *quick access to rewards* like social networking, communications, and news. *Checking habits* are automated behaviors where the device is quickly opened to check the standby screen or information content in a specific application. These habits are triggered by various different cues outside the device, such as situations and emotional states. The automated behaviors take the users, very quickly, to different screens that provide informational value or rewards. These rewards help users avoid boredom and cope with a lack of stimuli in everyday situations as well as make them aware of interesting events and social networks. Looking at qualitative data, we found that users themselves do not necessarily describe habit-formation as problematic. Even when the phone usage is dominated by frequent checking, people described the use as, at worst, slightly annoying. Our conclusion is that checking habits constitute an important part of the behavior driving smartphone use. Indicative of their importance for a device being frequently used, we found some evidence that increases in the occurrence of certain habits coincides with a net increase in usage overall. In other words, checking habits may function as a "gateway" to other functionality and content on the device.

1.1 Habits as addictions versus enabler of multitasking

The cues that trigger habitual behaviors can be external events or internal states that are only partly related to the situation at hand [21]; for example, the lack of stimulation or a desire to "stay on top" could become a cue associated with the behavior of picking up the phone to see what is available. The cue could also be the mobile device itself—for example, seeing the phone lying on the table reminds us of rewards that could be accessed, triggering the associated usage behavior.

The theory [21] posits that habits have both positive and negative outcomes for behavior. On the one hand, habits are necessary in control of action, their automatic execution enabling multitasking and learning of complex skills as well as retaining adequate performance in *novel* situations [4]. Knowing that the cognitive resources of a mobile user are heavily competed for [11], habits may enable a host of interactions not possible if attention should be fully concentrated to the device. Habits are also important socially—habits perceived by others shape who you are as a computer user [1], and adherence to a predictable pattern of behavior facilitates maintenance of social relationships [20].

On the other hand, the downside is that behavior may become excessively controlled by extrinsic factors, undermining the pursuit of the more self-guided goals. Computer-related *addictions*, such as those associated with Facebook or email (both recognized by psychologists and in popular media), are abnormal habits where computers (or their content) have become overly strong cues for behaviors.

Technically, an *addiction* is defined as a repetitive habit pattern that increases the risk of disease and/or associated personal and social problems, often experienced subjectively as "loss of control" [9]. The *Diagnostic and Statistical Manual of Mental Disorders DSM-IV* recognizes gambling but not internet or media use as potential addictions. Recent theories suggest that internet and media "addiction" is rather a struggle to maintain effective self-regulation over problematic habit-driven behavior. In other words, addiction and habits are parts of the same continuum [5], but what we colloquially ascribe as Internet or media addiction is better described as *overuse* due to loss of self-control.

It is an open question what the good versus bad habits of smartphone users are and to what extent they resemble overuse and even addiction.

2 Study 1: longitudinal logging of smartphones and laptops

We present results from two usage tracking studies. The most recent study, conducted between May and July of 2009, tracked existing Android G1 smartphone (see Fig. 1) users in the continental US participants were recruited to fulfill general demographic criteria, subject to the constraint that they had owned their G1 smartphone for at least 1 month prior to the start of the study. 136 participants completed the study, which involved a pre-survey, at least 6 weeks of tracked usage data (median = 52 days), and a post-survey. Twenty participants were chosen at random from two major cities, Denver and Seattle, for semi-structured, ethnographic interviews to help contextualize the tracked data. Of the 136 participants, 43% were men, 35% were between the ages of 18 and 25, 50% were between the ages of 26 and 39, and 14% were between the ages of 40 and 54.

The data were collected via custom software written for the Android G1 smartphone. It tracked a variety of hardware and operating system variables (e.g., processor utilization and active network interfaces) as well as user input, focal application, and screen state. Due to limitations in the performance of the smartphone platform, user input, focal application, and screen state were only tracked approximately every 3 s (the frequency would decrease if the device went into a standby or sleep mode). Log files containing between a few minutes (if logging at highest frequency) and a few hours (if logging from standby or sleep mode) were encrypted and uploaded to central servers. In this data, the top applications for Android G1 smartphones are, in terms of amount of active use: the home screen application (used 21.77% of the time), SMS/MMS (17.57%), browser (10.67%), phone/calls (9.38%), contact book (7.07%), Gmail (3.73%), 3rd party SMS applications (2.75%), default email (2.55%), and the application market (1.41%).

The other study we draw on, which helps contextualize the smartphone data, involved the tracking of personal laptop users between August and October of 2007. As with the smartphone study, participants were recruited in the continental United States. Usage data were collected from 160 laptop users, with an average of 50 days per user. The data were collected using custom tracking software that measured aspects of hardware, software, and user behavior at a frequency of once per second. Semi-structured ethnographic interviews were conducted with 15 of the participants. Some findings from this study have been published elsewhere [17]. The top applications used were as follows: iexplore.exe (used 42.11% of the time), firefox.exe (15.13%), ybrowser.exe (2.83%), msimn.exe (1.82%), waol.exe (1.55%), aim.exe (1.55%), aim6.exe (0.92%), outlook.exe (0.86%), juno.exe (0.34%), and yahoomessenger.exe (0.27%).

Working from usage sessions in the two data sets, we highlight three points in the following. First, the incidence of brief (short duration) habitual usage sessions on smartphones is significantly more common than on laptops. Second, smartphone usage tends to be more evenly spread throughout the day than laptop usage. Finally, increased use of reward-based applications, e.g., SMS messaging clients and web browsers (and experience and awareness of the reward values offered by these applications), coincides with an increased incidence of habit behaviors involving these applications.

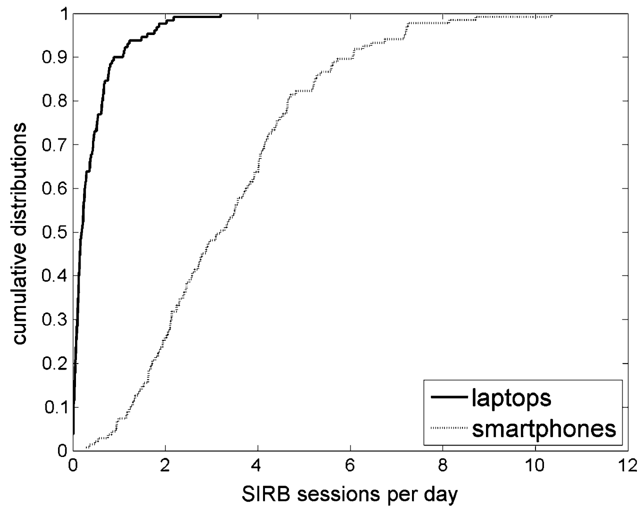


Fig. 2 Plot of cumulative distributions of SIRB usage sessions per day for laptop and smartphone users. A Kolmogorov–Smirnov test comparing the two cumulative distributions revealed a significant difference: $p = 3.17e^{-044}$

We use *SIRB*—*s*hort duration (less than 30 s), *i*solated (separated from preceding usage session by at least 10 min), *r*eward-*b*ased (at least 50% of the usage session duration is spent interacting with applications that provide the reward values discussed above)—usage sessions as a proxy for habitual device usage. Clearly, this proxy does not account for habitual use occurring in long duration or non-isolated usage sessions. Unfortunately, distinguishing which long duration, non-isolated usage sessions, or parts of such sessions correspond to habits was not possible in a retrospective analysis setting based on logging data only.

To our first point, we measured the average number of SIRB sessions per day per user (pdpu) for smartphones and laptops.[3] We filtered the original data sets to exclude users for whom less than 100 usage sessions were recorded during the study duration. This left 130 laptop users (from the original 160) and 135 smartphone users (from the original 136). For laptops users, SIRB sessions pdpu had the following summary statistics: mean = 0.39, median = 0.20, standard deviation = 0.52—the median number of usage sessions pdpu for laptops was 7.39. For smartphone users, SIRB sessions pdpu had the following summary statistics: mean = 3.39, median = 3.19, standard deviation = 1.88—the median number of usage sessions pdpu for smartphones was 34.11. If we compare the distributions of SIRB sessions per day between laptops and smartphones, we see a significant difference skewed

[3] Different temporal thresholds were used for the laptop and smartphone data. The thresholds (29 s session duration for the laptop data and 24 s for smartphone data) were chosen because they are the median 20th percentile session durations in the respective data sets. Equivalent results were achieved with other threshold values.

toward more sessions on smartphones. In Fig. 2, we plot the cumulative distributions for the SIRB sessions per day for laptops and smartphones.

Additional proxy measurements of habitual behavior are the percentage of usage sessions where reward-based application usage initiates or terminates the session. For the laptops we studied, the correlation of these proxies with percentage of usage sessions that are SIRB sessions are as follows: $r^2 = 0.33$ ($p = 6.8\mathrm{e}^{-013}$, $N = 130$) relative to the incidences at the beginning of sessions and $r^2 = 0.38$ ($p = 8.33\mathrm{e}^{-015}$, $N = 130$) relative to the incidences at the end of sessions. Analogous analyses on smartphones does not provide useful results, because the nearly all usage sessions on the Android G1 start and end with home screen application, which provides reward value (and hence does not vary significantly across users or across usage sessions).

Next, we compare the cumulative distributions of the amount of time per day these devices were used and the spread of this use throughout the hours of the day. In terms of hours of use per day, the distribution for laptops (median duration was $\sim$87 min/day) is significantly skewed shorter than for smartphones (median duration $\sim$160 min/day): $p = 6.44\mathrm{e}^{-008}$. In terms of spread of use throughout the day, measured as the entropy of usage split into 15 min blocks covering the 24 h of the day, the Kolmogorov–Smirnov test of the cumulative distributions for laptops versus smartphones shows that laptops skewed significantly smaller (i.e., less spread) than smartphones: $p = 1.99\mathrm{e}^{-020}$.

Finally, we investigated the relationship between SIRB sessions and overall use of a device. In Fig. 3, we plot

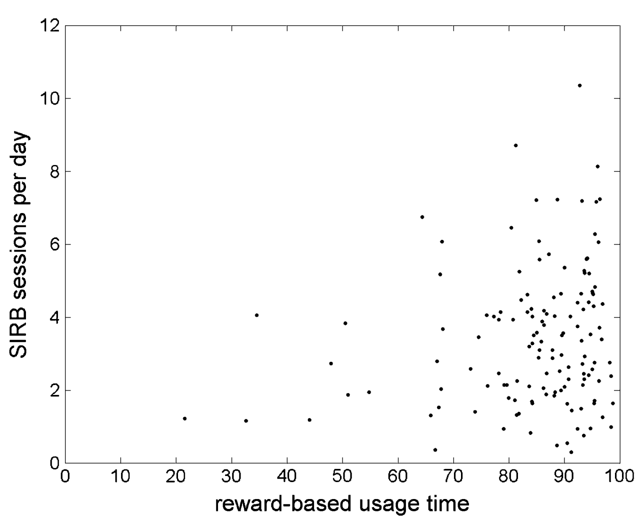


Fig. 3 A slightly positive correlation between SIRB sessions per day (y-axis) and percentage of usage time spent interacting with reward-based applications (x-axis) in our smartphone data: $r^2 = 0.031$ ($p = 0.0397$)

SIRB sessions per day versus the percentage of total usage time spent interacting with reward-based applications for the smartphone users. SIRB sessions per day are slightly positively correlated with percentage of reward-based: $r^2 = 0.031$, $p = 0.0397$. Analogous calculations on the laptop data shows a slightly positive correlation between SIRB sessions per day and percentage of reward-based: $r^2 = 0.054$, $p = 0.0080$.

In sum, smartphone use is more aptly characterized by SIRB—short duration, isolated, reward-based—sessions than are laptops. Our present explanation is that, relative to laptops, smartphones are significantly more pervasive in everyday life due to being carried around (see however [15]). Because of this, they are a much more constant and present *situational cue* than laptops based on the total amount of usage and the distribution of this usage throughout the day. Furthermore, smartphones offer a wider variety of channels to connect to remote information and people than do laptops, increasing the overall reward value of "checking" habits.

3 Study 2: a field experiment where the reward value of a quickly accessible application was increased

The ideal evidence for the existence of habit-formation in smartphone use would come from a study where the informational value of an application (amount of up-to-date information) was changed and changes in usage sessions recorded. In this section, we report on such an experiment [12]. An "A-B intervention experiment" consists of two equally long periods A and B where period A is used to record a baseline where no intervention (treatment) is given. The intervention, which takes place in period B, consists here of turning on *awareness cues* on a contact book (GSM cell-derived district labels, recent use of the phone, Bluetooth presence of friends, and calendar events). The smartphone used in this study was one of the first successful Nokia smartphones, the Symbian S60 model 6600 (see Fig. 1). The idea of the A-B design is that period A provides a baseline for comparison.

Three user groups participated: the *Family* (A-B-A design), the *Entrepreneurs* (A-B), and the *Schoolmates* (B only). The Family group consisted of a mother and three teenaged children, the Entrepreneurs group include one woman and four men, all in the same high school. The Schoolmates are comprised of five women and one man, also attending the same high school. Data gathering took place over a period of year in 2004 and 2005 so that each group participated between 2 and 4 months. ContextLogger1 [16] was used for data collection, allowing recording of sensor data, communication transactions, including the contents and transaction logs of all SMS and voice communication, all commands given to specific applications (stand-by screen, contact list), and all application launches.

The full data are reported in an earlier paper [12], whereas we here revisit the data to examine habits. One problem we faced with this data is that the user may stay in a certain application at the end of a previous session and that application is not recorded as "the anchor" when user returns after idling. However, for the home screen and contact book, we could perform an analysis.

There were 30,287 total usage sessions over the three groups (8,864, 9,849, and 11,582, for Family, Entrepreneurs, and Schoolmates) in the data. We concentrate on two habits prevalent in the data:

1. *Scrolling*: From idle/off/locked mode, going directly to the contact book and (optionally) navigating it by scrolling up/down and then idling or turning on the keypad lock.
2. *Touching*: Turning off the screen saver by touching the joystick and/or unlocking the screen lock. This action results in either the standby screen or an open application if the screensaver went when it was foregrounded.

When we examine the 30,295 sessions in the log data, we find that 3.7% are scrolling sessions and 35% are touching sessions. In other words, touching behavior is very prevalent in the data. Moreover, these sessions are very brief. The median session activity time of scrolling is 7 s with 92% of samples shorter than 1 min. Moreover, the median session activity time of touching is 1 s with 90% of samples shorter than 35 s. The two habits are differently spread throughout the day. Scrolling takes place mainly in the afternoon and evening, while touching is more equally distributed across throughout the waking hours.

As the decisive piece of evidence, we compared the A periods to the B periods to understand whether the addition of dynamic content increases habit strength. This analysis was done only for the Family and Entrepreneurs groups who were part of the A-B design that allow this sort of comparison. As Fig. 4 shows, adding the real-time cues increased both touching and scrolling behaviors. Scrolling increased from an average of 0.1 behaviors per day per user (*pdpu*) to 0.9, and touching from 5.4 to 12.1 pdpu. To test if these increases are statistically significant, we used the Wilcoxon signed-ranks test for two dependent samples, comparing median number of behaviors during A and B periods. The p values for both touching and scrolling were <0.001, indicating an effect of the intervention.

Interestingly, the frequency of *other* application use also increased from phase A to B, from 9.7 pdpu to 16.0 pdpu, the difference being statistically significant with a p value < 0.001.

4 Study 3: self-reports on repetitive use of smartphones

In winter 2010, twelve students of the Helsinki School of Economics were given smartphones (Nokia model N97), asking them to keep a diary for the first 2 weeks of use from the moment they received the phones.

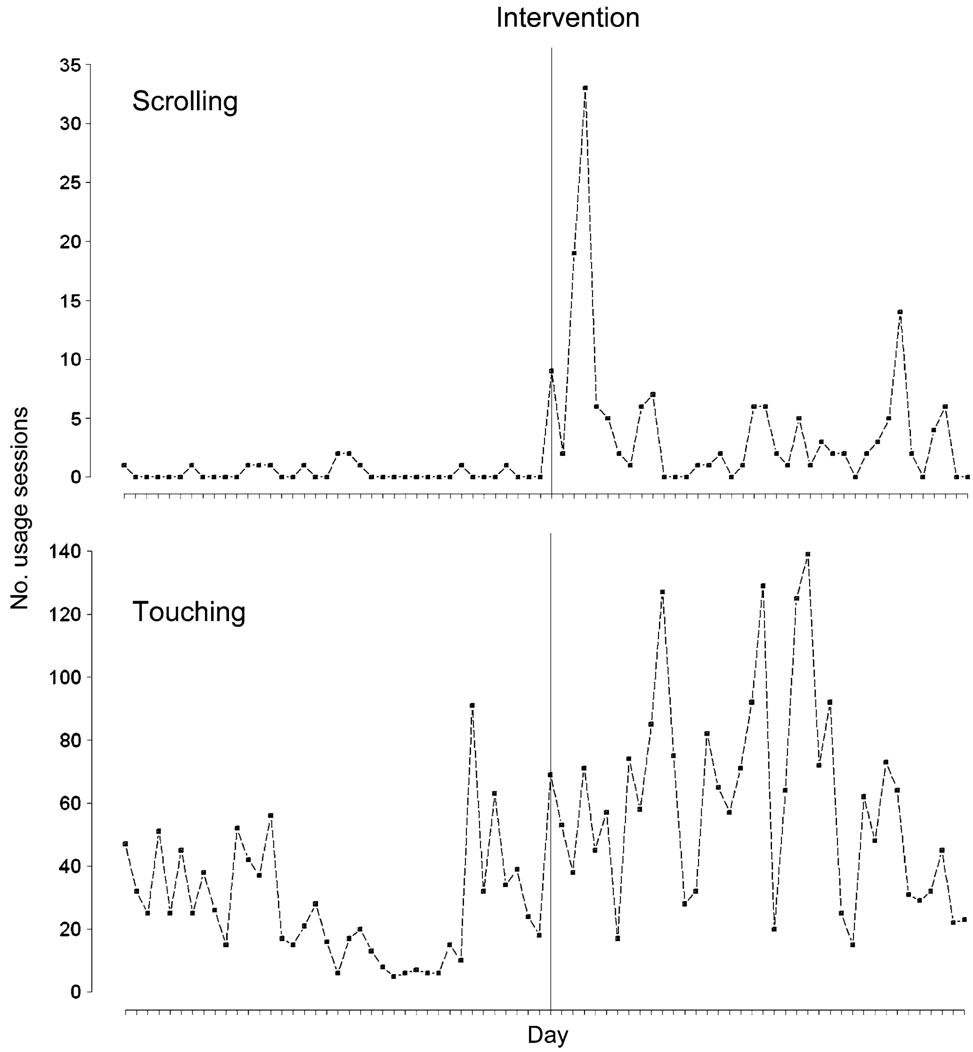
The data collection method was a modification of the *day reconstruction method* [6]: in the diary, a participant first fills in all daily activities for the each of the five given time slots (morning, forenoon, afternoon, evening, and night), after which she/he reports what the device was used for in each activity, describing the feelings, ideas, opinions, and emotions linked to the events. After the study, the participants were extensively interviewed for their diary entries. All participants also filled in a questionnaire surveying the extent of device use before and after the study.

Altogether 702 use sessions were self-reported. These sessions were analyzed by first classifying them into activity categories (e.g., social media, calling, news, and browsing) and then tabulating the frequency, with the associated real-world situation where the use took place, and the time of day. A limitation of the method is that part of repetitive use probably went unreported, most likely because some use sessions were very quick or deemed too unimportant to be reported. Additionally, the descriptions of news and feed applications (news site apps, RSS) were often very brief, hardly mentioning anything else than the name of the application. This shows up in a discrepancy in between the users' general descriptions and their daily reports, favoring unexpected over routine use cases.

The strongest habitual patterns in this data related to the use of Internet in various forms: checking e-mails, Facebook, update feeds, and news headlines.

- *E-mail*: All except one participant used their phone for checking e-mails. Four users checked their e-mails only a couple of times, two approximately every other day, and the rest five participants daily (at least 5 times/week). E-mails were mostly checked either at home (30%), on the go (30%), or during a lecture (16%). Descriptions of the use of e-mail were mainly related to checking e-mails and, thus, achieving a sort of awareness that nothing important is missed, as opposed to actively writing messages to others.
- *Facebook*: Ten participants used the phone for checking Facebook, five doing this only occasionally (1–4 times/week), while the other five checked Facebook more often (at least 7 times/week). Just like e-mails, Facebook was checked mostly either at home (30%), on the go (36%), or during a lecture (10%). A female student described her Facebook checking: "I spent my whole day in the reading room doing homework. I usually keep breaks when using [the device], but

Fig. 4 Effects of intervention on frequencies of touching and scrolling behavior



nowadays I take my phone to the room, putting it on silent, and checking it every half-an-hour either for Facebook or email."

- *Update Feeds and News Headlines*: Eleven participants used the phone for reading the news. Seven did this occasionally (1–8/2 weeks) and the rest five more often (11–16 times/2 weeks). The news was mostly checked on the go (60%) and additionally at home (18%) or during a lecture (9%). The participants reported appreciating the easy form of information and the ability to stay in touch with the world.

Overall, these habits were concentrated to the "empty" moments when the students had very little else to do—the dominant contexts being lectures, commuting, and mornings/evenings at home. Moreover, they mostly took place when alone instead of when with interacting others. Weekends involved clearly less habit sessions than weekdays. In the interviews, the participants (university students) told that they slept late in the weekends, went out with friends, partied, etc. There were fewer changes, and probably less need to use the phone alone. The comparison between the first and the second week showed no increase in the frequency of use.

We then estimated *habit strength*: (1) the frequency of execution and (2) association with particular situational cues [21]. From our data, habit strength was calculated from *frequencies of application use in a particular context*. To distinguish among potential habits versus regular use, we focused on a subset where the user reported at least 10 occurrences over the time period of 2 weeks. *Nineteen* potential habits were identified this way across the twelve participants, distributed to nine participants. The most popular applications were, in order: e-mail (five habit candidates), Facebook (4), the news (4), feed (3), music (2), calendar (1), and browsing (1). The average number of habit candidates per person was 1.67. We then calculated the number of contexts (activities during which smartphone use took place) required to explain *at least*

50% of occurrences within this subset. Interestingly, the average number amounted to only 1.35, which conveys the regularity of habit-to-context association in the data. In other words, 1.35 contexts were enough to describe at least 50% of the occurrences of a habit. Also noteworthy was that sometimes, although rarely, a *set* of applications was repeated together. "Don" is a good example, describing the use of news (Helsingin Sanomat), Facebook, and Gmail together in 31 of the 73 reported instances. Don typically used these while "killing time" in lectures or transit.

The most often mentioned *motivation* for the habits related to the novel content the phone provided an access to. The main motivators for habits were: entertainment, killing time, and awareness. In relation to the first motivator a female participant described her use of Facebook and e-mail as "entertainment" during reading and homework. In addition, she used the navigator and Google Maps, her "favorite applications," to "amuse herself." Besides entertainment, the participants described habit behaviors as ways to restore attention and make boring moments feel like going faster (killing time):

> "During the lecture, I used the Internet to quickly browse news, because I wasn't able to concentrate on the teacher. A small pause returned my interest to the lecture."
> "In the bus, I again key Facebook and e-mail, feeling that the trip goes faster this way."

The third motivator for habits was awareness, as the following excerpt illustrates:

> "I follow [the newspaper's] updates almost in real-time. Within 15 min, I've seen the new things. I guess I feel like an individual following her time. Or not."

But awareness was not appreciated by all. One participant contemplated whether continuous checking takes away part of the fun in e-mail, because there will be no surprises as the e-mails do not accumulate. Additionally, other participant was wondering whether constant checking of e-mail was causing her too much stress.

We also looked at the way the participants described the experience of repetitive use. A handful of the participants were *aware* of their repetitive use of the phone:

> "I glance at the Facebook status page and read my e-mails even every half-an-hour, every time reading [for a test] starts to bore me."

Another user commented on her glancing of update feeds on the "desktop" every 20 min even when she was trying to do her homework: "The temptation is great, because there's always friends' update on the screen."

Repetitive use was experienced as annoying at times. Two participants described their relationship to Facebook by using the word *addiction*: the first in a jocular manner and the second describing it as a "mild" addiction. Third participant described games as "hooking."

Another participant describes repetitive checking as distracting from regular activities:

> "I was browsing the depths of Internet with the phone and it slowed down my eating. It annoyed me, I'd have to finish my Master's thesis."

In another excerpt, the same participant describes *not* using the phone while writing the Master's thesis as a good thing that enables him to concentrate on work.

A few times in the data, we see participants reporting annoyance with repetitive habitual use. However, the majority of the participants did not consider habitual use negatively, even if it was very frequent.

5 Discussion

To summarize, the findings are:

1. *Brief usage sessions repeating over time, or "checking behaviors," comprise a large part of smartphone use*. Brief usage sessions were prevalent in all the three data sets. In the first study (Android G1, US users), about 18% of use sessions were brief and included focus on only one application. In the second study (Nokia 6600, Finnish users), 35% of use sessions were "touching" sessions where the home screen was viewed for one second. In the third (diary study of Finnish N97 users), a user had on average 1.6 potential habits (10 or more uses over 2 weeks). Over the studies, the applications associated with checking behaviors included the home screen, contact book, e-mail, social media, and news.
2. *Checking habits are particularly characteristic of smartphone use*. Comparing smartphones to laptops, we observed that smartphone use is significantly shorter in duration, more evenly spread throughout the day, and nearly twice as abundant (in terms of total time spent using the device).
3. *Habits may increase overall phone use*, especially other applications. We call these "gateway habits." In our data, the frequency of brief "checks" to a phone showed a slight increase with the use of a small set of applications.
4. *Quick access to dynamic content can induce habits*, as persuasive computing research suggests [2]. We saw in the second study (Nokia 6600) that when the informational value (reward value) of an application is

increased, habit strength (frequency of checking behavior) increases.

5. *A smartphone use habit is tightly associated with a particular triggering context*, as the theory predicts [21]. In the diary data, a habit was associated with only 1.35 contexts (e.g., lecture, bus trip, and home) on average.
6. *Smartphone-related habits are not yet perceived as problematic*. The diary study users spontaneously bring up the issue of repeatedly checking their phones. Some users considered it an annoyance. Many positive experiences of repetitive uses were mentioned as well, mostly relating to entertainment, time-killing, and diversion. It may be that the small sample size of the diary study, together with brief duration, did not allow for addictions to be observed.

Overall, we believe that the evidence is clear about the existence of checking habits and their prevalence in the use of smartphones. Checking behaviors, frequent in our data, are typically very short and include only one application, promoted by quick access to information and people that smartphones can offer. More interestingly, the data suggests that checking habits can act as a "gateway" to other applications, leading to other actions being taken with the device. Users start by opening portals to dynamic content to check something or to acquire the stimulus for diversion or entertainment. Based on the content that is accessed, though, the habit may lead to a diverse variety of "next actions." This may be the main hook for designers to think about how to work with habits as a portal. In other words, application designers could built multi-part applications where the use of one part is designed to become habitual—for example, the target screen of checking habits—while the other, connected parts, could be designed to leverage the frequent attention of user to expose new content or trigger other behaviors as suggested by the Behavior Change Model [2].

The results also draw a distinction between smartphones and laptops in what comes to the importance of repetitive habitual use in the repertoire of use behaviors. In comparing laptops and smartphones, their availability as a physical cue is significantly different—smartphones are available and used more often throughout the day and are used more in terms of total usage time. The more opportune moments are those where the mobile device is the primary computer available (see also [15]), for example, during transit or lectures. Moreover, smartphones provide quicker access to content, and we know from studies of mobile interaction that users are not able to concentrate on mobile interaction for long times before abrupt events in the environment and more highly prioritized tasks interrupt [11]. Because of these factors, it is understandable that smartphone-based habits are briefer than laptop-based habits and more pervasive throughout the day.

To conclude, we hypothesize that the reward values associated with checking habits can be broken into three kinds: (1) informational, (2) interactional, and (3) awareness. *Informational reward* is provided by dynamically updated, but non-interactive information that the user cannot affect. The clock on the home screen is a prime example and the news feed another. *Interactional value* extends the informational to include things that the user can immediately act upon. It also includes social interaction, which is supported through many channels on portable computing devices. An example interaction value comes from social networking status updates: Checking out the latest updates, the user can immediately respond and thus engages with the content for a longer period of time. Finally, *awareness reward* value is a specialized form of information value. Whereas informational value corresponds to the user learning something they did not know before, or confirming something they did know about, awareness value corresponds to the goal of maintaining a representation of the dynamically changing external reality; for example, a user might refresh their e-mail inbox to see whether any new messages have arrived—and often no new messages have arrived, providing awareness value. Or a user might check Facebook to see whether a certain person has logged in in order to directly communicate with him/her.

The most interesting opportunity we predict is that checking habits may lead to more use overall, which can be intelligently leveraged to get users to try new things and adopt the device in richer ways to their everyday activities. Habits spur new uses. As an example of using interactional reward-value for new uses, a common usage pattern by Android G1 users was to access the Android App Market, where new applications can be browsed and installed. In fact, some users even developed habits around accessing the App Market, driven by a need to see which new applications were available since their last visit. Making this even easier by design will increase the frequency of application download and thereby potentially increase the utility of smartphones to users.

Driving wider behavioral changes by placing appropriate behavioral triggers in the display path of smartphones is another way to leverage the informational value derived by habits. Klasnja et al. [7] describe many key design considerations in driving health behavior change—in particular, the deployment of a persistent, glanceable display that acts as a reminder to pursue the behavioral change. Viewing such a display could become its own habit; however, it is more likely that other habitual uses of the smartphone will simply make such a display more ubiquitous throughout a person's day.

In designing cross-platform applications, which are increasingly popular at the moment, one should keep in mind that minute changes in surface features of interaction may change essential aspects of habit-execution, such as the habit-triggering cues (e.g., user interface elements) or the resulting action (e.g., interaction sequences), and lead to confusion, effortful re-learning, or abandonment of a service. In the diary study, for example, we observed that users who previously had a non-smartphone device were happy to have the opportunity to try new applications with the new (Nokia N97) smartphone and invested the necessary amount of time to achieve a sufficient level of competence, whereas users who previously had had Apple's iPhone were reluctant to relearn use patterns and got much less out of the phone and were also less happier with it.

All in all, we see that habit-formation, although obviously a delicate matter, presents a grand opportunity for making mobile devices more "personal" and "pervasive."

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