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SMARTPHONE MEASUREMENT: DO PEOPLE USE MOBILE APPLICATIONS AS THEY SAY THEY DO?

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Abstract

Designing viable mobile services requires in-depth understanding of how people deal with their mobile phones on a daily basis. Most studies on the use of mobile phones are based on surveys that ask people how often they think they use mobile applications. While such survey studies have provided numerous insights, they also pose issues of recall, accuracy and common method bias. Fortunately, smartphones enable more direct ways of collecting usage data by installing a background application that logs all user activities. Such smartphone measurement approach has only been applied in a handful of studies, typically limited to Nokia handsets. This paper scrutinizes the reliability of survey-based measures on the perceived use of mobile services by contrasting them with log data obtained in a smartphone measurement study. We analyze the results of a smartphone measurement study carried out in the Netherlands among 129 users of iPhone, Blackberry and Android phones. Users appear moderately accurate in assessing the use of mainstream services like SMS, email and browsing, but not regarding navigation and weather information services. The findings suggest that traditional survey approaches should be complemented with smartphone measurement in order to really understand how users deal with mobile services.

Keywords: Smartphone measurement, log data, smartphones, mobile services

1 Introduction

The mobile Internet is becoming an integral part of our daily life. Over 20% of all handsets shipped in 2010 worldwide was a smartphone, which is expected to grow to 46% by 2015 (Portio Research, 2011). Smartphones like iPhone, Blackberry and Android have made it a lot easier to browse the mobile Internet and to use email, entertainment and multimedia applications (West, 2010). As a result, many economically and societally important activities will increasingly take place on mobile devices. For example, mobile VoIP services like Skype will increasingly bypass the traditional operator-centric voice services (Nikou, Bouwman, & De Reuver, 2012). Mobile payment and barcode scanning services enable new types of transactions (Mallat, Rossi, & Tuunainen, 2004). Augmented reality services from providers like Layar will create new realities in which economic transactions may take place. Smartphones will also become a tool to remotely control home appliances, for example using applications like Android@Home.

Designing viable mobile services in such a dynamically changing marketplace is challenging, and requires in-depth understanding of how people deal with smartphones and applications. Typically, scholars rely on survey methods to study how mobile services diffuse through the market over time (e.g., Bouwman, Carlsson, Walden, & Molina-Castillo, 2008). Survey methods have provided numerous insights into how mobile service adoption depends on factors like context-of-use (e.g., Mallat, Rossi, Tuunainen, & Öörni, 2009), fit with daily routines (e.g., Carlsson, 2006), personal innovativeness (e.g., Mao, Srite, Thatcher, & Yaprak, 2005), lifestyle (e.g., Okazaki, 2006), fixed-mobile reinforcement (e.g., De Reuver, Ongena, & Bouwman, 2011), demographics (e.g., Nysveen, Pedersen, & Thorbjørnsen, 2005), TAM variables (e.g., Wu & Wang, 2005) and social norms (e.g., López-Nicolás, Molina-Castillo, & Bouwman, 2008). However, the dominance of survey methods have led to methodological concerns about common method bias (Sharma, Yetton, & Crawford, 2009). Moreover, survey methods inevitably introduce measurement errors, as users may be unable to accurately recall the extent to which they use mobile services.

Smartphone measurement is emerging as a much more direct way to observe how users deal with smartphones and mobile applications. By installing an application on the smartphone that logs all user activity, the researcher can directly observe user behaviour (Verkasalo & Hämmäinen, 2007). By running this application on the background of the device, measurement takes place unobtrusively, i.e. without distorting the natural behaviour of the user. The resulting log data allows for a very detailed understanding of how users deal with their smartphone. Smartphone measurement makes it possible to the study the question in the title of this paper: Do people use mobile applications as they say they do?

This paper aims to provide insight in the reliability of survey-based measures on the use of mobile services by contrasting survey metrics with log data from a smartphone measurement study. Specifically, we analyze whether the *perceived* use of mobile services like SMS, MMS, email, browsing, navigation and productivity tools can explain the *observed* use of those services as measured in log data. Answering this question is highly relevant as most studies on mobile service adoption and acceptance are based on survey metrics rather than actually observed behaviour. While a handful of studies that utilize smartphone measurement have been published over the past few years (Eagle & Pentland, 2006; Falaki, Mahajan, & Kandula, 2010; Raento, Oulasvirta, & Eagle, 2009; Verkasalo & Hämmäinen, 2007) , to our knowledge there is no previous study that confronts survey-based self-reports with smartphone-based log data.

We answer the research question by analyzing the results of a self-administered smartphone measurement study over a 28-day period in September and October 2011. From a representative sample, 129 Dutch smartphone users were drawn owning an iPhone, Blackberry or Android phone.

Section 2 provides a short note on related work on smartphone measurement. The method of the study is extensively described in Section 3. Descriptive results from the log data are provided in Section 4.

Regression analyses that relate survey metrics to log data metrics are provided in Section 5. Section 6 discusses the findings, including limitations and suggestions for further research.

2   Related work on smartphone measurement

A number of smartphone measurement studies have been published over the past few years. In Finland, Nokia and Aalto University developed smartphone measurement software specifically for Symbian 60 devices (Verkasalo & Hämmäinen, 2007). Using this software, Smura (2008) compares the usage of different types of mobile applications based on the hour of the day and the location of usage (e.g. at work, home or on the move). Smura, Kivi and Toyli (2011) use the software to study different classes of mobile applications, finding that voice, SMS, browsing, MMS and music are most popular. Verkasalo et al (2010) combine the smartphone measurement software with survey measures to investigate differences between users and non-users of specific applications. Recently, Nokia has released smartphone measurement data from a Swiss sample of users freely to the academic community in their so-called Mobile Data Challenge.

In the US, Eagle and Pentland (2006) apply smartphone measurement on Nokia smartphones to track their students at MIT, focusing on the social and geographical proximity networks within student working groups. In another publication, Raento, Oulasvirta and Eagle (2009) suggest various avenues for applying smartphones in ethnographic studies. Falaki, Mahajan and Kandula (2010) study a sample of 255 mainly Windows Mobile users, and report strong differences in the usage patterns.

Smartphone measurement is also being applied to study more technical issues. Shye, Scholbrock and Memik (2009) use handset software to log power and network consumption of mobile devices in order to suggest more optimal power management schemes. Similarly, Oliver (2010) measures user activity on Blackberry phones but simply uses the LCD backlight as an indicator of user activity, without distinguishing the type of application being used.

3   Method

3.1   Field study setting

To carry out smartphone measurement, a number of software tools are available, for example LiveLab (Shepard, Rahmati, Tossell, Zhong, & Kortum, 2011) and Device Analyzer (deviceanalyzer.cl.cam.ac.uk). The present study utilizes the smartphone measurement application from Arbitron Mobile, a company earlier known as Zokem, and before as MobiTrack. The company is a spin-off based on the work for the PhD thesis of its founder. The measurement application runs on the background of the mobile phone, and transmits log files regularly to the server, see Figure 1. The application can be downloaded from the app store. Participants were given the opportunity to view a dashboard with their personal usage numbers during the period of the study. The software was pretested using a small sample of students in spring 2011; identified technical problems with the software were solved afterwards. The actual study took place during a 28-day period in fall 2011.

Privacy of participants is guaranteed by conforming to both Finnish and Dutch regulation, and data were processed after anonimization. Potential participants for the study received an extensive description of the purpose and procedure of the study. Participation is based on informed consent, as required by regulation. Furthermore tasks like data-collection and data-analysis were separated. Combination of handset measurement data with survey data was done based on unique identifiers. Data analysis was done by the researchers who also coordinated all the processes, but didn't have access to personal data.
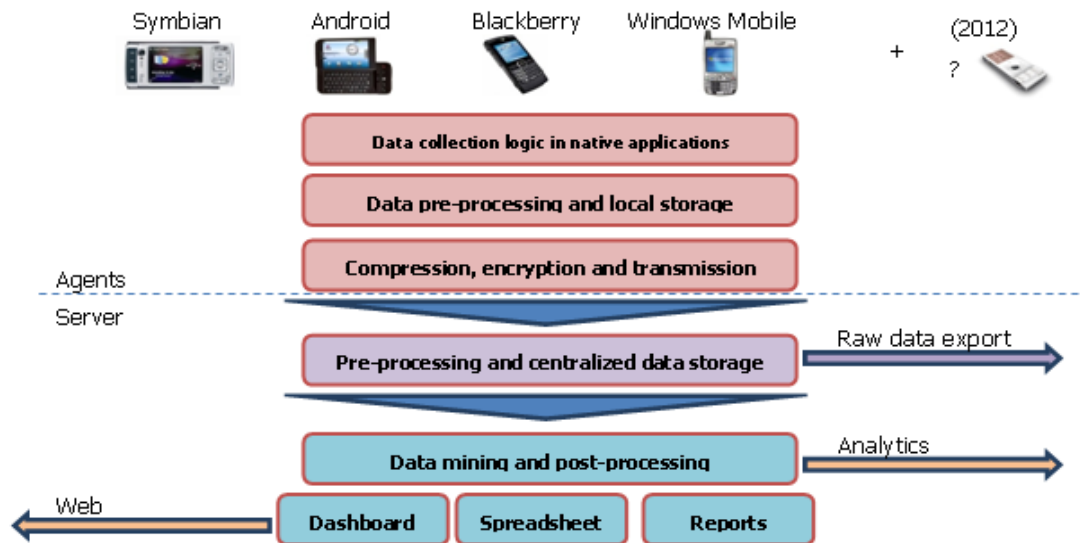
Figure 1.   *Technical architecture for smartphone measurement study*

3.2   Sample

Potential participants for the study have been randomly selected from an existing user panel of 20,000 households in the Netherlands. Around 20% of the panel is refreshed annually by inviting new participants, i.e. there is no self-selection involved. For the present study, potential participants were offered a 5 euro fee to compensate any extra data traffic our application would generate.

We invited 3125 potential participants, out of which 2182 responded. Out of those 2182 people, 28% was not eligible as they did not use mobile Internet services and 12% because they did not possess a smartphone. Others refused to participate due to privacy concerns (18%), not having permission to install applications on their business phone (8%), not knowing how to install applications (9%) or concerns about the performance of their smartphone (2%). Another 7% rejected participation for reasons not directly related to the study.

Finally, 324 users agreed to install and use the measurement application. Out of this group, 198 users actually downloaded and installed the application. Out of these 198 users, 68 users removed the application before the end of the study due to privacy concerns, errors or excessive battery consumption. For the final sample, we retain 129 users that had the measurement application running for at least 14 days. It should be noted that 50 of those 129 users removed the application before the end of the 28-day time frame. Therefore, all aggregate metrics resulting from the log data have been weighted to the total number of days that panellists had the measurement software running on their device.

The original sample of 3125 potential participants was checked against population statistics and found to be representative. The next step is to compare the final sample of 129 participants to the 1180 eligible smartphone owners that chose not to participate in the study. We find that participants do not differ significantly from non-participants regarding age, gender, working status, family income, geographical region and education level. For example, both participants and non-participants are about 45 years old and typically male (55%). Participation also does not differ between different mobile operators. The only background variable that differs between the two groups is the device. The final sample contains significantly more Samsungs and HTCs, and significantly less Nokias, see Figure 2. It should be noted that especially Nokia owners dropped out of the study as the Symbian version of the

measurement application contained several bugs. Windows Mobile users were not eligible to participate as the measurement application did not work for that operating system. Blackberries are somewhat underrepresented in the final sample as they are used more often as a business phone.
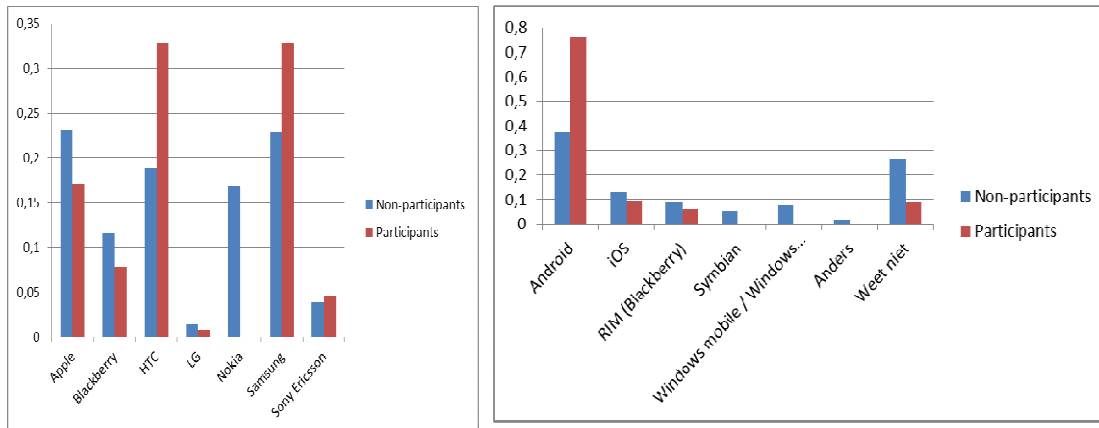

Figure 2.　　　*Distribution of panellists according to smartphone brand (left) and OS (right)*

3.3　　Survey measures

To measure the perceived use of mobile applications, the initial invitation to participants included a short questionnaire. Potential participants were asked to which extent they were currently using eight mobile Internet services that we found to be mostly used or most innovative in an earlier study (Bouwman, Bejar, & Nikou, 2011). Table 1 displays the mean values and standard deviations for those respondents that were included in the final sample.

Table 1.　　　*Survey measures on perceived use of mobile services (N=129)*

Service	To what extent to you use… (five-point scale: daily, weekly, few times per month, have tried it, never used it)	Mean value	Standard deviation
SMS	SMS: Text messages via a mobile phone (from one person to another)	3.35	.88
Email	Email: Reading / sending mobile e-mail via a mobile phone	3.13	1.31
News and weather	Mobile news and weather	2.93	1.24
Browsing	`Surfing' the mobile Internet (e.g. retrieving information) via a mobile phone	2.85	1.07
Messaging	Mobile messaging services (e.g., MSN, Ping, Whatsapp)	2.75	1.54
Social networking	Mobile social networking, communities: sharing (contact) information (LinkedIn, Hyves, Facebook)	2.55	1.62
Calender / productivity	Specific business tools like calendar functions and other productivity enhancing applications	2.32	1.66
Navigation	Navigation services via mobile phone, e.g., using Google Maps	1.88	1.05

As the invitation survey was also filled out by the 1180 eligible respondents that chose not to participate in the study, we can conduct an extra check for representativeness of the final sample. T-tests indicate that there are no significant differences regarding the perceived use of SMS and Calender / productivity services. However, participants do significantly use more Email ($t(160) = 2.13$, $p = .034$); News and weather ($t(160) = 2.78$, $p = .006$); Browsing ($t(164) = 4.13$, $p = .000$); Navigation services ($t(157) = 4.29$, $p = .000$); Social networking ($t(156) = 5.96$, $p = .000$); and Messaging ($t(162) = 6.28$, $p = .000$). This indicates that participants are generally more heavy users than respondents that did not take place in the measurement study.

4 Descriptive statistics

A massive amount of log data was generated in the study. For example, our 129 participants launched mobile applications 130,000 times over the 28-day period. To harness the complexity of the log data, we used automated content analysis to categorize the application names into classes: Email; Chat and instant messaging; General messaging; Social networking; Browsing; Calender; Maps; and Weather information. To capture the use of SMS, we aggregated the total number of SMS messages sent by the user (i.e., outbound SMS).

Next, we aggregated the log data to the appropriate level of analysis, i.e. the participant. We did so by computing (1) the average number of sessions per day, i.e. the average number of times a specific class of applications was launched by the user per day; and (2) the average facetime per day, i.e. the average number of seconds in which the user had a specific class of applications running on the foreground of the device.

The observed use differs strongly between participants, and the resulting metrics are severely non-normally distributed. Logarithmic transformation makes most metrics almost normally distributed, and the resulting metrics are used for the statistical analyses. Still, chat and social networking applications are hardly used by a large number of users, which creates a high peak in the distribution at the utmost left side. For the comfort of the reader, the plots provided in this section are based on the original, non-transformed data.

Data exploration revealed two issues with the data: SMS messages were not captured from Apple users, and email application usage was not captured from Blackberry users. The respective values are therefore coded as missings.

On average, 1.29 *SMS messages* were sent per day per panellist (SD =1.857, N = 108). More SMS messages are sent by younger people (Pearson r = -.366, p = .000), children (F (5) = 5.715, p = .000) and Blackberry users (F (5) = 2.470, p = .037).

The use of *email* is highly diverse, ranging from almost never to over 1000 times per day, see Figure 3. Overall, men use email more frequently (t (128) = 2.768, p = .006) and for more minutes per day (t (128) = 2.554, p = .012) than women. Higher educated persons use email for more minutes per day (F (6) = 2.428, p = .030) and more frequently (F (6) = 2.367, p = .034). E-mail is used for more minutes per day by Apple owners than other handsets (F (5) = 14.606, p = .000).
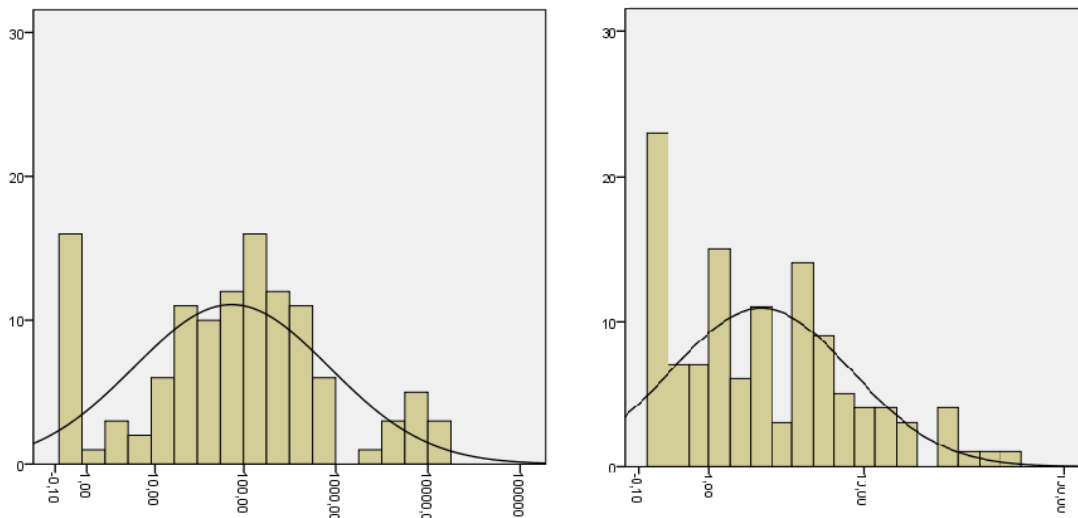

Figure 3.   E-mail: Average number of usage sessions (left) and seconds per day (right) N = 118; Blackberry users not included)

Chat and instant messaging refer to applications like Whatsapp, ebuddy and MSN. Women use them for more minutes per day than men (t (128) = -2.501, p = .014), but not more frequently. Chat is also used more frequently (r = -.328, p = .000) and longer (r = -.404, p =.000) by younger people. Chat and instant messaging is also used more by adult children living at home in terms of frequency (F (5) = 4.134, p = .002) and duration (F (5) = 3.257, p = .008).

All *other messaging applications* that fall outside of the mainstream ones are classified as `general messaging'. General messaging is also used for more minutes by women (t (128) = -2.007, p = .047), and again more by younger people in terms of frequency (r = -.256, p = .01) and duration (r = -.245, p = .01). Messaging is also used more by Blackberry owners and less than average by Apple users in terms of frequency (F (6) = 11.61, p = .000) and duration (F (6) = 12.50, p = .000). General messaging applications are not used at all by as much as 73 panellists.

Social networking (e.g., Facebook, LinkedIn, Twitter) is used more by younger people in terms of frequency (r = -.302, p = .000) and duration (r = -.351, p = .000). No other significant differences are found, although a lot of participants hardly use social networking apps.

Browsing is used more by younger people in terms of frequency (r = -.215***) and duration (r = -.217***), and is also used more frequently by HTC and Samsung users than Apple users (F (6) = 2.385, p = .033). Of all application classes, browsing appears to be closest to the normal distribution when transformed logarithmically.

Other applications. Calender apps are used for more minutes per day by working individuals (F (5) = 2.297, p = .049), although not significantly more frequently. Maps are used more by men than women (t (128) = 2.207, p = 0.29). Weather applications are used more by HTCs and Apples than Blackberries in terms of frequency (F (6) = 3.698, p = .002) and duration (F (6) = 3.801, p = .002).

Income only affects the number of minutes browsing per day (F (4) = 2.579, p = .041), but not any of the other metrics.

5 Explanatory models

We now analyze if the perceived use from the survey measures can predict the observed use from the log data. We do so by estimating simple regression models for each log data metric described in the previous section. First, we estimate regression models regarding the average number of sessions an application class was used per day, see Table 2.

Table 2.   Regression models for average number of sessions per day

Observed use: Application class	Perceived use (Survey measure)	β	R^2(adjusted)
Chat / Instant messaging	Messaging	.624***	.384
Email	Email	.585***	.336
Social networking	Social networking	.532***	.308
SMS	SMS	.502***	.245
Messaging General	Messaging	.308***	.087
Calender	Calender / productivity	.299**	.081
Browsing	Browsing	.294***	.079
Weather	News and weather	n.s.	.035
Maps	Navigation	n.s.	.021

*** p<.001; ** p<.01

Table 2 shows that the observed use from log data can be reasonably explained by the perceived use from the survey measures for SMS, Email, Social networking and Chat, with explained variance ranging up to 38%. While the effect of perceived use is still significant for Browsing, Messaging and

Calender applications, the explained variance is very low. Observed use of Weather and Map applications can even not be significantly predicted at all by the perceived use levels.

Of course, the perception of use may also be influenced by the number of minutes spent with an application. To control for this effect, we compute regression models to explain the average number of minutes the application classes were used per day, see Table 3.

Table 3.   Regression models for average number of minutes used per day

Observed use: Application class	Perceived use (Survey measure)	β	R^2 (adjusted)
Chat / Instant messaging	Messaging	-.621***	.379
Email	Email	-.570***	.319
Social networking	Social networking	-.399***	.150
Calender	Calender / productivity	-.301**	.082
Browsing	Browsing	-.279**	.070
Maps	Navigation	-.284**	.070
Messaging General	Messaging	-.213*	.037
Weather	News and weather	n.s.	.000

*** p<.001; ** p<.01

This second set of regression models exhibits even lower explained variance than the first set. Email and instant messaging can still be reasonably well predicted from the survey data, and social networking is still at 15%. However, explained variance for the other applications is close to zero.

6   Discussion

Users appear moderately accurate in assessing the use of mainstream services like SMS, email and browsing, but not regarding navigation and weather information services. Only up to 38% of variance in observed use can be explained by considering people's perceptions on how much they use applications. For several applications, this percentage is even much lower. The findings suggest that survey studies on how people use mobile services should be interpreted with care, as respondents are at least 62% off-base when asked to assess their own behaviour. In many acceptance models studies (TAM or related approaches) only behavioural intention is used, and sometimes actual usage is used as a concept based on survey data. Although behavioural intention is relevant in itself, the fact that seldom the relation with actual use is studied, make most studies on TAM rather vulnerable in terms of validity. We are convinced that including handset study data will lead to alternative models. Moreover, as mobile communications is around for several decades and is becoming more and more ubiquitous, it becomes even more urgent to shift attention use and effect models and research.

Smartphone measurement as a method is far from straightforward and we encountered several limitations in the present study. We could only obtain a relatively small sample of eligible and willing users. Although we set out to have a much larger sample, and invited more than a thousand smartphone owners, 90% refused to participate or left the study earlier due to privacy concerns, lack of self-efficacy and technical problems. Partly, this can be improved in subsequent studies by improving technical functionality of the application and especially reducing the load on the battery. The sample size is not per se representative for the wider population of smartphone owners, as their perceived use of mobile applications was found to be higher than for non-participants. Still, there are no significant demographic differences between participants and non-participants. Another limitation is that the measurement software did not work flawlessly on all smartphones. Symbian phones were unable to install the application correctly, SMS traffic was not captured on iPhones, and email applications were not logged on Blackberries. While this poses restrictions on how to interpret the results, the handful of existing smartphone measurement studies typically focus on one type of device (i.e., often Nokia),

which also has limitations for generalizability. Another issue is that several services can also be accessed through the browser of the smartphone, i.e. they need not necessarily be accessed using an application. Exploring the URLs browsed in more detail and aggregating them somehow with the applications being used is a next step for our research.

Obviously, guaranteeing privacy for panellists is a crucial issue in this type of studies. Ensuring users that their privacy is maintained, separating data collection and data analysis at two different organizations, using well-known and trusted project partners, and informing users fully about the procedures and aims of the study are critical success factors. Still, we experienced in this project that willingness to participate in a smartphone measurement study can strongly be influenced by things outside the control of the researcher. Discussions on deep packet inspection in the Dutch media made many people reluctant to participate, upon which we had to postpone the study. The final participants to the study were in any case very positive about participation, as over 80% would participate in a similar study in the future. Over 85% did not take additional privacy measures, and only 1% indicated they changed their behaviour or switched off the application due to privacy concerns during the study.

The study has shown that smartphone measurement provides insights in usage patterns that can be considered complementary to survey methods. While smartphone measurement allows for more direct observation of actual usage behaviour, it also has its methodological weaknesses. Especially representativeness of samples is an important issue, as many users reject to participate due to technical issues, privacy concerns or lack of self-efficacy. We expect that reliability issues with the data due to technical problems will be solved over the coming years as smartphone measurement software will mature.

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