In-Situ Investigation of Notifications in Multi-Device Environments

Dominik Weber, Alexandra Voit, Philipp Kratzer◇, Niels Henze
VIS, University of Stuttgart – Stuttgart, Germany
{firstname.lastname}@vis.uni-stuttgart.de – ◇st101215@stud.uni-stuttgart.de

ABSTRACT

Smart devices have arrived in our everyday lives. Being able to notify the user about events is a core feature of these devices. Related work investigated interruptions caused by notifications on single devices. In this paper, we investigate notifications in multi-device environments by analyzing the results of a week-long in-situ study with 16 participants. We used the Experience Sampling Method (ESM) and recorded the participants' interaction with smartphones, smartwatches, tablets and PCs. Disregarding the type or content of notifications, we found that the smartphone is the preferred device on which to be notified. Further, we found that the proximity to the device, whether it is currently being used and the user's current location can be used to predict if the user wants to receive notifications on a device. The findings can be used to design future multi-device aware smart notification systems.

ACM Classification Keywords

H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

Author Keywords

Multi-Device; Notifications; Experience Sampling Method; Context-Awareness; In-Situ

INTRODUCTION AND BACKGROUND

Smart devices are becoming more and more ubiquitous. From desktop computers to laptops, smartphones, tablets and smartwatches — always connected devices have arrived in our everyday lives. One of the core features of *smart* devices is the ability to notify the user about various events, such as new messages or software updates. Depending on the application, notifications about an event can be shown on one or on multiple devices at the same time. Figure 1 shows an exemplary multi-device scenario where a user is interacting with a laptop, while wearing a smartwatch, with a smartphone and tablet placed on the desk. Assuming every device in this scenario has an email client installed, a single email causes all four devices to notify the user. Disruptive effects caused by notifications are therefore amplified by the increasing number of devices around us. On the other hand, a text message on the smartphone might not be shown on other devices. This might prompt the user to pick up the smartphone and therefore interrupts the current work on the laptop.

Figure 1. An exemplary multi-device environment with a laptop, smartphone, tablet and smartwatch.

A body of related work already investigated interruptions caused by notifications and resulting distractive effects on different types of devices. Iqbal and Horvitz conducted a field study about email notifications on computers at the workplace [9]. They show that notifications can disrupt the users' current task. In the field study, they disabled email notifications for two weeks and noticed that some participants interrupted themselves to check for new emails. The researchers conclude that, while notifications are distracting, they are valued by users because they enable "passive awareness". Pielot et al. conducted an in-situ study of mobile notifications with 15 participants [12]. Participants in the study received on average 63.5 notifications per day. Even in silent mode, notifications were viewed withing minutes. Sahami Shirazi et al. assessed mobile notifications using a research in the large approach [14, 16]. Using an Android app, the researchers collected almost 200 million notifications from more than 40,000 users. They conclude that important notifications are about messaging, people and events. While not all kinds of notifications are important, many were clicked within 30 seconds. Sahami Shirazi and Henze also conducted an in-situ study about notifications on smartwatches [15]. The results of the study show that on smartwatches participants favored notifications from calendar and VOIP applications.

UbiComp '16, September 12-16, 2016, Heidelberg, Germany
© 2016 ACM. ISBN 978-1-4503-4461-6/16/09…$15.00
DOI: http://dx.doi.org/10.1145/2971648.2971732

To lessen the impact of interruptions caused by notifications, prior work mainly focused on detecting opportune moments, so called breakpoints, to notify the user. In a diary study, Czerwinski et al. showed that returning to tasks after being interrupted is hard [4]. Fisher et al. investigated episodes of mobile phone activity as indicators of opportune moments to deliver notifications [5]. Iqbal and Bailey investigated effects of intelligent notification management on users and their tasks [8]. The researchers built a system that uses statistical models to defer notifications until breakpoints, resulting in reduced frustration and reaction time. Using a context-aware computing device, Ho and Intille detected activity transitions [7]. They found that messages delivered in this activity transitions were better received. Using machine learning techniques, Pielot et al. investigated the possibility to predict the user's attentiveness for text messages [13]. In a large-scale observational study Leiva et al. investigated the cost of mobile app interruptions showing that in some cases the completion of tasks was delayed by up to four times [10]. Recent work by Okoshi et al. investigated the possibility of reducing the perceived mental effort of interruptive notifications in multi-device mobile environments, in this case smartphones and smartwatches [11]. The researchers developed a middleware that identifies breakpoints for notification delivery. According to the researchers, determining on which device to notify the user is a challenge for future research.

In summary, most prior research on notifications and interruptions only focused on single devices. What is missing is an understanding of how future notification systems should be designed with multiple devices in mind. In this paper, we gain first insights about notifications in multi-device environments. We report a week-long Experience Sampling Method (ESM) study with 16 participants and 4 different types of smart devices. We analyze if the device proximity, interaction and location are indicators for whether or not a device should be used to notify the user. The findings can be used to design future multi-device aware smart notification systems.

METHOD OF THE STUDY

To reduce the effect of interruptions caused by notifications, previous work focused mainly on the time to display notifications. While this is certainly important, the large number of devices, including PCs, smartphones, smartwatches and tablets, suggests that the device that displays notifications is also important. Therefore, we conducted a study to investigate notifications in multi-device environments. In the following we describe the design of the study, the used apparatus, the procedure and the participants that took part.

Design

In the study, participants used a smartphone, a tablet, a smartwatch and a PC, the four most commonly used devices that are able to display notifications. Over the course of one week we collected responses from participants using the Experience Sampling Method (ESM) [2, 3, 6]. To reduce interference with other tasks, we designed the ESM questionnaire in a way that allows completing it without any text input. The questionnaire consists of two questions and two statements (see Figure 2):

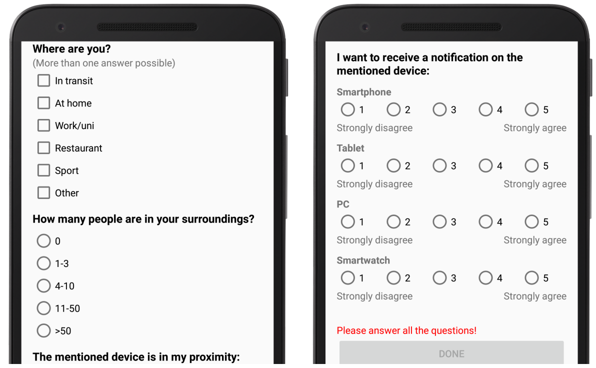


Figure 2. Screenshots of the ESM questionnaire app.

- **Q1: Where are you?** Possible answers are *In transit*, *At home*, *Work/uni*, *Restaurant*, *Sport*, and *Other*. When selecting *Other* an optional text field appears. Participants can select multiple answers to allow combinations such as working on a train or doing a workout at home.
- **Q2: How many people are in your surroundings?** Possible answers are "0", "1-3", "4-10", "11-50", and "more than 50". Here only one answer could be selected.
- **Q3: The mentioned device is in my proximity.** Followed by a 5-point Likert scale for each device (smartphone, tablet, PC, smartwatch).
- **Q4: I want to receive a notification on the mentioned device.** Followed by a 5-point Likert scale for each device (smartphone, tablet, PC, smartwatch).

Participants received EUR 0.20 at the end of the study for each completed questionnaire. In addition to the ESM responses, we recorded activity data on each of the participants' four devices. For example, we recorded screen-on events and if the user is interacting with the device.

Apparatus

To not interfere with the participants' device usage, we used a dedicated device to present the ESM questionnaires. All participants were equipped with an additional smartphone for the sole purpose of collecting ESM responses. Therefore, we implemented an ESM survey Android application that consists of a background service and the survey view itself. The background service triggers a survey every 45 to 90 minutes. Between 0am and 6am, no surveys are triggered. We asked the participants to carry the ESM device with them during the active times, and told them that they are free to change the volume/vibration. When a survey is triggered, a survey notification is shown and clicking it opens the survey view. If the notification is not clicked on within 10 minutes, it is removed. The ESM answers are stored locally. For the study, we disabled all other apps and data connections on the ESM device, resulting in a battery life of over one week. Therefore, participants could carry the ESM device for the entire duration of the study without having to charge it.

We implemented logging applications for Android devices (smartphone, tablet, smartwatch) and Windows PCs to record the status of each of the four devices. The Android application consists of a background service, set to "high priority" to avoid termination by the Android system. Because we were concerned about causing a noticeable impact on the battery, which could influence the study results, the application only collects event-based information. The collected events are *display on/off*, *connection status (WiFi/mobile/offline)*, *power on/off*, *headset connected* and *charging/not charging*. In addition, the app records *touch events* using a transparent layer above other apps. This, too, was limited and we only logged one touch event per minute. We use Google Play Services APIs to record the current *location* and the current *activity*. The Activity Recognition API returns a probability for the events *foot*, *bicycle*, *still*, *running*, *tilting*, *walking* and *unknown* without negatively affecting the device's battery life. The logging application runs on all devices with Android 4.3 (or newer) including smartphones, tablets and smartwatches.

The Windows application also consists of a background process and automatically adds an entry to the Windows auto start. The application records *log-in* and *log-out* events and *times of inactivity*. *Times of inactivity* are calculated similar to a screen-saver. Once a minute, the application checks if the user has interacted with the computer by either moving the mouse or typing on the keyboard. If there was no interaction, the inactivity was logged with a timestamp and another timestamp once the mouse was moved again or something was typed on the keyboard. We also record the name of the current foreground process to detect, for example, when a video is being watched and therefore no interaction happened.

Procedure

To capture weekdays and weekends, the duration of the study study was 7 full days for each participant. On the day before the start of the study, we invited participants to sign a consent form and to fill a demographic questionnaire. We also gave them a smartwatch and the additional ESM device, and explained how to use them. If the participant did not own a tablet, we also handed out a tablet. Because all participants owned Android smartphones, they were already familiar with the operating system on the tablets. We installed the logging applications together with the participants and explained in detail what information is recorded and that they should use all devices as usual. The day after the study, we again invited participants to export the locally stored data, retrieve the devices, and hand out the monetary rewards depending on how many ESM questionnaires were completed. This resulted in a total participation time of nine days.

Participants

We recruited participants using a university mailing list by describing the study and stating that we are looking for participants with an Android 4.3 smartphone and a Windows PC or laptop. We also stated that owning a tablet is preferred but not required. In total, 18 people participated in the study. However, we excluded two participants. In the first case, exporting the log file from the smartwatch failed, resulting in an incomplete set of log files. In the second case, the participant only answered one ESM questionnaire in seven days. Of the remaining 16 participants, 4 were female and 12 male. They were between 19-58 years old ($M = 26.25, SD = 8.76$).

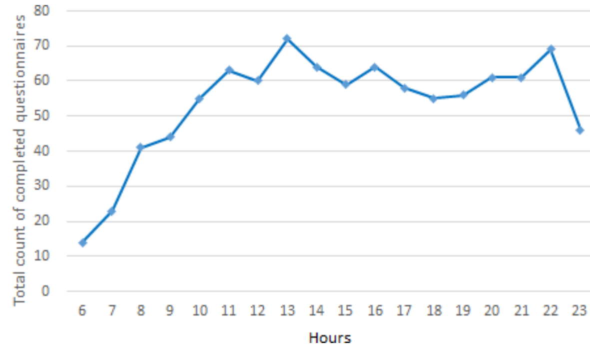


Figure 3. Total number of completed ESM questionnaires from all participants for each hour of the day. Between 0am and 6am no questionnaires were triggered.

Eleven participants were students, 4 employees and one retiree. All participants used their own smartphone and PC. Ten participants used their own tablet, and we handed out six tablets. Of the ten participants who used their own tablet, two shared a tablet with their partner, but used different profiles. Furthermore, we handed out smartwatches (Motorola Moto 360) and the additional ESM devices (Samsung Nexus S) to all participants. Only one participant used a smartwatch before.

RESULTS

At the end of the study, we collected the ESM responses and the automatically recorded data. In the following, we provide an overview of the collected ESM responses. We investigate if the participants' location, the proximity of the device, and the number of people in their surrounding have an effect on participants' preference for receiving notifications on the four devices. Afterwards, we investigate the effect of device usage on participants' preference. Finally, we analyze the correlation between the answered questions in the questionnaire (Q1, Q2 and Q3), the corresponding logged events, and the preferred device to receive an incoming notification (Q4).

Analysis of the ESM questionnaires

Participants answered between 14 and 90 ESM questionnaires ($M = 60.31, SD = 21.26$) which totals to 965 answered questionnaires. On working days, more questionnaires were answered than on the weekend. However, even on Sundays, the day with the lowest amount of answered questionnaires, more than 110 questionnaires were answered. Figure 3 shows the total number of answered questionnaires for each hour of the day between 6am-0am (the time the ESM questionnaires were triggered). The number of answered questionnaires increases as the day progresses, with highest number of answers between 1pm-2pm. A second peak can be seen between 10pm-11pm.

According to the participants' recorded locations (Q1), we found that the participants were mostly at *home* (70.55%), followed by *work/uni* (14.01%), *in transit* (11.04%), *other* (2.66%), *restaurant* (0.92%) and *sport* (0.82%). One participant mentioned that he did not carry any device when working out and therefore might have missed questionnaires. According to the second question (Q2), most of the time participants were either with "1-3" other people (47.46%) or alone (35.54%), followed by "4-10" people people (10.78%), "11-50" (4.77%) and "more than 50" people (1.45%).

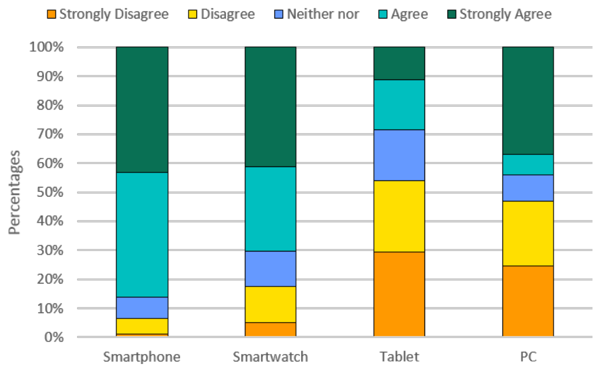


Figure 4. Agreements to "*The mentioned device is in my proximity*" (Q3) for smartphone, smartwatch, tablet and PC.

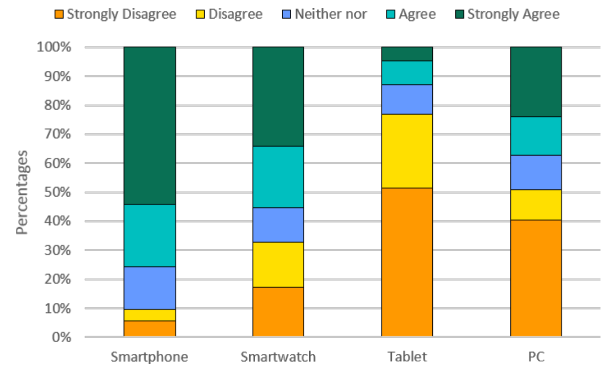


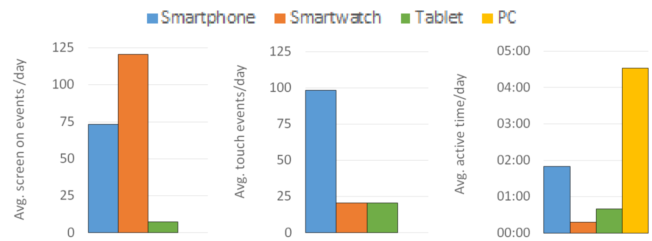
Figure 5. Agreements to "*I want to receive a notification on the mentioned device*" (Q4) for smartphone, smartwatch, tablet and PC.

We used a Friedman test to investigate if the proximity of the devices is significantly different (Q3, see Figure 4). We used Wilcoxon signed-rank post hoc tests with Bonferroni correction (resulting in a significance level of $p \leq 0.008$) for pairwise comparison. We found that the proximity of the four devices significantly differ, $\chi^2(3) = 19.390$, $p < .001$. The device closest to the participants was the smartphone ($M = 4.31, SD = 0.60$) and smartwatch ($M = 4.31, SD = 0.79$), followed PC ($M = 3.53, SD = 1.38$) and tablet ($M = 2.69, SD = 1.20$). The smartphone is significantly closer than the tablet ($U = -3.22, p = 0.001$). Similarly, the smartwatch is significant closer to the participant than the tablet ($U = -3.09, p = 0.002$). There are no significant differences for all other combinations, $p \geq 0.035$.

We again used a Friedman test and Wilcoxon signed-rank tests to investigate the preferred device for receiving notifications (Q4, see Figure 5). We found that the device has a significant effect on participants' preference, $\chi^2(3) = 21.401$, $p < .001$. The most preferred device to receive notifications is the smartphone ($M = 4.12, SD = 1.26$), followed by the smartwatch ($M = 3.69, SD = 1.40$), the PC ($M = 2.56, SD = 1.31$) and the tablet ($M = 1.63, SD = 0.81$). Participants rated the smartphone significantly higher than the tablet ($U = -3.33, p = 0.001$) and the PC ($U = -2.66, p = 0.008$). The rating for the smartwatch is significant higher than the tablet ($U = -3.10, p = 0.002$). There are no significant differences for all other combinations, $p \geq 0.055$.

Analysis of the device usage

Regarding the device usage, the device with the most screen-on events per day (see Figure 6a) is the smartwatch ($M = 120.57, SD = 87.79$), followed by the smartphone ($M = 73.25, SD = 43.74$) and the tablet ($M = 7.35, SD = 9.38$). The device with the most touch events per day (Figure 6b) is the smartphone ($M = 98.39, SD = 84.89$), followed by the tablet ($M = 20.56, SD = 40.69$) and the smartwatch ($M = 20.51, SD = 19.14$). The device with the highest average active time per day (see Figure 6c) is the PC ($M = 4:32h, SD = 3:48h$), followed by the smartphone ($M = 1:50h, SD = 1:38h$), the tablet ($M = 0:39h, SD = 1:03h$), and the smartwatch ($M = 0:17h, SD = 0:14h$). For PC, the active time is the time between logging in and out minus the time without user interaction. For Android devices, the active time is the time the screen was on.



(a) Screen-on events (b) Touch events (c) Time active

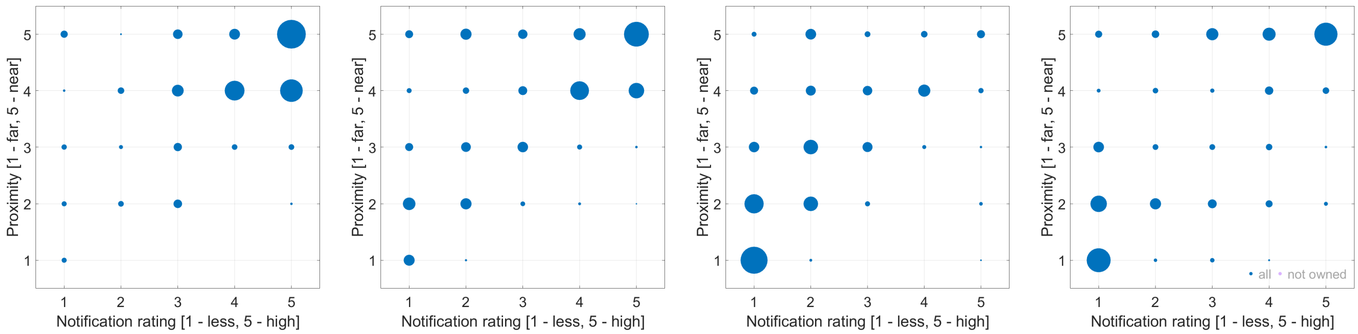
Figure 6. Average daily number of screen-on events, touch events and active time.

Correlations

We analyzed the correlations between the device proximity (Q3) and whether participants want to be notified on the device or not (Q4) (see Figure 7). First, we calculated the correlation coefficient r for the proximity to the devices and if the participants want to be notified on the devices for every participant and every device. Then we calculated the average correlation for all participants for the four devices. For a better overview, we only report average effect sizes of $r > \pm 0.1$. Using Cohen's conventions [1] to describe the effect size, for all devices we found moderate to strong positive correlations between the device proximity and whether or not notifications should be shown on the device. We found the strongest correlation for PC ($M = 0.73, SD = 0.21$), followed by smartwatch ($M = 0.63, SD = 0.30$), tablet ($M = 0.61, SD = 0.24$) and smartphone ($M = 0.45, SD = 0.26$).

Furthermore, we calculated the correlations of participants' location (Q1) and Q4. For *in transit*, we found weak negative correlations for PC ($M = -0.27, SD = 0.17$) and tablet ($M = -0.22, SD = 0.20$). For *at home*, we found weak to moderate positive correlations for tablet ($M = 0.30, SD = 0.33$) and PC ($M = 0.26, SD = 0.31$), and weak to moderate negative correlations for smartwatch ($M = -0.25, SD = 0.35$) and smartphone ($M = -0.09, SD = 0.23$). For *at work/uni* we found a weak positive correlation for smartwatch ($M = 0.26, SD = 0.23$) and a weak negative correlation for tablet ($M = -0.18, SD = 0.30$). *Restaurant* and *sport* were not selected often enough for meaningful results.

We calculated the correlations of the number of people in participants' surrounding (Q2) and Q4. When alone, we found weak positive correlations for the PC ($M = 0.26, 0.15$)



(a) Smartphone (b) Smartwatch (c) Tablet (d) PC

Figure 7. Correlations between the proximity to the devices and if the participants want to receive notifications on the devices. The size of the points in the scatter plots represents the frequency of occurrence of the single, normalized ratings.

and tablet ($M = 0.13, SD = 0.22$). When with "4-10" people, we found weak negative correlations for PC ($M = -0.17, SD = 0.23$) and tablet ($M = -0.14, SD = 0.18$). When with "11-50" people, we found weak positive correlations for smartphone ($M = 0.10, SD = 0.11$) and smartwatch ($M = 0.14, SD = 0.26$), and weak negative correlations for PC ($M = -0.14, SD = 0.14$) and tablet ($M = -0.13, SD = 0.14$). "More than 50" was not selected often enough for meaningful results.

We also calculated the correlations between screen-on events right before or after a questionnaire was triggered and Q4. We found moderate positive correlations for smartwatch ($M = 0.34, SD = 0.24$) and tablet ($M = 0.31, SD = 0.28$), and a weak correlation for smartphone ($M = 0.18, SD = 0.20$). We did not log screen-on events for the PC. We also calculated the correlations between whether the devices were *still* (using the Activity Recognition API) and Q4. We found weak negative correlations for smartwatch ($M = -0.29, SD = 0.30$), tablet ($M = -0.27, SD = 0.25$) and smartphone ($M = -0.13, SD = 0.24$). Again, the PC is excluded because no activity recognition events were logged. We also calculated the correlations between the active time and Q4. We found a strong positive correlation for PC ($M = 0.51, SD = 0.20$), a moderate positive correlation for the tablet ($M = 0.37, SD = 0.32$), and weak positive correlations for smartwatch ($M = 0.20, SD = 0.12$) and smartphone ($M = 0.18, SD = 0.20$).

DISCUSSION AND LIMITATIONS

We conducted an ESM study with 16 participants and 4 different types of smart devices for 7 days. All participants used their own smartphones and PCs. Ten participants also used their own tablets. We handed out smartwatches for all participants. Although all participants were used to the Android platform, in the future we plan to investigate if longer device usage has an influence on the preferred notification location.

On average, participants preferred to be notified on the smartphone, followed by the smartwatch, the PC and the tablet. The smartwatch ranking second is interesting, because only one participant had used a smartwatch before. Comparing the device usage of smartphones and smartwatches, we saw more touch events on smartphones but more screen-on events on smartwatches. This is likely because the screen of the smartwatch turns on automatically when tilting the device.

We found that the device proximity has an influence for whether or not the user wants to be notified on the device. To an extend, this finding seems obvious, as notifications will not be noticed when the device is not near the user. Regardless, this is something that should be considered when creating future multi-device aware notification systems. Past research investigated the possibility of inferring where phones are kept [17], work which should be extended to other devices. For the smartphone, the correlation was only moderate, but this can be attributed to the fact that the smartphone was almost always with the participants. Further, the participants preferred to receive notifications on devices which have an activated screen and they are currently interacting with. On the other hand, *still* devices are less suitable for notifications. Regarding the user's current location, PC and tablet both showed negative correlations for *in transit* but positive for *at home*. At *work/uni* the smartwatch was favored.
To keep the questionnaire simple, we purposely did not specify details about the incoming notification in Q4. In future research, the type and content of notifications should be considered by, for example, conducting interviews. Furthermore, notifications might be device specific (e.g. available updates) or independent (e.g. email, messaging). We also did not address which modalities should be used to notify the user, which is another important aspect for future research.

CONCLUSION

In this paper, we investigated notifications in multi-device environments. We conducted a 7-day in-situ study using the Experience Sampling Method (ESM) with 16 participants and 4 different types of smart devices (smartphone, smartwatch, tablet and PC). Apart from ESM answers, we also collected device usage data, such as screen-on events, touch events and whether or not the device has been moved lately. Disregarding the type or content of notifications, we found that the smartphone is the preferred device on which to be notified, followed by the smartwatch, PC and tablet. Further, we found that the proximity to the device, whether the device is currently being used and the user's current location can be used to predict if the user wants to receive notifications on a device. The findings can be used to design future multi-device aware smart notification systems. Future work should investigate the role of the notification type and content, and collect qualitative data to gain further insights.

ACKNOWLEDGMENTS

This work is supported by the German Ministry of Education and Research (BMBF) within the DAAN project (13N13481) and by the DFG within the SimTech Cluster of Excellence (EXC 310/2).

REFERENCES

1. Jacob Cohen. 1988. Statistical Power Analysis for the Behavioral Sciences. 2nd edn. Hillsdale, New Jersey: L. (1988).

2. Sunny Consolvo and Miriam Walker. 2003. Using the Experience Sampling Method to Evaluate Ubicomp Applications. *IEEE Pervasive Computing* 2, 2 (2003), 24–31. DOI: http://dx.doi.org/10.1109/MPRV.2003.1203750

3. Mihaly Csikszentmihalyi and Reed Larson. 2014. Validity and Reliability of the Experience-Sampling Method. In *Flow and the Foundations of Positive Psychology*. Springer, 35–54.

4. Mary Czerwinski, Eric Horvitz, and Susan Wilhite. 2004. A Diary Study of Task Switching and Interruptions. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '04)*. ACM, New York, NY, USA, 175–182. DOI: http://dx.doi.org/10.1145/985692.985715

5. Joel E. Fischer, Chris Greenhalgh, and Steve Benford. 2011. Investigating Episodes of Mobile Phone Activity As Indicators of Opportune Moments to Deliver Notifications. In *Proceedings of the 13th International Conference on Human Computer Interaction with Mobile Devices and Services (MobileHCI '11)*. ACM, New York, NY, USA, 181–190. DOI: http://dx.doi.org/10.1145/2037373.2037402

6. Joel M Hektner, Jennifer A Schmidt, and Mihaly Csikszentmihalyi. 2007. *Experience Sampling Method: Measuring the Quality of Everyday Life*. Sage.

7. Joyce Ho and Stephen S. Intille. 2005. Using Context-aware Computing to Reduce the Perceived Burden of Interruptions from Mobile Devices. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '05)*. ACM, New York, NY, USA, 909–918. DOI: http://dx.doi.org/10.1145/1054972.1055100

8. Shamsi T. Iqbal and Brian P. Bailey. 2008. Effects of Intelligent Notification Management on Users and Their Tasks. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '08)*. ACM, New York, NY, USA, 93–102. DOI: http://dx.doi.org/10.1145/1357054.1357070

9. Shamsi T. Iqbal and Eric Horvitz. 2010. Notifications and Awareness: A Field Study of Alert Usage and Preferences. In *Proceedings of the 2010 ACM Conference on Computer Supported Cooperative Work (CSCW '10)*. ACM, New York, NY, USA, 27–30. DOI: http://dx.doi.org/10.1145/1718918.1718926

10. Luis Leiva, Matthias Böhmer, Sven Gehring, and Antonio Krüger. 2012. Back to the App: The Costs of Mobile Application Interruptions. In *Proceedings of the 14th International Conference on Human-computer Interaction with Mobile Devices and Services (MobileHCI '12)*. ACM, New York, NY, USA, 291–294. DOI: http://dx.doi.org/10.1145/2371574.2371617

11. Tadashi Okoshi, Julian Ramos, Hiroki Nozaki, Jin Nakazawa, Anind K. Dey, and Hideyuki Tokuda. 2015. Reducing Users' Perceived Mental Effort Due to Interruptive Notifications in Multi-device Mobile Environments. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '15)*. ACM, New York, NY, USA, 475–486. DOI: http://dx.doi.org/10.1145/2750858.2807517

12. Martin Pielot, Karen Church, and Rodrigo de Oliveira. 2014a. An In-Situ Study of Mobile Phone Notifications. In *Proceedings of the 16th International Conference on Human-computer Interaction with Mobile Devices & Services (MobileHCI '14)*. ACM, New York, NY, USA, 233–242. DOI: http://dx.doi.org/10.1145/2628363.2628364

13. Martin Pielot, Rodrigo de Oliveira, Haewoon Kwak, and Nuria Oliver. 2014b. Didn't You See My Message?: Predicting Attentiveness to Mobile Instant Messages. In *Proceedings of the 32Nd Annual ACM Conference on Human Factors in Computing Systems (CHI '14)*. ACM, New York, NY, USA, 3319–3328. DOI: http://dx.doi.org/10.1145/2556288.2556973

14. Alireza Sahami Shirazi, Niels Henze, Tilman Dingler, Martin Pielot, Dominik Weber, and Albrecht Schmidt. 2014. Large-scale Assessment of Mobile Notifications. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '14)*. ACM, New York, NY, USA, 3055–3064. DOI: http://dx.doi.org/10.1145/2556288.2557189

15. Alireza Sahami Shirazi and Niels Henze. 2015. Assessment of Notifications on Smartwatches. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct (MobileHCI '15)*. ACM, New York, NY, USA, 1111–1116. DOI: http://dx.doi.org/10.1145/2786567.2794338

16. Dominik Weber, Alireza Sahami Shirazi, and Niels Henze. 2015. Towards Smart Notifications Using Research in the Large. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct (MobileHCI '15)*. ACM, New York, NY, USA, 1117–1122. DOI: http://dx.doi.org/10.1145/2786567.2794334

17. Jason Wiese, T. Scott Saponas, and A.J. Bernheim Brush. 2013. Phoneprioception: Enabling Mobile Phones to Infer Where They Are Kept. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '13)*. ACM, New York, NY, USA, 2157–2166. DOI: http://dx.doi.org/10.1145/2470654.2481296