MobileDNA: Relating Physiological Stress Measurements to Smartphone Usage to Assess the Effect of a Digital Detox

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Abstract. The ever-connected world created by smartphones has led to initiatives like a 'digital detox', in which smartphone users consciously disconnect from email, social media and internet in general for a certain period of time. Since research based on subjective self-reports indicates that extensive smartphone usage and stress are often related, we checked whether a digital detox is effectively associated with a decrease in stress in the short-term and whether this could be measured with objective markers of both smartphone usage and physiological stress. More particularly, we monitored participants for two consecutive weeks: one week of normal smartphone usage and one week of digital detox. We asked them to continuously wear a state-of-the-art wristband device, measuring physiological stress based on skin conductance (SC). In addition, we developed an app called 'mobileDNA' to capture detailed information on which apps participants use throughout the day and how much time they spend on them. Although this was a pilot study with a rather low sample size, we found decreased levels of stress during a digital detox week. This finding provides evidence that a digital detox can be an interesting coping mechanism for people experiencing problematic smartphone usage and that further and more extensive research with our methodology has a lot of potential in the future.

Keywords: Mobile DNA · Smartphone usage · Digital detox · Stress
Technostress · Physiology

1 Introduction

Over the last couple of years, smartphone usage has increased dramatically, infiltrating every aspect of our life [1, 2]. Its usage is often highly enjoyable and feels so naturally that people are often not conscious of their 'constant connectedness' [3–5]. Whereas most smartphone users do not experience this constant connectedness as problematic, some studies have shown that smartphone overuse and constant connectedness can have a substantial negative impact on people's daily life activities and well-being [1, 5]. For

C. Stephanidis (Ed.): HCII Posters 2018, CCIS 851, pp. 356–363, 2018.
https://doi.org/10.1007/978-3-319-92279-9_48

instance, smartphone overuse has been found to be associated with poorer sleep quality [6], professional performance [7], personal relationship quality [8] and lower well-being in general [9]. In addition, the constantly connected world created by smartphones blurs the boundary between work and home, reflected in expectations of employers to be 'always online', to immediately reply to emails and to keep up with online conversations [10].

When users experience their constant connectedness as an exceeding environmental demand that threats their well-being, they can experience *technostress*. Technostress is a specific type of stress that results from the use of modern technology [11]. Based on the Transactional Model of Stress (TMS), technostress can be defined as an imbalance between an individual's resources and demands by the environment related to technology use [12]. In order to deal with technostress, people will develop certain coping abilities [12]. One technostress coping strategy is a digital detox, which entails an entire and conscious disconnection from e-mail, social media, news and internet in general. Smartphone digital detox is an increasing practice [2], for which people have indicated that they do it because they prefer not to be reachable for a while or to have more time for other things. The behavior of disconnecting oneself has not limited itself to the individual, also in work-contexts there is a debate whether employees should go offline after the working hours. For example, emails that are received after working hours are either put on hold or deleted in certain companies [13].

In this study, we wanted to investigate whether a smartphone digital detox effectively decreases stress in the short-term. This research question is especially interesting because two opposing hypotheses can be put forward: whereas a digital detox is likely to decrease stress because people are less preoccupied by notifications and emails, it can also increase stress because of withdrawal-like symptoms and the loss of interconnectedness [14]. In order to investigate both opposite hypotheses, we made use of an in-house developed smartphone application ('mobileDNA') to log smartphone usage. In addition, we used a wearable wristband device that can objectively and continuously measure skin conductance (SC) and skin temperature as a proxy for stress with high temporal precision. For decades, it has been known that increased skin conductivity can be a sensitive psychophysiological index of changes in autonomic sympathetic arousal and stress [15]. An important objective was to be as less intrusive as possible and monitor participants' behavior for fourteen consecutive days, consisting of seven days of normal smartphone usage and seven days of digital detox.

2 Method

2.1 Participants

In the context of a student assignment on smartphone usage and stress, fifteen participants were asked to wear a stress wearable and to allow us to log all their smartphone activity for two consecutive weeks. These participants were recruited in the student population and were on average 22 years (range: 21–24 years) and mostly female (10 out of 15). Unfortunately, there were some technical problems with some of the sensors, so we had to exclude the physiological data of 4 people from further analysis. In addition, for one participant, we were not able to link the logging data to the physiological data, so his/her data was excluded in the analysis of the physiological data. All participants signed an informed content before participating and were paid 30 euros after two weeks.

2.2 MobileDNA: Logging Smartphone Usage

In order to collect data on one's actual smartphone usage, a logging application (mobileDNA, available in Google Play Store) was used. MobileDNA allowed us to capture precise information on which apps participants used, how much time they spent on using them and how frequently they received notifications. This app can be both used as a research tool (outputting raw data) and a way to raise awareness for personal smartphone usage. With respect to the latter, users of the app can log in on https://mobiledna.be/ and check their personal data throughout the day (see Fig. 1).

Fig. 1. mobile DNA – screenshot of the application interface on https://mobiledna.be/. Vertical lines indicate app events (opening an app and using it for a certain time), whereas the dots represent notifications. The color indicates which app is used (Color figure online).

For this study, we analyzed the raw data and simply counted the total number of app events during the first four days of both the normal and detox week. We specifically limited the scope of our app event data to those apps that require a data connection. An app event can therefore be defined as the self-initiated act of opening an app and using it for at least a couple of seconds. This means that app events for apps like Facebook, Facebook Messenger, Instagram, Twitter, Whatsapp or the browser were counted, whereas apps for traditional messaging (SMS), camera or system settings were not.

2.3 Physiological Measurements

With respect to objectively measuring stress, we used the Imec Chillband. This wearable was specifically designed for long-term stress measurements (>1 week battery autonomy, storage capacity of 30+ days of data) and is attached to the lower side of the wrist. Skin conductance (i.e. galvanic skin response or electro dermal activity) and skin temperature are measured with high dynamic range (0–20 µs) and sampled at 256 Hz and 1 Hz, respectively. However, skin temperature was not analyzed for this study. Participants had to wear the sensor the entire day but could take it off during the night and while taking a shower. Data was internally stored on the sensor and uploaded to a computer via USB afterwards. Since this wearable does not have a display, participants were not aware of their current physiology and stress level, avoiding effects of self-adjustments during the normal smartphone usage week.

With respect to the analysis, features were calculated based on the raw skin conductance signal in a window of 5 min, with a step size of 1 min. Data quality was assessed based on the wearable's internal confidence indicator (CI), leaving out all samples with a CI lower than 0.8 [16]. Just like [17], we chose to look at the skin conductance response rate (SCRR) instead of the absolute skin conductance level. The SCRR reflects the number of SC responses in a time window divided by the total length of the window (in this case 300 s) or the number of SC responses per second. Then, SCRR was averaged across the entire duration of the day, starting when people woke up and put on the wristband until they went back to bed.

2.4 Procedure and Design

A within-subjects design was used to compare stress between the regular and detox week. In contrast to a between-subjects design, this type of design is less affected by intersubjective and baseline variability. All participants started with the normal smartphone usage week and were asked to use their smartphone like they always do. After this week, they got a new sensor and were asked to use their smartphone as a "dumb phone": they were allowed to take pictures, send texts or make calls, but had to switch off their mobile data (3G, 4G, 5G) and Wifi connection. In addition, they were asked to make a note in a diary whenever they experienced stress that was not related to their smartphone usage (e.g. relationship arguments or traffic jams), which allowed us to control for alternative explanations of stress during both weeks. In this study, we excluded the data of participants who experienced highly unusual stressful events, but did not use the subjective data to exclude portions of data within subjects. Because not every participant started at the same time of the day, we took the next day of data collection as day 1. In order to have a balanced amount of data for each participant and because there were some participants who dropped out after 5 days, we only analyzed 4 out of 6 days per week (normal and detox).

3 Results

3.1 MobileDNA

A repeated-measures ANOVA with factors week type (normal vs. detox) and day of the week (day 1 to 4) was performed on the average number of app events. Mauchly's test indicated that the assumption of sphericity had been violated for the main effect of day and the interaction effect, $\chi^2(1) = .18$, $p = .02$, and $\chi^2(2) = .15$, $p = .01$, respectively. Therefore, for these effects, Greenhouse-Geisser corrected tests are reported. The main effect of week was significant, $F(1, 9) = 26.80$, $p < .001$, $r = .87$ (*large* effect according to [18]). The main effect of day was not significant, $F(1.57, 14.10) = 1.64$, $p = .23$, $r = .39$, just like the interaction between week and day, $F(1.57, 14.12) = 1.25$, $p = .31$, $r = .35$. As Fig. 2 illustrates, the average number of app events was on average much higher during normal days ($M = 69.45$, $SD = 51.25$) than during detox days ($M = 2.53$, $SD = 2.71$).

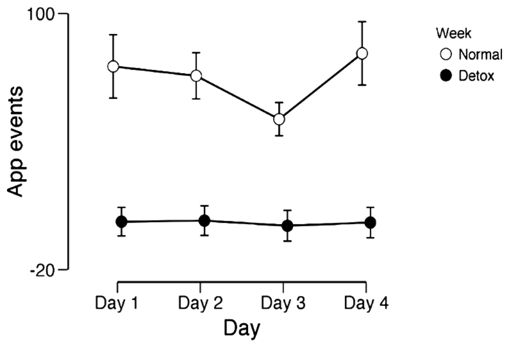

Fig. 2. Mobile DNA – average number of app events per day of each week (normal vs. detox). Participants used their smartphone significantly less during the detox week.

3.2 Physiological Measurements

A repeated-measures ANOVA with factors week type (normal vs. detox) and day of the week (day 1 to 4) was performed on the average SCRR. Mauchly's test indicated that the assumption of sphericity had been violated for the interaction effect, $\chi^2(2) = .26$, $p = .04$. Therefore, for this effect, a Greenhouse-Geisser corrected test is reported. The main effect of week was significant, $F(1, 10) = 5.63$, $p = .04$, $r = .6$ (*large* effect according to [18]). The main effect of day was not significant, $F(3, 30) = .7$, $p = .56$, $r = .25$, just like the interaction between week and day, $F(1.69, 16.9) = .26$, $p = .74$, $r = .16$. As Fig. 3 illustrates, the average SCRR was on average higher during normal days ($M = 0.042$, $SD = 0.029$) than during detox days ($M = .029$, $SD = 0.018$).

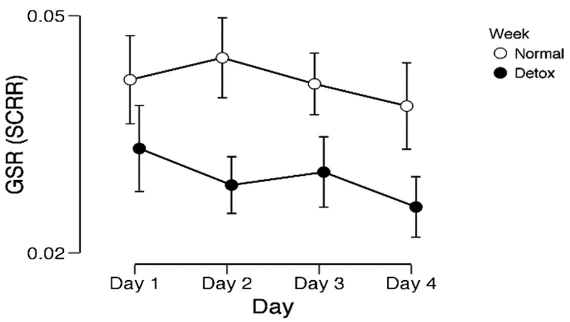

Fig. 3. Main effect – average skin conductance response rate per day of each week (normal vs. detox). Participants experienced significantly less stress during the detox week.

Violin plots showing the full distribution of each cell in the design (2 weeks × 4 days) indicate that this significant main effect of week was not driven by outliers and that most participants did indeed show a decreased SCRR on average during the detox week (Fig. 4).

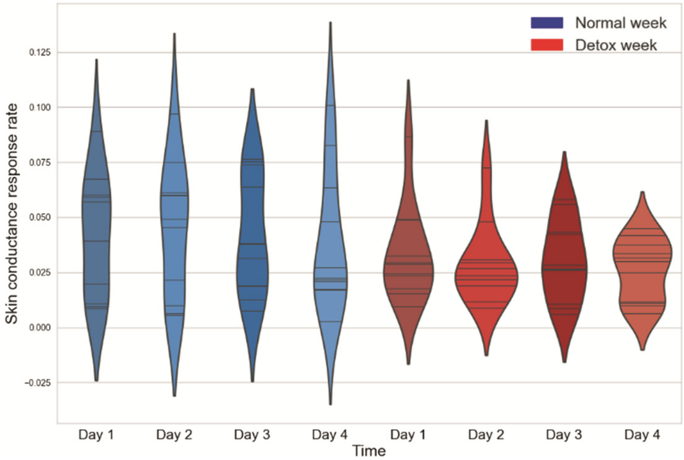

Fig. 4. Violin plots. Each horizontal black line indicates the average skin conductance response rate throughout the day during the normal and detox week, respectively. The outer sides of each violin plot represent a rotated kernel density plot, showing the probability density of the data at different values.

4 Discussion

Recently, *digital detox* or the coping strategy to deal with smartphone overuse, constant connectedness and increasing technostress has become more and more popular [2]. When digitally detoxing, people consciously decide to disconnect entirely from email, social media, news and internet in general and use their smartphone as a "dumb phone". However, at the moment it is not clear whether this coping strategy effectively decreases stress, since it can also be argued that detoxing could lead to an increase in stress because of withdrawal-like symptoms and the loss of interconnectedness with other people [14].

In order to investigate whether or not a digital detox is associated with changes in stress-levels in the short term, we measured smartphone usage and stress in an objective way. In essence, we made use of an in-house developed smartphone application ('mobileDNA') to measure smartphone usage in great detail and used the Chillband to measure skin conductance (SC) as a proxy for stress. Our goal was to monitor participants' behavior for fourteen consecutive days, consisting of seven days of normal smartphone usage and seven days of digital detox (although in the end only four days were used in the analysis). Interestingly, the data showed some clear patterns. First, as a manipulation check, we were able to verify that participants effectively used less apps requiring a mobile data/wifi connection during the digital detox week. In contrast to a normal week with on average almost 70 app events a day (i.e. opening an app and using it), people refrained from using their smartphone most of the time during the detox week. Interestingly, we found a highly significant main effect of type of week in the physiological data: during the detox week, the physiological stress signal based on the skin conductance response rate (SCRR) was lower than during the normal week. This main effect was present for each of four consecutive days during the normal and detox week, making it unlikely that the effect was driven by a certain event or day of the week. In addition, we based our stress measurements on SCRR instead of the absolute skin conductance signal, likely minimizing confounding effects of physical effort and large baseline differences between participants. Our findings add to the literature, especially in the light of studies showing that smartphone overuse and constant connectedness can have a substantial negative impact on people's well-being [1, 5]. If a digital detox effectively decreases stress, this means that it can be an effective coping mechanism for people who experience this negative impact on a daily basis and that more research is needed on how employers have to deal with constant connectedness outside the office hours.

However, although this study demonstrates that there is good evidence for significant beneficial effect of a digital detox on stress, it is important to note that the sample size was rather small. More participants were initially recruited, but the number of participants we had to exclude was quite high because of sensor issues, people forgetting to wear the wristband during one or more days and synchronization issues with the mobileDNA data. In addition, the low sample size made it impossible to do correlational analyses and to check whether large decreases in stress were also associated with large decreases in smartphone usage. Another issue relates to order effects: because each participant started with the normal week followed by the detox week, our main finding can also be explained by the fact that participants were initially stressed out about wearing the wristband and got used to it during the detox week. One way to rule this out, is by setting up an experiment in which we monitor three weeks (normal week – digital detox week – normal week). For these reasons, we consider the results as preliminary and are rather cautious with over-generalizations.

Nevertheless, we think this pilot study indicates it is quite promising to collect additional data, in which we need to strive for a larger number of participants, a counterbalanced design and the inclusion of subjective annotations. Research on smartphone overuse and the beneficial effects of digital detox has only just begun.

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