**Working Paper**

*Title*

Mobile DNA: complementing self-reporting with log data to gain insights in smartphone use

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**Introduction**

In the past years, smartphone usage has increased dramatically, up to 2.4 billion users worldwide, infiltrating every aspect of our life. Smartphones have not only replaced cellphones, but to a certain degree also personal computers and several other internet communication technology (ICT) devices (Samaha & Hawi, 2017). Its usage feels so naturally that people feel inseparable from their smartphones (Lepp, Li, Barkley, & Salehi-Esfahani, 2015). Particularly adolescents and young adults are heavy users. For most of them, the lines between personal lives, school and work have blurred. The desire, or need, for constant connection has led to a variety of issues associated with problematic, sometimes even addictive, use of their constant companion, the smartphone (David, Roberts, & Christenson, 2018).

In 2014, the World Health Organization has considered that the pervasiveness of cyber technologies exposes people to new abuse and detrimental health risks (Billieux, Maurage, Lopez-Fernandez, Kuss, & Griffiths, 2015; Chóliz, 2010; Haug et al., 2015; Long et al., 2016). The past decade, several authors consider the constant checking and use of smartphone applications as the main culprit for increased levels of stress, anxiety and depression (Demirci, Akgönül, & Akpinar, 2015; Tamura, Nishida, Tsuji, & Sakakibara, 2017; Thomée, Härenstam, & Hagberg, 2011), deterioration in well-being and life satisfaction (Andreassen, Pallesen, & Griffiths, 2017; Marino, Gini, Vieno, & Spada, 2018; Roser, Schoeni, Foerster, & Röösli, 2015; Satici & Uysal, 2015), poorer sleep quality (Lemola, Perkinson-Gloor, Brand, Dewald-Kaufmann, & Grob, 2015; Tamura et al., 2017; Thomée et al., 2011), and decreased academic performance (Felisoni & Godoi, 2017; Judd, 2014; Karpinski, Kirschner, Ozer, Mellott, & Ochwo, 2013). A recent study conducted among Lebanese university students revealed that prevalence rates of smartphone-related compulsive behavior, functional impairment, tolerance and withdrawal symptoms were substantial (Boumosleh & Jaalouk, 2017): 35.9% felt tired during daytime due to late-night smartphone use, 38.1% acknowledged decreased sleep quality, and 35.8% slept less than four hours due to smartphone use more than once. Another recent representative study conducted in the Flemish part of Belgium indicated that 34% of adults admit that they are spending too much time on social media, and 27% claims that they can't spend a day without social media (Van Haelewyn & De Marez, 2017).

However, there is also a concern over unwarranted moral panic (Livingstone, 2018). In recent years, several studies have been conducted to identify, define and analyse problematic or pathological use of the smartphone and its adverse consequences. Causal relations between smartphone use, and impaired well-being or function are, however, not always justified and often relies on taken-for-granted assumptions (Sonnentag & Pundt, 2017). Authors have pointed out that smartphone use could be a way of coping with daily problems such as work stress (Blanchard & Henle, 2008), anxiety, or depression (Billieux, Maurage, & Lopez-fernandez, 2015). As Samaha and Hawi (2016, p. 324) state: "Anything that raises the level of perceived stress might increase the risk of smartphone addiction. Meanwhile anything that raises the risk of smartphone addiction might influence an increased level of perceived stress".

Furthermore, less research has been devoted on healthy smartphone use or the positive side effects of its usage. Early studies have, however, shown that mobile phone optimizes the communication between individuals and systems (Geser, 2004). In addition, smartphone use can improve not only interpersonal relationships (Dyer, 2018; Vanden Abeele, Schouten, & Antheunis, 2016), but also communication and socialising (Besoli, Palomas, & Chamarro, 2018) and enhance productivity in the workplace (Demircioglu, 2018; Leftheriotis & Giannakos, 2014) and in school (Buabeng-Andoh, 2018; Godwin-Jones, 2011), as smartphone use while working or studying can serve as a recreational break or way of psychological detachment (Fritz, Lam, & Spreitzer, 2011). Moreover, a number of studies have also underlined the efficacy of smartphone supported psychological interventions to promote healthy behaviors, such as smoking cessation, diabetes self-management and weight loss maintenance (Firth et al., 2017; Free et al., 2011; Head, Noar, Iannarino, & Harrington, 2013; Kim & Kim, 2008).

In sum, smartphone usage seems to have both positive or negative consequences on individuals' wellbeing and functioning, The numerious associations with wellbeing, on the one hand, and the pervasiveness of smartphones, on the other hand, have made a popular and highy researched domain of smartphone usage. However, this domain is currently lacking accurate and detailed measures of smartphone usage resulting in a knowledge gap: we do not fully understand individuals' smartphone usage and the consequences of smartphone usage. This paper focusses on some methodological shortcomings that hinder nuanced claims about the link between smartphone usage and wellbeing. Below we first highlight five crucial shortcomings. Thereafter, we propose a new app, called MobileDNA, that overcomes these shortcomings. MobileDNA enables an accurate measurement of smartphone usage with the ability to analyse aggregate as well as individual smartphone usage to a great level of precision.

**Methodological shortcomings related to smartphone usage**

*Shortcoming 1: Actual behavior cannot be measured by self-reports*

Several studies have reported on individuals' smartphone usage, but most of them involve self-report estimates of usage by means of questionnaires or interviews, which may not be entirely reliable measures (Andrews, Ellis, Shaw, & Piwek, 2015b; Wilcockson, Ellis, & Shaw). Self-report measures enable to measure people's perceptions about their smartphone use, but this does not necessary reflect their actual behavior (Kobayashi & Boase, 2012; Scharkow, 2016). Much of the cognitive literature on time-perception indicates people are poor at estimating durations (Grondin, 2010). Studies comparing logdata with self-reported data found the accuracy of self-reported frequency and duration of Internet use is quite low, with a general tendency of people to underestimate or overreport their total time and frequency of mobile communication (Kobayashi & Boase, 2012; Scharkow, 2016); and to be unaware of rapid, yet pervasive, checking behaviors or other mobile use patterns (Andrews, Ellis, Shaw, & Piwek, 2015a; Rachman, 2002). Such habits are often unconscious and automatic behaviors and therefore hard to be accurately estimated by individuals. For instance, it is possible that people truly believe they only use their smartphone on rare occasions, while in reality they develop a gateway behavior of compulsive conditioned reaction to the notifications of one specific app (e.g., Whatsapp), systematically followed by the same set of apps (e.g., Instagram, mail, Facebook) in each session starting with the specific app (e.g., Whatsapp). Indeed, a smartphone logging study conducted by Oulasvirta, Rattenbury, Ma and Raita (2012) revealed that the habit of checking a smartphone on notifications may function as a gateway to other applications. Also, smartphone use is often combined with other activities, making it difficult for individuals to allocate the real time spended on certain applications. Hussain, Griffiths and Sheffield (2017) reported, for example, that 54% checked their smartphones while lying in bed, 39% checked their smartphone while using the bathroom, and 30% checked it during a meal with others. Another study conducted in the Flemish part of Belgium showed that 68% uses their smarphone while eating alone, 60.7% uses their smartphone while wachting TV shows, series, or films, and 41.7% uses their smartphone when meeting up with friends (Vanhaelewyn & De Marez, 2017).

In recent years, several logging tools have tried to overcome the methodological shortcoming resulting from subjective self-report data. A lot of these tools prove to have a high face validity when it comes to logging the average smartphone usage or how many minutes certain apps are used (Wagner, Rice, & Beresford, 2013). They, however, often lack the temporal dimensions of smartphone usage like timing (when did a smartphone usage occur) and sequence (what combination and flow of apps was used), or don't go into logging one-app events (Morrison, Xiong, Higgs, Bell, & Chalmers, 2018; van Berkel et al., 2016; Zhu, Chen, Peng, Liu, & Dai, 2018). Most of the existing tools generate high level statistics on traditional temporal dimensions (e.g., average smartphone usage, types of apps used) that are valuable to offer a general overview of smartphone usage. To get more detailed information, however, micro-usage (short interactions with applications) and sessions (a sequence of one or more apps) data should be taken into account as well.

*Shortcoming 2: Smartphone usage differs across people and across usages*

Lin, Su and Potenza (2018) recently developed an online/offline integration hypothesis for healthy internet use. This hypothesis proposes that healthier patterns of internet usage may be achieved through harmonious integration of people's online and offline worlds. According to the hypothesis, internet use – and by extension smartphone use – may thus have positive or negative effects depending on individual differences. Today, research has already demonstrated that individuals, especially adolescents, are trying to create a more harmonious and balanced relationship with their smartphones by submitting to, for example, a complete digital detox or imposing certain generic rules (such as switching notifications off and keeping the smartphone away from the bedroom) (Löchtefeld, Böhmer, & Ganev, 2013). At the same time however, recent studies as imec's yearly Digimeter study (Van Haelewijn & De Marez, 2018) or a 2018 study of Ernst and Young revealed that half up to two third of smartphone users admit that these initiatives are insufficient to restore a healthy smartphone relationship and online/offline-balance. Generic 'one size fits all' coping tips don't seem to work out well for most; and the lack of insight into which behavioral smartphone use pattners causes the negative consequences of smartphone use remains prevalent.

Although most existing studies have aimed to find global regularities underlying user behavior on mobile phone uses, certain studies have explicitly acknowledged the existence of individual differences (Falaki & Estrin, 2010; Welke, Andone, Blaszkiewicz, & Markowetz, 2016). Also in behavioral therapy, personalized advices based on individual patterns are claimed to be an effective way to counteract a diverse array of psychological problems (Van Roekel et al., 2017). Simultaneously uncovering both global regularities and individual variabilities hence, is highly desirable (Zhu et al., 2018). Current methodological solutions often offer duration logging (e.g., moments, screentime) that can answer global questions like the amount of overall screen use, but this is however no solution to tackle other temporal characteristics such as frequency, timing and sequence in smartphone use on the individual level (Zhu et al.,2018).

*Shortcoming 3: Making sense of log data requires contextualization*

A huge amount of objective behavioral data is collected when logging all event records on a smartphone (Boyd & Crawford, 2012). Nevertheless, big data shouldn't stand alone, different interpretations are needed for different contexts. For instance, two people can rely on the recently launched Facebook screen time monitoring tools[1] and learn they both use Facebook for 50 minutes a day, with one using it during work and another one using Facebook almost exclusively in the evening while watching TV in primetime; are two totally different contexts (Morrison et al., 2018; Oulasvirta et al., 2012). The most difficult part in big data research is not collecting the data, but to interpret the data (Boyd & Crawford, 2012; Ørmen & Thorhauge, 2015). For a valid interpretation of smartphone usage, contextual information is required. Therefore, tools that enable detailed logging are needed (e.g., log data of every dimension of temporal use such as time, location, notification triggered use), but also complementing methods that capture contextual information (Oulasvirta et al., 2012). One way to do, is by combining log data with (experience sampling method) questionaires, in-depth interviews and observations (van Berkel et al., 2016; Wagner et al., 2013).

[1] https://9to5mac.com/2018/08/01/facebook-screen-time-limits/

*Shortcoming 4: Appropriate tools for visualizing smartphone behaviors are lacking*

Visualization has often been used to simplify the complexities of data and plays a key role to grasp difficult to understand patterns (Andrews, Ellis, Shaw, & Piwek, 2015; Knigge & Cope, 2006; Ørmen & Thorhauge, 2015). Visualizations can also be used as a starting point to spark further analyses, as it highlights information otherwise invisible in raw data (Vlassenroot, Gillis, Bellens, & Gautama, 2015). To date, visualizing smartphone usage already exists to a basic level in certain logging tools that are incorporated into the newest versions of iOS and Android (Gartenberg, 2018), but a fine-grained look is not yet possible and ,no information of sequential smartphone usage is provided. Furthermore, the data these logging tools collect are not available for researchers. Therefore, some authors claim that more research is needed in the field of smartphone logging using visualization techniques rather than descriptive statistics and charts (Morrison et al., 2018).

*Shortcoming 5: Sample attrition and ecological validity*

Log based studies often suffer high attrition rates of their sample (Harari et al., 2017; Wilcockson, Ellis, & Shaw, 2018). These high drop-out rates could be due to difficulties in the onboarding process or technical issues with the logging (e.g., difficulty to install the app, compatibility issues with different phone models, battery drain, …) (Ørmen & Thorhauge, 2015), and low ecological validity (e.g., providing users a pre-installed mobile instead of their own mobile) (Hossein, Deborah, 2010). Other explanations can be found within the field of Living Labs, that suggest attrition is affected by immediate feedback (Georges, Schuurman, & Vervoort, 2016). Most logging-tools lack a sufficient feedback for the users that log their smartphone usage to keep it worthwile enough to stay involved. It has been shown that hose that do provide feedback have a lower attrition rate (Morrison et al., 2018).

**Methods**

Research design

The study was conducted in four phases in the period April 2017 and June 2018. In a first phase, we started by confronting a panel of experts with the above-mentioned shortcomings and questioned them about the desired features and design of a new logging tool for smartphone usage. In a second phase, MobileDNA was developed and evaluated by the same expert panel evaluated the content of MobileDNA. In a third phase, the internal validity of MobileDNA was tested by two small test-panels of non-experts (n = 30 and n = 70). In a fourth phase, MobilaDNA was installed by 7000 users and the external validity was evaluated by comparing total usage time and number of pickups with data from existing logging tools for smartphone usage.

Phase 1:  Pre-development phase

In the fist phase, an expert panel (n = 16) with detox experts, addiction experts, and communication and ict researchers were questioned about the desired specifications and design of a new logging tool for smartphone usage. The consensus process incorporated a three-step Estimate-Talk-Estimate Delphi method (Gustafson, Shukla, Delbecq, & Walster, 1973) in the period April and August 2017. This method is is an iterative process that uses a systematic progression of repeated rounds of opinions and is an effective process for determining expert group consensus where there is little or no definitive evidence and where opinion is important (Eubank et al., 2016; Meshkat et al., 2014). The modified Delphi method was chosen because it allowed for expert interaction in the different rounds.

In a first round, the panel was face-to-face confronted with the five above-mentioned methodological shortcomings of current logging tools. Consensus was found by the expert panel on the common denominator that both academics and practitioners struggle (a) to confront end-users with their own smartphone behavior, and (b) to make the often unconscious latent use patterns more tangible. In two additional rounds both struggles were made more concrete.

With regard to the first, the expert panel putted forward that problematic smartphone behavior, should be measurable in a way that transcends its traditional conceptualization of a monolithical concept in terms of e.g. overuse. It needs disentanglement for better, more fine-grained insights. To facilitate this disentanglement, more information of the smartphone usage is needed in terms of temporal dimensions and triggers. This information includes the sequence of apps (i.e. a session), the duration of a session, the time of day a certain session is conducted, and whether a session is triggered by a notification.

With regard to the latter, the expert panel brought on the table that smartphone behavior needs to be made tangible for the end-user, because self-reporting doesn't allow for internally valid data on smartphone usage. This point of view is consistent with the literature in which has been demonstrated that , asthat people under- or overestimate their own usage with as much as 40% (Kobayashi & Boase, 2012; H. Lee, Ahn, Nguyen, Choi, & Kim, 2017; Scharkow, 2016). As such, it was agreed that unconscious smartphone usage (or habits), like checking, gateway and conditioned behavior, needs to be recognized, understood and made visible in order to obtain a better comprehension of habitual smartphone use.

Phase 2: Development phase

In the second phase,the findings from the expert panel were elaborated in a design and requirement specification for the development of app and visualization platform by two companies (August 2017 – December 2017). During a four-months development period, MobileDNA went through four iterations. After every new release of the app a feedback loop with members of the Delphi experts was incorporated to finetune the visualizations and operationalizations of the different constructs.

Phase 3: Internal validity phase

To ensure internal validity, a small test-panel (n=30) of friendly test-users (colleagues, friends, family) was set up to test and increase the log accuracy. During a period of two months (October- November 2017) each of the panel members installed each iteration of the app, and was closely monitored by researchers to check if the logged (and visualized) smartphone behavior correspondend to their actual smartphone behavior. Using screen captures to ensure precision, diaries to ensure long-term validity, and face-to-face or telephone interviews (at least every 3 days), quick feedback loops to check anomalies and internal validity was ensured.

In a next step, a bigger sample of students (n=75) installed the application in the periode December 2017 – January 2018 to validate a variety of smartphone models and operationg systems, test a bigger load on the server side and further finetuning of the logging itself. Also the students were followed using screen captures, diaries, interviews and quick feedback loops (1 contact moment/week). These internal validity tests changed, among other things, our operationalization of notifications and sessions and de-bugged the app for some operating systems and devices.

Phase 4: External validity phase

In January 2018 (24/01/2018) a public release of mobileDNA (Google Play Store) took place. From that period till June 2018, more than 7000 people installed MobileDNA for varying time periods (cumulatively already resulting in more than 750 years of combined smartphone log data after 7 months).

To assess the external validity of mobileDNA, we elaborated on a recent study of Zhu et al. (2018) in which five studies are compared on three key estimates of mobile phone use (i.e., total length, session length, and frequency of sessions). In Table 1, Mobile DNA log data are compared with the five studies on the same three key estimates of smartphone usage for a random subset of N:1000 Mobile DNA testers that had the app running for at least 3 weeks.As shown in Table 1, no systematic difference can be observed between the results of mobileDNA and the other studies. The total usage time (171 minutes per day) as well as the number of pickups or sessions (n = 66/day) is very close to the observed total usage time of Zhu et al. (2018). The mean session length is in line with Yang et al. (2015) and Van Canneyt et al. (2017), contrary to the other studies Mobile DNA was able to distinct well between single app sessions and multiple app sessions. In the latter, the average number of app events in each session was 3,8 (illustrating gateway behavior as described by Oulasvirta et al.; 2011). And the ratio between multiple app (gateway) sessions vs single app sessions was 60,5 vs 39,5.

Table 1.

Comparison with benchmark studies, adapted from Zhu et al. (2018)

| | MobileDNA | Zhu et al. (2018) | Winnick (2016) | Falaki et al. (2011) | Yang et al. (2015) | Van Canneyt et al. (2017) |
|---|---|---|---|---|---|---|
| Total time length (min) | 171 | 175 | 145 | 30-500 | 300 | n/a |
| Mean session length (min) | 6,6 | 17 | n/a | 0,2 – 4,2 | 8-41 | 5-7 |
| Mean N of sessions | 66 | 24 | 76 | 10-200 | n/a | n/a |
| N of apps per session | Multiple (60,5%) & Single (39,5%) | Multiple | Multiple | Single | Single | Single |
| Mean # apps per session | 3,8 | n/a | n/a | n/a | n/a | n/a |

## Results

MobileDNA as a logging tool

In line with the study of Zhu et al. (2018) and Falaki et al. (2010), MobileDNA follows a screen-based and session-based approach to log smartphone usage. This means that MobileDNA does not log smartphone usage if the screen is not active, but only when the attention of a user is required. Using the smartphone to listen to music (with headphone, without an active screen) for instance, is not considered and logged as active smartphone time.

As requested by the panel of experts and academic scholars(Humphreys, 2013; Morrison et al., 2018; Oulasvirta et al., 2012; Zhu et al., 2018), analyses on the sequence and triggers of certain app usage is possible: MobileDNA granularly logs everything on the app level for all apps on one device (location, app-usage time, battery percentage and smartphone type), in combination with notifications and the sequence of apps.

User friendliness

As MobileDNA is a stand-alone app that is freely available in the Google Play Store, it ensures availability across different countries and different smartphones. Offering mobileDNA through the Google Play Store also simplifies the onboarding process and lowers the risk of drop-out; and ensures ecologic validity as the app is installed on their own phone, instead of a device for sake of the research (Do & Gatica-Perez, 2010). The data collection happens continuously and is stored locally until the device detects a wifi connection. Only then, all the -not yet backed up- data is transferred through a secure connection to servers. This way, per device, an average amount of 5MB, representing approximately 15.000 entries, is transferred on a monthly basis. With a data transfer only over wifi, logging that happens locally, and all calculations on the server-end, the battery resources required to run Mobile DNA remain marginal (<1%).

Privacy protection

Before any logging takes place, respondents need to agree with the user policy and give a set permissions on their smartphone to allow MobileDNA to log data. To ensure anonimity of the respondent, an anonymous ID is created when the app is activated. Also the respondents' e-mail address is asked during the activation of the app to enable users to invoke their rights (e.g. right to be deleted). This e-mail address is stored with a trusted third party ensuring anonimisation of log-data. Depending on research design this anonymous ID can automatically be linked to other research data (e.g. collected through interviews, surveys…) using an intermediary anonymous identifier. In those cases other informed consents are used to reflect these properties.

All the data are stored on a secured server, for which two members of the MobileDNA research team act as the only gatekeeper. Each time data is transferred to other researchers there is a timeframe contractually agreed upon when all data needs to be deleted from their storage. This enables to act upon requests from test users to delete their data as the only copy of the data is kept on the mobileDNA servers.

MobileDNA as a research tool

To make mobileDNA as transparent as possible, the log-data are managed and aggregated in three layers, where each layer incorporates another level of interpretation by the researcher.

*Layer 1: Base level*

On the base level, all app-events of every activity on the smartphone are recorded without any interpretation (apart from the decision not to log what someone does in an app) is given. This level consists of the raw log-data and can be used by researchers that want to apply a machine learning or bottom up data driven angle on behavioral smartphone research. Variables on this level are ID, appname, session, start time, stop time, notification trigger, battey percentage, smartphone model and location.

*Layer 2: App-sessions level*

A first aggregation level is the level of app-sessions (sequence of apps that were used in the duration the smartphone screen was on). On this level extra aggregations can be made using the app-events level (e.g. fraction of social apps in one session…). These aggregations are the result of a certain interpretation of researchers / developers. Variables on this level include ID, session, Date, Timestamp, and app count.

*Layer 3: Respondent level*

A second aggregation level is the level of the respondent where all data concerning one respondent is bundled. Also in this level extra aggregations are possible using data form the app-events of app-sessions level. Variables on this level include ID, appcount and sessions.

Visualisation of MobileDNA

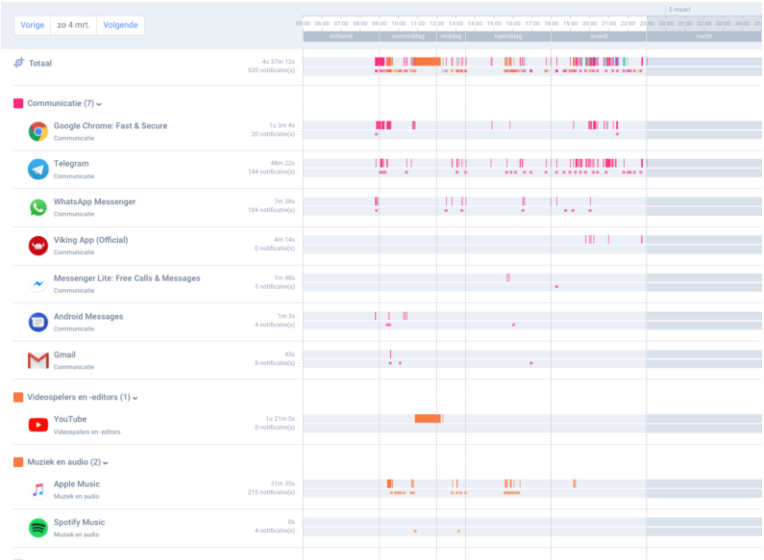
To make the latent and often unconscious smartphone usage more tangible, different visualizations are built on top of above-mentioned three layers.

*Layer 1: Base level*


MobileDNA enables the users to make a general assessment of their behavior by showing them a dashboard with an overview of their usage in terms of the average amount of apps used, average daily usage, overview of concentrated use during the week, average amount of notifications and the top 5 listing of apps (based on duration as well as the number of pickups). This first insight gives an answer to the common demand for easy and quick low level insights (Wijk, 2009).

*Layer 2: App-sessions level*

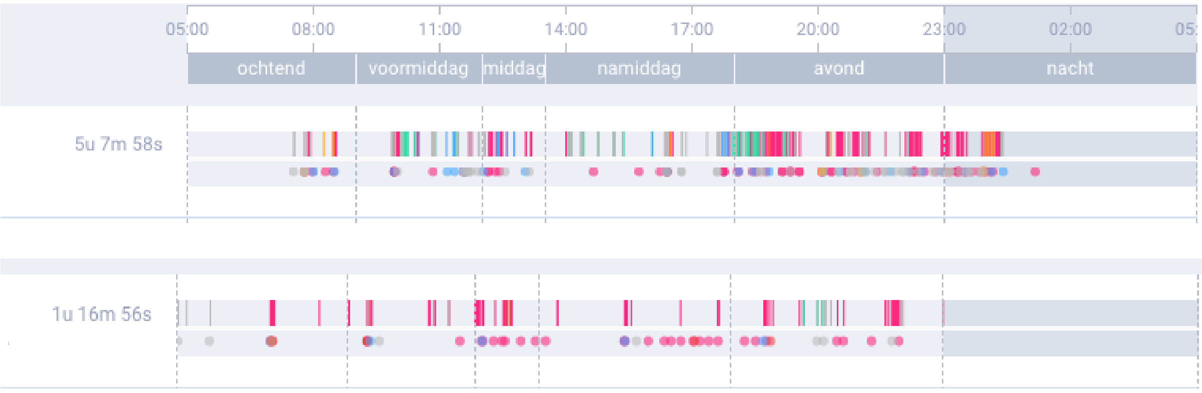
## 2. Mobile DNA




**What?**
**Daily Overview of:**

- Notifications
- App usage

**When?**
After 1 full day of logging

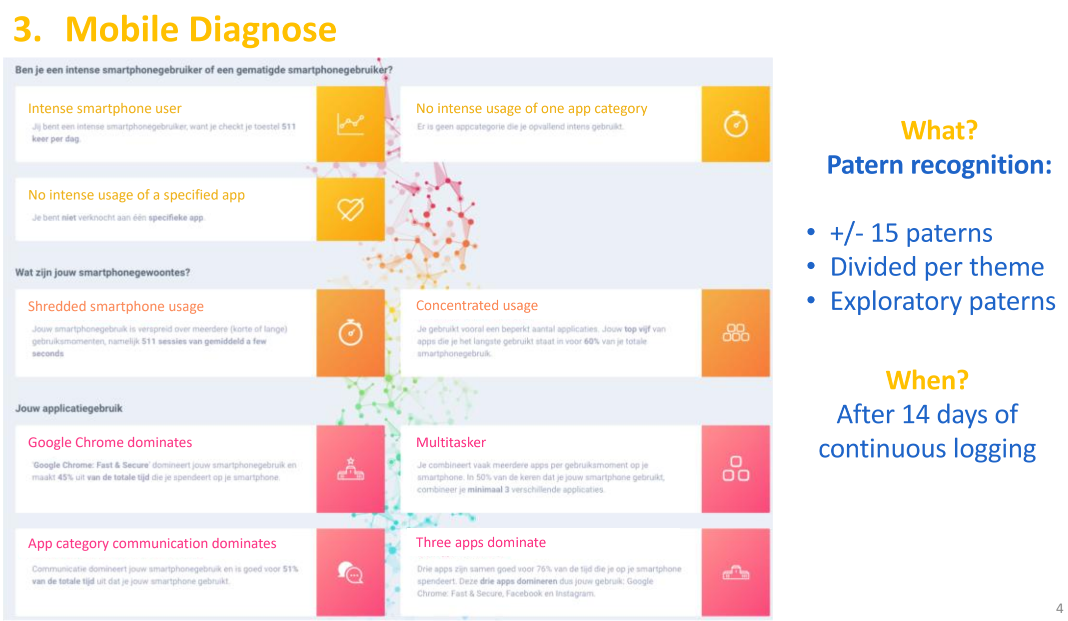



MobileDNA enables the user to dig deeper and investigate their usage of one day. By plotting the usage as a timeline, data are presented in a relational form, where the users are able to gain insight in their consecutive behavior (Shen & Kwan-Liu, 2008). This DNA visualization is based on frequency, timing and sequence of sessions, apps and notifications. It facilitates a better detection of use patterns and should enable a better understanding of smartphone habits.

The figure below for example surfaces the use and notifications of two specific apps of one person, Instagram and Whatsapp. Instagram for example adds up to 1h21minutes per day for this person, but also nicely illustrates the behavioral pattern of an influencer. In the morning the app is hardly consulted. Over noon it is a few times consulted, but then als 21 minutes are spent in an photo app (PicsArt Studio) to work on a photo. As soon as the photo is posted in Instagram, the notifications (dots) start coming in, acting as a trigger to start checking behavior and on the number of likes and comments (lionpart or the time spent).


The combination of time spent and notifications on whatsapp illustrates how Mobile DNA can easily reveal compulsive checking behavior and conditioning by apps and notifications. During the day this person received 78 notifications (pink dots), but as the sequential visualization illustrates, most (56 out of 78) notifications are immediately (within 60 seconds) followed by usage of the app. No matter where the person was (at home, in car, at work …).

*Layer 3: Respondent level*




Lastly, both types of data form the basis for a mobile diagnosis, in which the tool automatically identifies patterns in individuals' smartphone behavior (e.g. is there a dominant app, responsible for a large share of the smartphone usage; is the participant a 'wanderer', meaning that using one app automatically leads to opening other apps; does (s)he instantly open notifications as a Pavlovian reflex;…).

**Conclusions and discussion**

With MobileDNA a new logging tool is presented that enhances the process of smartphone logging with a mutual reinforcing  benefit for researchers as well as respondents in terms of ease-of-use, validity and transparency. By combining macro-level time expenditure, notification and pickup metrics with a more accurate captation of data on the level of app (sequence) and notifications, as well as a simultaneous visualization to make sense of those data to end-users and less tech-savvy researchers and practitioners, MobileDNA overcomes limitations of self-reporting in terms of underestimation (time spent) or unawareness (habitual use patterns or context triggers); and broadens the potential for user, market, academic as well as policy stakeholders to get closer to actual smartphone behavior. This combination of data captation and visualization on different levels, is a methodological leap forward that transcends the (five) methodological shortcomings of traditional self-reporting and existing log tools for smartphone use. Apart from a general overview of use stats – comparable to other log tools – MobileDNA allows users to compare their use vis-à-vis a larger group, and makes the difference by feeding back data to end-users in terms of a 'DNA'-like visualization. This DNA not only gives an overall overview of ones combined app use per day, but also allows a disentanglement of that DNA per app (sequence) in terms of time spent as well as notifications. Combined with an extra level of feedback in terms of 'pattern detection' in one's DNA, Mobile DNA gives significant added value for end-users that make it worthwile using for themselves. As a consequence of this higher value and intrinsic motivation, research panels have longer retention, less drop-out, and more accurate data collection over time. With this immediate and more granulated insight in one's smartphone use, also practitioners and researchers are provided with a tool that brings them in a more comfortable position (cf. point of pain revealed in the Delphi stage) to start interacting and reflecting on the smartphone use of their respondents, as Mobile DNA immediately reveals an accurate insight in the total as well as unconscious habitual use patterns, equally graspable for researcher, practitioner, respondentor end-users .

Hence, for the researcher – also for those not mastering programming skills to make sense of big (logging) data - , mobileDNA ensures a transparent data-collection by including different levels of aggregation together with the raw data. Furthermore, the process of linking log data (from mobileDNA) with other collected data is simplified and automated in a way that ensures anonymity for the respondent and validity for the researcher. The level of precision together with this linking method enables researchers to easily take into account individual differences and thus retain a great level of granularity.

For the respondent, mobileDNAs' continuous development and optimization ensures a performant app, minimizing the impact on battery life and performance of the smarphone. The comprehensive set of visuals based on individual logdata that is feeded back to the respondents or other end-users allows them to get an overall insight in their smartphone use patterns.  An insight that will help to overcome users' current struggle (Digimeter, 2018; Ernst & Young, 2018) to find appropriate, more efficient and personalized (Van Roekel et al. 2017) coping strategies to domesticate their smartphone in a way that is prefered by the individual.

A contextualizing insight that might also help to bridge the chasm with the tools that are currently provided by the market[2]. In the first half of 2018 alle major players in the 'mobile economy' (Samsung, Google/Android, Facebook, Apple …) came with their tools(et) to enable end-users to take back control over their screentime. Appropriate use of these tools however (and I refer to the example given earlier in the paper about 2 persons with a similar Facebook use on their smartphone) require a broader contextualized insight in one's smartphone use, that can be provided by Mobile DNA.

Policy stakeholders at last, currently struggling with discussions on the value of legislative restrictions of smartphone use (e.g. ban in schools (Macron, France) or for truckers on the road), or how to integrate 'device literacy' into media literacy educational programmes; might benefit from Mobile DNA based research to base decisions on true data rather than moral panic. Monitoring smartphone use on

[2] In August 2018 Facebook announced Screen Time tools fort heir main Facebook app as well as Instagram (https://9to5mac.com/2018/08/01/facebook-screen-time-limits/ ). In May 2018 Google reported their plans to come up with Android tools the help manage screen time (https://www.engadget.com/2018/05/07/google-android-tools-manage-screen-time/?guccounter=1); and device manufacturers as Samsung launched their own app (Thrive: https://news.samsung.com/us/introducing-thrive-marc-mathieu-focus-on-what-matters-most/ ) to domesticate the smartphone, or got confronted with shareholders (Apple) urging them to do the same (https://www.forbes.com/sites/alicegwalton/2018/01/09/investors-pressure-apple-over-psychological-risks-of-screen-time-for-kids/#2cceb38f38df)

app level might for example learn up to which degree smartphones in classrooms facilitate interaction or distraction.

**Challenges for the future**

Despite the potential value for user, market, policy maker and scholar, Mobile DNA also suffers from limitations that require some further research. The choice not to log what people do in a certain app reduces privacy concerns, but also limits what information we have on specific app usage. Other methods like ESM (e.g. PACO) could substitute this. Furthermore, mobileDNA can be used on a broad range of Android smartphone, however, not on iOS. The architecture of iOS is completely different from Android and the properties needed for this type of logging are not accessible for developers in iOS. Other research has developed a loggingstool for a specified subset of jailbroken iOS devices(Morrison et al., 2018). Their findings add confidence in claims of consistency across different operating systems. In iOS 12 a certain kind of logging is baked into the OS. This logging tool is not able to produce the kind of precision mobileDNA does. Researchers, furthermore, don't have access to this data or to the raw data.

Furthermore, mobileDNA lacks a clear breakdown of notifications. Currently, no division is made between system notifications (e.g. low battery percentage) and app notifications or between notifications that demand attention (e.g. messages, game notifications…) and informative notifications that doesn't require any attention (e.g. the name of the song playing on spotify). It is, however, possible to manually disregard the notifications that are of less interest to certain research studies. This division is important to ensure accurate and precise insights in the notification triggered activities.

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