Understanding, Discovering, and Mitigating Habitual Smartphone Use in Young Adults

ALBERTO MONGE ROFFARELLO, Politecnico di Torino, Italy
LUIGI DE RUSSIS, Politecnico di Torino, Italy

People, especially young adults, often use their smartphones out of habit: they compulsively browse social networks, check emails, and play video-games with little or no awareness at all. While previous studies analyzed this phenomena *qualitatively*, e.g., by showing that users perceive it as meaningless and addictive, yet our understanding of how to discover smartphone habits and mitigate their disruptive effects is limited. Being able to automatically assess habitual smartphone use, in particular, might have different applications, e.g., to design better "digital wellbeing" solutions for mitigating meaningless habitual use.

To close this gap, we first define a data analytic methodology based on clustering and association rules mining to automatically discover complex smartphone habits from mobile usage data. We assess the methodology over more than 130,000 phone usage sessions collected from users aged between 16 and 33, and we show evidence that smartphone habits of young adults can be characterized by various types of links between contextual situations and usage sessions, which are highly diversified and differently perceived across users. We then apply the proposed methodology in Socialize, a digital wellbeing app that *i)* monitor habitual smartphone behaviors in real time, and *ii)* uses proactive notifications and just-in-time reminders to encourage users to avoid any identified smartphone habits they consider as meaningless. An in-the-wild study with 20 users (age 19-31) demonstrates that Socialize can assist young adults in better controlling their smartphone usage, with a significant reduction of their unwanted smartphone habits.

CCS Concepts: • **Human-centered computing** → **Empirical studies in HCI**; **Smartphones**; **Empirical studies in ubiquitous and mobile computing**; User models; • **Computing methodologies** → *Cluster analysis*; Machine learning;

Additional Key Words and Phrases: Smartphone Usage; Smartphone Habits; Digital Wellbeing.

ACM Reference Format:
Alberto Monge Roffarello and Luigi De Russis. 2021. Understanding, Discovering, and Mitigating Habitual Smartphone Use in Young Adults. *ACM Trans. Interact. Intell. Syst.* 1, 1, Article 1 (January 2021), 34 pages. https://doi.org/0000001.0000001

1 INTRODUCTION

Just as personal computers in the 1990s, smartphones have become an integral part of our daily lives, and their usage is so increased [56] that we cannot longer leave home without them [49]. Through smartphones, we can nowadays perform many different tasks with a handful of taps on the screen: we can read New York Times news while chatting with a friend on WhatsApp, we can watch films, check our emails, and browse social networks to pass the time. Despite many advantages and increasing opportunities for social support [76], however, the last few years have

Authors' addresses: Alberto Monge Roffarello, Politecnico di Torino, Corso Duca degli Abruzzi, 24, Torino, TO, 10129, Italy; Luigi De Russis, Politecnico di Torino, Corso Duca degli Abruzzi, 24, Torino, TO, 10129, Italy.

2160-6455/2021/1-ART1 $15.00
https://doi.org/0000001.0000001

seen a growing amount of research attention on the negative aspects of overusing smartphones, with several studies talking about excessive smartphone usage as an addictive behavior [44, 81]. In response, many different mobile apps for achieving what Google defined "digital wellbeing [1]" and controlling smartphone use are nowadays used by millions of users [54].

Classifying widespread and everyday behaviors like mobile devices use under the umbrella of addictions is not supported, at least at this moment, by sufficient evidence [40]. Indeed, while previous studies [5, 71] have found that many people feel conflicted about the time they spend with Internet-connected digital technologies, yet other studies [23, 40, 41] suggest that such feelings are influenced by the "moral panic [78]" emerging from public discussions and news on popular media [12, 62]. What is clear, however, is that users experience difficulties in controlling their smartphone use [25, 36, 37, 44], especially when this is the result of a compulsive *habit* [42, 49, 56, 78]. Indeed, people often use mobile devices to compulsively browse social networks, check emails, and play video-games with little or no awareness at all: such habit-driven sessions with smartphones are typically associated with a meaningless experience, which erode users' intentions and make them feel a loss of autonomy over their own behavior [49].

Previous works provide an overall view of such a phenomena, e.g., by conducting various kinds of surveys and/or interviews [49, 78]. Furthermore, prior research that aims at characterizing smartphone use do not explicitly target complex habitual behaviors, e.g., they compare application use across all users [69], or explore simple usage patterns such as checking habits [56] and revisitation patterns [31], only. As such, our understanding of how to discover smartphone habits and mitigate their disruptive effects is limited. Being able to comprehensively and automatically assess habitual smartphone use might have different applications, such as, in the digital wellbeing context, and it could be the first step towards designing new solutions that promote meaningful experiences with mobile devices, as called for by recent studies [49, 78].

Fig. 1. An overview of the steps we conducted in our work. In the first phase, we characterize smartphone habits and we define a data analytic methodology to automatically discover them. In the second phase, we apply the methodology in Socialize, a digital wellbeing mobile app that assist users to avoid the smartphone habits they consider as meaningless.

To close this gap, this paper presents a novel approach to automatically discover habitual users' behaviors with their smartphones, along with its application in a digital wellbeing app that assists users to avoid what they perceive as meaningless smartphone habits. We focus, in particular, on the smartphone habits of young adults: prior studies [44, 85], indeed, demonstrate that young generations are highly susceptible to problems related to habitual smarthpone use. Figure 1 provides an overview of the steps conducted for this work. The contribution is twofold:

(i) We present a **data analytic methodology** based on clustering and association rules mining to automatically discover complex smartphone habits from usage data (Figure 1, phase 1). Stemming from previous work on habitual smartphone use, we characterize smartphone habits by taking into account contexts, mobile apps, and user differences. Contextual cues such as a given location or a performed activity unconsciously spur the user in performing a behavioral routine, e.g., browsing the Facebook timeline through the smartphone app.

When the routine ends, the user experiences a reward, e.g., the feeling of social success, that, over the time, transforms the link between the contextual situation and the performed routine, i.e., the used applications, into an automatic habit. To automatically detect such habitual behaviors, the proposed methodology first preprocesses smartphone usage data to build usage sessions. Then, sessions are filtered through clustering and aggregated with contextual information. Finally, data is analyzed to extract association rules that model strong correlations between contextual cues and used applications. By assessing the methodology over a dataset containing more than 130,000 phone usage sessions collected in-the-wild from users aged between 16 and 33, we show evidence that smartphone use of young adults can be characterized by different types of complex links between contextual situations and usage sessions, that are highly diversified across users. A follow-up interview with 10 participants that contributed to the dataset further validates the proposed methodology, and confirms that the users' perception on their smartphone habits depends on the kind of habit [78]. Behavioral routines triggered by precise contextual cues, for example, are more likely to be considered negative and meaningless behaviors, and the less a habit is positively perceived, the more the user would like to change it.

(ii) We apply the proposed methodology in *Socialize*, a digital wellbeing mobile app that assist users to avoid the smartphone habits they consider as meaningless (Figure 1, phase 3). Socialize constantly monitors the user's behavior with her mobile device, and it proactively notifies detected smartphone habits in real-time. If the user considers a notified habit as meaningless, she can activate a personalizable just-in-time reminder to be encouraged to avoid the identified behavior when it happens again. An **in-the-wild evaluation** with 20 participants (age 19-31) shows evidence that Socialize can effectively assist young adults in better controlling their smartphone use. About 40% of all the calculated habits were considered as meaningless behaviors to be avoided, and the provided just-in-time reminders helped participants to significantly reduce their unwanted smartphone habits, thus promoting a more meaningful experience with mobile devices.

The remainder of this paper is structured as follow. Section 2 reviews previous works on habitual smartphone use. Section 3 presents a characterization of complex smartphone habits and describes the data analytic methodology to automatically discover them from usage data. Section 4 reports on the assessment of the habit-discovery methodology on real-world data, along with the follow-up interview with 10 users. Section 5 presents Socialize, the digital wellbeing mobile app that makes use of the proposed data analytic methodology, and describes its in-the-wild evaluation. Section 6 reports on the results of the in-the-wild evaluation. Eventually, Section 7 discusses the implications of our work, while Section 8 concludes the paper.

2 UNDERSTANDING SMARTPHONE HABITS

To gain an initial understanding on smartphone habits, we reviewed previous studies in the last 10 years that talk about smartphone use under the lens of habits. Relevant papers were identified by searching the electronic database of Google Scholar[1] and the ACM Digital Library[2]. The ACM Digital Library is one of the most comprehensive bibliographic database in the field of computing and HCI research. We decided to include Google Scholar to have a broader perspective on the topic, e.g., to include research papers coming from psychology venues. The final corpus presented here is the result of two separated searches conducted on the 13th of January 2020 and on the 10th of October 2020, respectively. In the first search, we explored *what* smartphone habits are and *why*

[1] https://scholar.google.it/, last visited on November 5, 2020
[2] https://dl.acm.org/, last visited on November 5, 2020

they form, by using search terms like "smartphone habits," "smartphone addiction," and related synonymous. In the second search, we focused on *when* habitual use occurs and can be predicted, by using search terms like "smartphone behavior," "app usage prediction," and related synonymous. The adopted procedures, including the full set of search queries, are detailed in Appendix A. At the end of the two analysis, our corpus was composed of 30 papers. Of these papers, 21 were full-length conference publications, while 9 were journal articles. The majority of the analyzed conference papers have been presented at UbiComp (11) and MobileHCI (4), while the most common journal included in our analysis was Computers in Human Behavior[3] (6). Table 1 summarizes the codebook resulting from our two analysis.

Table 1. The codebook resulting from the analysis of the literature on habitual smartphone use. Items are classified in three main codes: *what* smartphone habits are, *why* they form, and *when* they can be automatically predicted.

Code	Description	Items
What	Among studies on smartphone use characterization, only a subset of them explicitly analyzes smartphone use under the lens of habits. They explore different types of simple habits, ranging from *checking* to *revistation* patterns.	Checking Habit [19, 31, 36, 56, 66, 81, 83] Launching Habit [22] Communication [10, 56] Texting while Driving [8] Complexity [83, 84] Revisitation [31]
Why	Instead of focusing on *what* smartphone habits are, different studies analyze *why* they form. Smartphone habits are triggered by a *cue*, and they make users experience a *reward*.	Intrapersonal Cue [19, 45, 56, 78, 85] Contextual Cue [10, 19, 28, 36, 56, 70, 83] Information Reward [31, 56, 81] Intrapersonal Reward [13, 49, 85] Social Reward [48, 56, 81]
When	Previous works started to investigate *when* certain habitual smartphone behaviors occur, e.g., to predict how users will interact with future *notifications* and used *apps*.	Notifications Interaction [15, 53, 59] Next App Prediction [6, 28, 57, 74] Mood Detection [46, 60] Usage Classification [26, 69]

2.1 What - The Different Types of Smartphone Habits

The habit-forming nature of smartphones is yet an underexplored topic. Despite a large body of literature on smartphone use characterization, we found that only a subset of studies explicitly analyzes smartphone use under the lens of habits, i.e., by exploring *what* smartphone habits are and how they can be defined. One of the most studied habitual smartphone behavior is the *checking habit*. Oulasvirta et al. [56] define it as a "brief, repetitive inspection of a dynamic content quickly accessible on the device." Checking is often the result of a self-interruption to check online contents, missed calls, or messages [36], and it is repeated since new messages, notifications and news satisfy the user's needs [81]. As reported by Ferreira et al. [19], checking habits are often manifested as application micro-usage, i.e., brief bursts of interaction with applications. Through different users studies, the authors found that micro-usage is a frequently occurring phenomena that is most likely to happen when users are alone, with 15 seconds the most common interval for many uses of an application. Despite micro-usage is not a behavior that characterize mobile devices, only [14, 21], smartphones promote by construction such a behavior: notifications, for example,

[3] https://www.journals.elsevier.com/computers-in-human-behavior, last visited on November 5, 2020

often spur the usage of other mobile apps [83], and mobile devices are nowadays the "companions" we can use in moments of "potential boredom [19]". In studying the correlations between phone usage sessions and problematic use of the smartphone, Shin et al. [69] demonstrated that users with problematic smartphone use tend to have more sessions triggered by checking events, and they also tend to open more mobile apps in the same session. In their 3-months analysis of application launch logs, Jones et al. [31] suggest that smartphones do induce usage habits at the micro level. By applying a methodology extensively adopted in the context of web browsing, i.e., revisitation analysis [77], the authors discovered that much of our habitual use of smartphones is not driven by the technology's characteristics, but rather by the characteristics of the services we have. On smartphones, in particular, we have a few installed applications to choose from, and we tend to use and re-use them within individual sessions.

Besides checking habits and revistation patterns, only few previous works take into account other types of habitual behaviors with smartphones. Bayer et al. [8], for instance, studied a very specific (and dangerous) behavior with smartphones, i.e., *texting while driving*. They demonstrated that texting while driving is a behavior that is partially attributable to individuals doing so without awareness, control, attention, and intention regarding their own actions. Hang et al. [22], instead, discovered that habits can be found in how users use launching menus. Individual *launching habits*, for example, include the usage of the notification bar, home screen panels, and widgets. Previous works also suggest that the need of *communicating* with other people is an important contributor for habitual smartphone use [10, 56]. Individuals often experience social success when communicating via their smart devices [56]: despite the variety of available apps, communication apps are almost always the first ones used when a user unlock the smartphone screen [10].

Overall, the reported analysis shows that, as for the majority of prior research that aim at understanding mobile device usage [56], even works that use the lens of habits still continue to explore very simple recurrent patterns in smartphone data, by comparing application use across all users. The commonly-held assumption that all smartphone users are either similar or can be classified into a small number of types, however, has been found to be too simplistic [83, 84]: in this work, we aim at investigating the *complex* nature of smartphone habits, by considering contexts, mobile apps, and user differences *at the same time*.

2.2 Why - How Smartphone Habits Form

Instead of focusing on *what* smartphone habits are, different studies analyze *why* smartphone habits form. According to prior research, smartphone habits are triggered by *cues* of different types. In some cases, such cues can be associated to users' internal states: the lack of stimulation or a desire to "stay on top," for example, could become a cue that spurs the users in checking social networks or messaging apps, e.g., to see if there are new information available, like posts or messages [56]. Such *intrapersonal* cues can be associated to the different emotional states, often negative, that individuals experience before using the smartphone [56, 85]: users, in fact, often turn to their phones to escape from negative emotions [49]. According to Lee et al. [45], five characteristics may increase an individual's risk of developing problematic smartphone habits: external locus of control, materialism, social interaction, anxiety, and the need for touch. Furthermore, through a qualitative study with 39 smartphone users, Tran et al. [78] demonstrated that a small set of common triggers, such as moments of downtime and social awkwardness, lead individuals to habitually check their phones. According to the authors, these habitual sessions last until an outside factor intrudes, e.g., the users' self-refection and recognition that their smartphone use is meaningless. Also loneliness has been found to be a significant predictor of habitual smartphone usage: lonely students, for example, are more likely to use a mobile phone as a matter of habit to get away from current situations in which they are involved [19]. Students, and, in general, young generations, have been found to be largely affected by problems related to smartphone overuse [44, 85]. For this reason, our work targets the smartphone habits of young adults. In particular, we report on the results of two studies (Section 4 and Section 6) involving participants aged between 16 and 33.

Besides intrapersonal emotions, the *context* in which the smartphone is used can be a cue for a habit [56], too. By collecting and analyzing a wide range of smartphone information from 23 users over a one-month period, Shin et al. [70] demonstrated that several contexts such as the last application and the hour of day are important influences for predicting the usage of a mobile app. The analysis of a large dataset of smartphone data [43] conducted by Huang et al. [28] confirms these findings: messages and notifications, in particular, often trigger other follower apps in a session [83]. Such studies suggest that users' behavior with smartphones is highly habitual and easily linkable to observable contexts. In this respect, also locations [19] and performed activities [36] can highly influence how users interact with their mobile devices. Users' group activities are often distracted by external usage cues, e.g., notification alarms [36]. Besides receiving notifications, users experience internal stimuli as well, e.g., they frequently interrupt themselves to check their smartphones for new content [56]. Furthermore, some users may have strong tendencies at a core set of tightly defined locations such as home and work, whereas others exhibit more diversity [83]: Bohmer et al. [10], for instance, discovered that people who are traveling are more likely to use multimedia apps but surprisingly less likely to use travel apps. Different studies, in general, demonstrate that smartphones can become a source of distraction by subjecting users to both external and internal stimuli.

Another important factor in the formation of smartphone habits is their ability to provide users with a *reward*. Rewards are often *intrapersonal*, i.e., related to the internal emotional states of the user: users who primarily use the value-added functions of a smartphone, in fact, may experience higher enjoyment and easily form habitual usage behavior [13]. A study with 216 smartphone users of different generations by Zhitomirsky-Geffet and Blau [85] further confirms that smartphone use may help relieve an individual's negative emotions and moods and increase fun and self-confidence. This emotional gain motivates users to use their smartphones even more excessively and habitually, e.g., as a distraction from ongoing tasks, without specific rational need and with less self-regulation and control. A particular type of intrapersonal reward is related to the *social* dimension [48, 81], since users may experience a feeling of social success when communicating via their smart devices. This behavior is accentuated by the characteristics of some specific apps, e.g., social networks and messaging services, that allow users to quickly get access to rewards like social networking, communications, and news [56].

Another type of reward is related to the craving for new *information*. Informational reward is provided by dynamic information quickly accessible from the smartphone, e.g., new contents posted on news feeds [56]. As suggested by Jones et al. [31], smartphone habits are often driven by the information needs we have: checking habits, for example, are repeated since new messages, notifications and news feeds function as rewards [81].

2.3 When - Predicting Habitual Smartphone Use

Stemming from studies describing *what* smartphone habits are and *why* they form, researchers started to investigate how to predict *when* habitual use occurs. Being able to predict habitual smartphone behaviors, indeed, may help developers to design mobile apps able to detect when the phone is used mindlessly or problematically [26, 69], thus promoting by construction meaningful and intentional experiences for their users [49].

Previous works identify the user's habitual *interaction* with *notifications* as one of the aspects that can be predicted and therefore improved. By analyzing how users habitually deal with notifications, in particular, it is possible to anticipate whether they will engage with a notification in a given context. To pursue such a goal, Pielot et al. [59] collected smartphone usage data and questionnaire notifications from 337 users over a period of 4 weeks, and they built a machine-learning model to predict opportune moments to interrupt users with a notification. With a similar goal, Mehrotra et al. [53] presented an in-depth analysis investigating the influence of user's location and activity on the interaction behavior with notifications. They found that users are more willing to accept and pay attention to notifications in specific locations, with different response behaviors that are associated to different places. Prior research in this field also demonstrates that predicting user's interaction with notifications may streamline specific app-related goals. In their QuickLearn mobile app, foe example, Dingler et al. [15] used interactive notifications deployed at specific moments, e.g., in-between tasks, to spur microlearning sessions to practice with foreign languages.

Besides notifications, researchers also propose to analyze contextual information and smartphone usage patterns to predict the *next app* the user is going to use. An efficient next-app prediction has several applications, e.g., pre-loading the right app to improve memory management and app execution [57] or highlighting desired apps in the home screen for quicker launches [74]. An example of a model for next-app prediction is the work of Huang et al. [28]. The authors presented a linear and a Bayesian model by exploiting different contextual features such as time, location, and last used app. They found that the last used app is a strong contribution to the prediction accuracy, with the linear model that turned to be the more effective in combining all the contextual information. Similarly, Baeza-Yates et al. [6] proposed a prediction mechanism to show users which app they are going to use in the near future. They modeled app prediction as a classification problem, and they exploited two kinds of features, i.e., basic features obtained from smartphones sensors and session features modeling sequential patterns of app usage. In their experiments, the authors demonstrated that session features are effective to boost the performances of their algorithm.

Instead of focusing on notifications or next apps, some previous works analyze smartphone usage data with the aim of *classifying* habitual smartphone use under well-defined categories. By leveraging state-of-the-art machine learning algorithms and different smartphone-based features, for instance, Shin et al. [69] presented a detection model to predict problematic smartphone usage. Hiniker et al. [26], instead, applied the Use and Gratifications Theory to develop a classification scheme for predicting ritualistic *vs.* instrumental smartphone use. The authors found that several factors, e.g., the type of app and the time of day, are associated with either instrumental or ritualistic smartphone use. Users that seek ritualistic gratification, for instance, are more likely to habitually browse social networks or playing games.

Rather than predicting smartphone behaviors, a few studies adopt an opposite approach: they analyze habitual smartphone use to predict the current *mood* of the user, i.e., they try to extrapolate the intrapersonal cues that spur users in habitually using their smartphones. The MoodScope system [46], for instance, infers the mood of its user based on how the smartphone is used. By analyzing communication history and application usage patterns, in particular, MoodScope can predict whether the user is in a neutral, active, or pleased state. The machine-learning model presented by Pielot et al. [60], instead, can automatically infer boredom from mobile phone usage. According to the authors, in particular, the most discriminative features to detect boredom are recency of communication, usage intensity, time of the day, and demographics.

The reported analysis shows that prior research aiming at predicting smartphone habitual use either focuses on specific interactions, e.g., notifications, or generic classifications, e.g., ritualistic *vs.* instrumental use. To complement previous work, we seek to predict different kinds of smartphone habits, by taking into account several contextual information and usage patterns.

3 DISCOVERING SMARTPHONE HABITS: A DATA ANALYTIC METHODOLOGY

In this section, we first present a characterization of smartphone habits that takes into account contexts, mobile apps, and user differences. Then, we describe our data analytic methodology based on clustering and association rules mining to automatically discover complex smartphone habits from usage data.

3.1 Smartphone Habits Characterization

Habits characterize much of our everyday life: we have habitual behaviors when eating [30, 64], in our environmental behaviors [35], and when we perform physical activities [2, 63]. Even the usage of technology [47], including the usage of social networks [65, 66], has been proven to promote the formation of new habits. Generally speaking, a habit arises when a behavior is constantly repeated in the presence of stable cues. These cues increase the automaticity of that behavior [38]: when the user performs the behavior non-consciously, i.e.,"*enacted with little conscious awareness* [55]", we are dealing with a habit. As suggested by Gardner [20], in particular, a habit can be viewed as a link in associative memory between a certain situation and a specific response, i.e., a learned impulse to perform a particular behavioral routine triggered outside of conscious awareness by a particular situation [61]. When the routine ends, the user can experience a rewarding feeling. When rewarded, the brain considers the routine as important: over time, the strength between the given situation and the behavioral routine grows, and the routine becomes even more automatic [52, 72]. The previous works we analyzed in Section 2 clearly confirm that also the usage of smartphones can be characterized by habitual behaviors: habitual behaviors with smartphones, including simple checking habits, are triggered by some external [70] or internal [56, 85] cues, and they make the user experience a rewarding feeling [13], e.g., increasing fun and self-confidence [85].

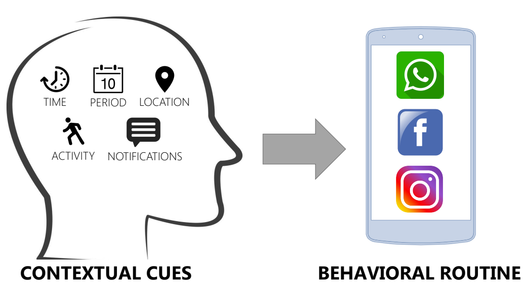


Fig. 2. The figure exemplifies the elements we take into account in our smartphone habits characterization. Discovering a habit means discovering the link between specific and measurable contextual cues and behavioral routines with the smartphone, i.e., the mobile apps used within recurrent phone usage sessions.

As suggested in the literature, the study of habits in the smartphone context is the study of two interrelated things, i.e., the recurrent behaviors performed by the user with her smartphone, and the cues that trigger these behaviors. Therefore, we assume that discovering smartphone habits means discovering possible *links* between specific contextual cues and behavioral routines (Figure 2).

Behavioral Routines. We define *behavioral routines* as specific usage sessions performed by the user with her smartphone. Several definitions of what is a phone usage session have been proposed in the past (see [80] for a comprehensive overview). In our work, we adopt a simple definition based on active screen time [7, 31, 56]. According to such a definition, a phone usage session starts when the screen is turned on and ends when the screen is turned off. We made such a choice deliberately. Indeed, while some previous works assume that a small gap in-between phone usage may not necessarily point to a separate usage session [11], the study of van Berkel et al. [80] suggests that classifying gaps in smartphone usage is an open challenge, and demonstrates that, in the majority of cases, users that return to their smartphone by unlocking it are actually beginning a new session. Moreover, since our smartphone usage sessions are aggregated and analyzed together to extract smartphone habits (see Section 3.2), we are confident that the adopted definition does not impact the presented results. Summarizing, we define a phone usage session as the consecutive period of time, i.e., the *session-window*, during which the user actively interacts with the device [27]. We consider, in particular, the set of unique mobile applications that are used inside each session-window. In Figure 2, for instance, the involved phone usage session is {*WhatsApp, Facebook, Instagram*}.

Contextual Cues. Although our work is generic and can be easily extended, our focus is on *contextual cues*, rather than intrapersonal cues. Our aim, indeed, is to automatically extract smartphone habits from usage data: differently from emotional states, indeed, several contexts can be easily detected through smartphone sensors. Following the analysis reported in Section 2, in particular, we consider the contextual cues as shown in Figure 2: the *time* and *period* during which a user uses her smartphone, the *location* and the physical *activity* of the user while using her smartphone, and received *notifications*. The set of specific contextual values that can be taken into account depends on the data that can be collected from the user. In the implementation of our data-analytic methodology (Section 4), for instance, a set of contextual cues is {*10-12 AM, home, holiday*}.

3.2 Methodology

We devised a data analytic methodology to automatically discover smartphone habits from usage data, i.e., to extract the links between contextual cues and behavioral routines in phone usage sessions. We adopted a mixed approach, personalized for each user, based on clustering methods and association rules (Figure 3).

3.2.1 Data Collection and Preprocessing. The user's mobile usage data is firstly preprocessed to build phone usage sessions. The computed sessions are then transformed in a Vector Space Model (VSM) representation [67]. Inspired by the Bag-of-Words (BoW) model, usually adopted in text mining [73], we devised a Bag-of-Apps (BoA) representation. With BoA, each session is a vector in the mobile applications space, where each vector element corresponds to a different app and is associated with a value describing the app relevance for the session. The value, in particular, is defined as the total time spent on the app inside the given session, i.e., the app duration. Values are weighted by using the Term Frequency-Inverse Document Frequency (TF-IDF) scheme [51]. Despite this scheme does not take into account the order in which applications are used in a phone session, it allows highlighting the relevance of specific apps for each session: it reduces the importance of common apps in the collection, ensuring that the matching of sessions is more influenced by discriminative apps with relatively low frequency in the collection.

3.2.2 Phone Sessions Clustering. After the preprocessing phase, the phone usage sessions of the user are clustered together. The computed clusters can be used to get a first overview of the different types of usage that characterize a given user. Furthermore, the aim of this phase is to act as a filter, i.e., to discover consistent groups of similar sessions from which extracting the user's habits, thus excluding phone usage sessions that can be considered as outliers. As demonstrated by previous works [69, 84], the idea is that users interact with their smartphones in many different, *predictable*, ways, i.e., people tend to repeat similar phone sessions day by day. Similar phone usage sessions are clustered by using the DBSCAN algorithm [18], a density-based clustering algorithm that groups together closely-packed points, marking as outliers points that lie alone in low-density regions.

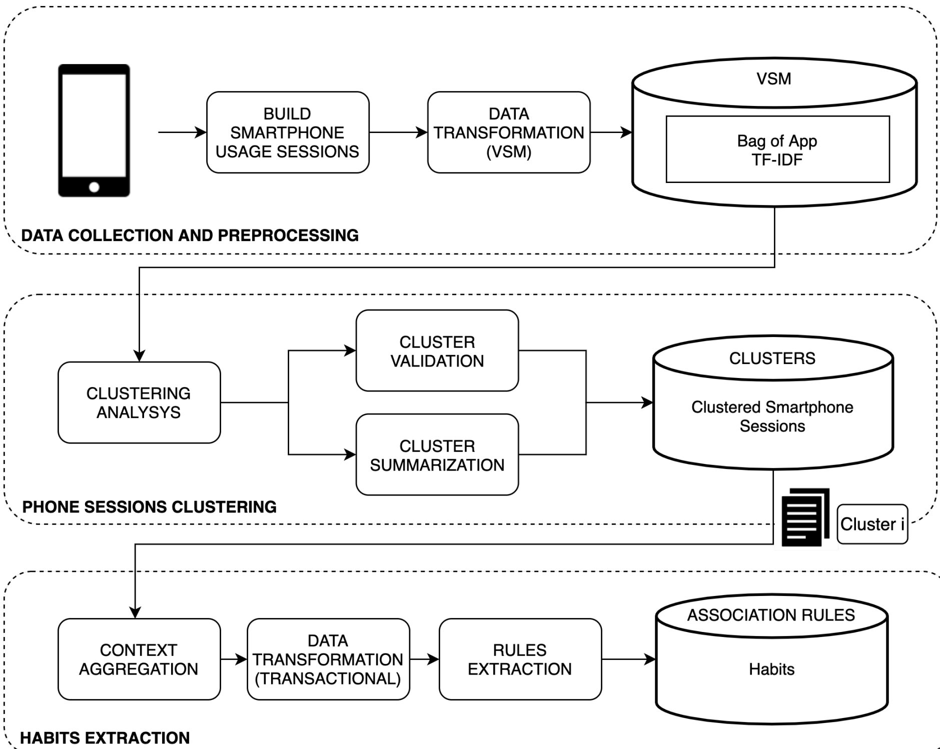


Fig. 3. The data analytic methodology we devised to automatically discover complex smartphone habits from usage data. The methodology is based on clustering and association rule mining.

Comparing to other algorithms, DBSCAN does not require to specify the number of clusters in the data a-priori, and it is able to deal with arbitrarily shaped clusters. To measure the "distance" between two different sessions, we adopt a cosine similarity metric, i.e., we calculate the cosine of the angle between the two BoA vectors. The DBSCAN parameters, instead, are selected by using the procedure described in the original paper [18], which suggests to iteratively compute and plot the k-nearest neighbor distances by varying the parameters.

For the internal validation of clustering results, the methodology adopts the Silhouette quality index. Silhouette allows evaluating the appropriateness of the assignment of a data object to a cluster rather than to another by measuring both intra-cluster cohesion and inter-cluster separation: clusters with silhouette values in the range $[0.51, 0.70]$, in particular, show that a reasonable structure have been found, while values in the range $[0.71, 1]$ demonstrate a strong structure [32].

To summarize clusters, instead, we extract the more frequent items, i.e., used apps, in the clusters, and we use them to label each cluster summary. As labels, in particular, we use the categories of the involved apps. Such categories can be easily extracted from digital marketplaces like the Google Play Store[4] or Apple's App Store[5].

3.2.3 Habits Extraction. After filtering phone usage sessions through clustering, we use association rules to extract smartphone habits, i.e., links between specific contextual situations and phone

[4]https://play.google.com/, last visited on May 11, 2020
[5]https://www.apple.com/us/search/app-store, last visited on May 11, 2020

usage sessions, from each computed clusters. In particular, we extract multiple association rules for each cluster separately, and we then pick up the most significant rules for each cluster, by using different quality indexes. Association rules are an exploratory data mining technique to mine correlations among data items that can be naturally used to describe "if-then" behaviors, including smartphone habits. Following the original definition of Agrawal et al. [3], the problem of association rule mining is defined as follows.

- Let $I = \{i_1, i_2, ..., i_k\}$ be a set of k binary attributes called items.
- Let $D = \{t_1, t_2, ..., t_l\}$ be a set of l transactions called database. Each transaction in D has a unique transaction ID and contains a subset of the items in I.

A rule is defined as an implication of the form $X \implies Y$, where $X, Y \subseteq I$. The two terms of a rule are known as itemsets, and are named *antecedent* and *consequent*, respectively.

To extract association rules, we aggregate each session belonging to a given cluster with the corresponding contextual cues, i.e., the set of contexts measured in the specific session-window. The aggregated sessions of each cluster are then transformed into a transactional data format. Given the user $u_i \in U$, in particular, we define the set of items I as $I = M \cup C$, where M represents the set of all the applications used by u_i, while C represents the set of all the possible contextual values included in our model that can be measured for the user u_i, e.g., the set of her locations, or the set of her performed activities. Given an aggregated phone usage session, the related transaction t_i is defined as the set of all the apps m_i used in that session, joined with the current set of contextual values c_i. Figure 4 exemplifies the structure of an aggregated phone usage session in a transactional format. In each box, the value 1 means the presence of the item in the corresponding transactional session, and the value 0 represents the absence of an item in that session. Items involve contextual information (green boxes) and used apps (yellow boxes).

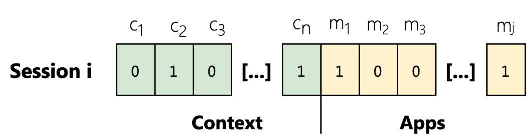


Fig. 4. The structure of an aggregated phone usage session represented in a transactional format. In each box, the value 1 means the presence of the item in the corresponding transactional session, and the value 0 represents the absence of an item in that session. Items involve contextual information (green boxes) and used apps (yellow boxes).

Association rules are finally mined on the transactional databases representing each cluster. For this purpose, we use the Apriori algorithm [4], an algorithm for frequent item set mining and association rule learning over transactional databases. We use different quality indexes to distinguish the most significant rules. Association rules extraction is commonly driven by rule *support* and *confidence*. Whereas the support index represents the observed frequency of occurrence of rule r in the transactional dataset, the confidence index represents the rule strength. However, measuring the strength of a rule in terms of support and confidence values, only, may be sometimes misleading. When the rule consequent has a high support value, in fact, the rule may be characterized by a high confidence value even if its actual strength is relatively low. To overcome this situation, the $lift$ index has been proposed [75] to measure the (symmetric) correlation between antecedent (X) and consequent (Y) of a rule. Lift values below 1 show a negative correlation between X and Y, while values above 1 indicate a positive correlation. In our work, we enforce $lift > 1$ and $supp > 1\%$ to prune both negatively correlated and uncorrelated item combinations. Our aim is to mine patterns representing strong correlations among contextual features and used applications characterizing phone usage sessions. Through rules with high lift and support, in particular, the methodology is able to extract meaningful and recurrent links between a given contextual situation and the usage of one or more applications, by filtering out the mobile apps that are used sporadically in that context.

4 EVALUATION I: ASSESSMENT WITH REAL-WORLD DATA

We assessed our habit-discovery methodology by applying it over more than 130,000 smartphone usage sessions collected from users aged between 16 and 33. Furthermore, we conducted a follow-up interview with 10 users involved in the data collection process.

4.1 Implementing the Habit-Discovery Methodology

To implement the habit-discovery methodology, we exploited data that we are collecting in-the-wild from young adults in the context of our current studies in the digital wellbeing context [54]. The exploited mobile app, in particular, silently collects different information about smartphone usage, and made them available, in an anonymous form, on a Firebase[6] dataset. We randomly selected 35 active users of the app, and we used an online form to get their consent to analyze their anonymized smartphone habits. In the form, we explicitly listed the data we wanted to analyze, e.g., used apps and locations, and we provided users with some examples of smartphone habits that can be extracted by our methodology. In case of pre-adults teenagers, i.e., participants under 18 years of age, we collected the consent of both the user and one of her parents. We also asked the selected users, on a voluntary basis, the possibility of linking their data to their email address, with the aim of conducting a personalized follow-up study (see Section 4.3). Twelve participants positively answered to this request.

Overall, participants (23 male and 12 female) were on average 23 years old (range = $16-33$, $SD = 4.40$), and had different occupations: 5 were high school students, 20 were college students, and 10 were professional workers. To assess our habit-discovery methodology, we extracted the last 3 weeks of available data, in chronological order, for each participant. Table 2 reports the information we used in our analysis.

Following the methodology described in Section 3, we preprocessed screen and app events to build smartphone usage sessions. For this purpose, we followed a 2 step procedure:

- first, we isolated pairs of consecutive lock-unlock screen events to delineate the start and the end of each usage session, i.e., the session-window;
- second, we used each session-window to analyze app events, with the aim of extracting the mobile apps used during the session.

Furthermore, after the clustering phase, we used the following information to aggregate contextual information to smartphone usage sessions:

- *Time* and *Period* information were extracted by considering the start of each usage session. For the time, we divided the day into 2-hours time-slots, e.g., *10-12 AM*. For the period, instead, we discriminated between *working day* or *holiday*;
- *Activities* were detected through the Google Activity Recognition APIs[7]. We were therefore able to model the following activities: *still*, *walking*, *running*, *cycling*, and *on vehicle*.
- *Locations* information included events related to the entering or the exiting from home, the workplace, and any other locations that users could optionally add. To model the same information for all the users, we decided to model *home* and *work* locations.

[6] https://firebase.google.com/, last visited on May 11, 2020

[7] https://developers.google.com/location-context/activity-recognition/, last visited on March 11, 2020

Table 2. The information collected in a ongoing field study [54] that we used to assess our habit-discovery methodology.

Information	Description
Activity Events	Start/stop a given activity, i.e., *still*, *walking*, *running*, *cycling*, and *on vehicle*. Each activity event includes a timestamp, an activity, and the type of the event, i.e., start or stop.
Location Events	Enter/exit a given location area. The application forces users to define at least their *home* and *work* locations. Each location event includes a timestamp, a location, and the type of the event, i.e, enter or exit.
Screen Events	Lock/unlock the smartphone screen. Each screen event includes a timestamp and the type of the event, i.e., lock or unlock.
App Events	Open/close a given mobile app. Each app event includes a timestamp and the type of the event, i.e., open or close.
App Notifications	The notifications received by the user. Each notification event includes the timestamp of reception and the timestamp the user reacted to it, along with the app that generated the message.

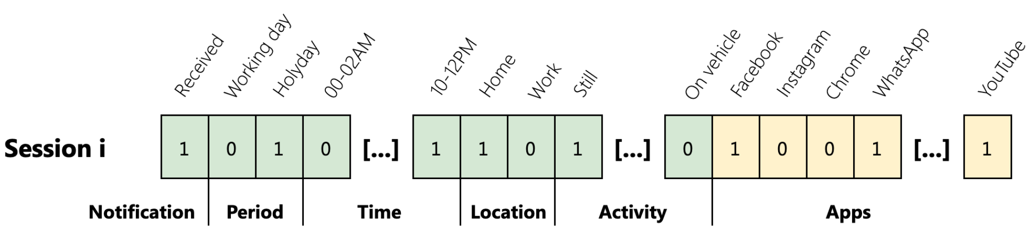


Fig. 5. An example of an aggregated phone usage session represented in a transactional format. Besides mobile applications, the vector involves the contextual information included in our smartphone habits model, i.e., preceding notifications, time, period, location, and activity.

- *Notifications* information included the timestamp of reception and the timestamp the user reacted to it, along with the app that generated the message. Since the used applications differed across participants, we modeled the event of receiving a notification, only, without considering the app that generated it.

Figure 5 shows the structure of an aggregated session transformed in a transactional format. The context part of the transaction, i.e., the green boxes, tells us that the session was performed during a holiday, between 10 and 12 PM, when the user was at home and still, and when she has just received a notification. During the session, in particular, the user used Facebook, WhatsApp, and YouTube.

4.2 Analysis and Results

4.2.1 Phone Sessions Clustering. Overall, we extracted a total of 137,230 phone usage sessions. On average, each user contributed with 3845.21 sessions (SD = 2384.04) and we were able to cluster 82.94% of phone usage sessions for each user (SD = 0.06), while 17.06% of sessions were filtered as outliers. We discovered, in particular, 9.77 clusters per user (SD = 4.44). By evaluating the clustering results, we found Silhouette values from 0.51 to 0.84 (M = 0.67, SD = 0.09), thus demonstrating reasonable to strong clustering structures. Consistent differences between users emerged for what

Table 3. The 10 most common categories of clusters we found in clustering phone usage sessions. Phone sessions including messaging apps and social networks were very common, and strongly characterized the majority of the computed clusters.

Category	# Of Clusters	Summary Example
Messaging-Social	128	Facebook - Instagram - WhatsApp
Messaging	73	Telegram - WhatsApp
Messaging-Web	58	WhatsApp - Chrome
Messaging-Social-Web	32	WhatsApp - Instagram - Opera Browser
Messaging-Social-Gaming	28	Telegram - Facebook - Instagram - Clash Royale
Messaging-Photo	28	WhatsApp - Camera - Gallery
Photo	26	Camera - Gallery
Messaging-Social-Video	25	Telegram - Instagram - YouTube
Messaging-Calling	25	WhatsApp - Contacts - Telephone
Social	15	Instagram - Facebook

concerns the number of clusters ($range = 4 - 22$). Some users consistently used their smartphones in a similar way, i.e., their smartphone sessions were grouped in a limited number of clusters. Other users, instead, demonstrated a more varied use of their devices, and their sessions were divided in more than 20 clusters. This confirms what Zhao et al. [84] already found in their analysis of smartphone usage data: users interact in many different ways with their mobile devices, and treating smartphone users as a homogeneous population with similar usage characteristics is a simplistic assumption.

Before analyzing the summaries of the computed clusters, we analyzed the Google Play Store category of each involved app, and we excluded all the clusters involving *productivity* and *tools* apps, only. *Productivity* and *tools* apps, indeed, are typically associated to an intentional use of the smartphone [49]. We therefore excluded clusters modeling specific operations like phone calls, payments, or usage of the settings. Table 3 reports the 10 most common categories characterizing the computed clusters across all the users. For each cluster category, the table reports the label, how many clusters of the given category we found, and an example of a summarized cluster. Not surprisingly [49], phone sessions including messaging apps and social networks were very common, and strongly characterized the phone use of all the users. For example, we found 128 "Messaging-Social" clusters, in which phone sessions typically included mobile apps like Facebook, Instagram, and WhatsApp. Even if our analysis methodology does not take into account the order in which applications are used, contextualizing "Messaging-Social" (or "Social-Messaging") clusters is straightforward. On the one hand, it is very common to receive (and answer to) a WhatsApp message when browsing Facebook or Instagram. On the other hand, everyone has experienced at least once the effect of a "checking habits": we receive a WhatsApp notification, and without even knowing why we are passively browsing the Facebook timeline.

4.2.2 Habits Extraction. Table 4 describes the three different types of habits we found by analyzing the retrieved association rules. Context Habits are represented by association rules that model a strong correlations between a contextual situation and a phone usage session, where period, time, activities, locations, and/or preceding notifications trigger the usage of one or more apps. App Habits, instead, are represented by association rules that model a strong correlation between mobile apps, only, where the usage of a given app triggers the usage of one or more other apps. The last type, i.e., App-Context Habits, is composed of hybrid association rules, where the usage of a specific app in a given context triggers the usage of one or more other apps.

Table 4. The 3 types of habits we found by analyzing the extracted association rules.

Type	Structure	Description	Example
Context Habits	$C \implies M$	Association rules that represent strong correlations between a specific contextual situation and phone usage session. In Context Habits, contextual cues such as the period, the time slot, the user activity and location, and/or a received notification trigger the usage of one or more apps.	*{business-day, 10-12 AM, work}* $\implies$ *{Facebook, Instagram}*
App Habits	$M \implies M$	Association rules that represent strong correlations between mobile apps inside a phone usage session. In App Habits, the usage of one app can be therefore considered a contextual cue itself, i.e., a preceding action that triggers the usage of one or more other apps.	*{WhatsApp}* $\implies$ *{Twitter, Facebook}*
App-Context Habits	$C, M \implies M$	Association rules that represent strong correlations between a specific contextual situation, including the usage of specific apps, and other apps. App-Context habits model the relationship between an application used in a given context and the usage of one or more other apps.	*{02-04 PM, work, Slack}* $\implies$ *{Chrome, Instagram}*

To exemplify the retrieved results, Table 5 reports the 10 most promising association rules extracted for the 4 clusters of the user U34, a high school student. From the rules, we can easily glimpse her habits.

In the morning, especially at home, the user typically uses Instagram by performing the 3 Context Habits R1, R2, and R3. R1 and R3, in particular, tell us that such habits occurs when U34 is still: we can reasonably speculate that the first thing the user does when she wakes up is to check her Instagram timeline. R2 and R3 also highlight another feature of our methodology, i.e., its ability to capture the context of a given behavioral routine, e.g., the usage of Instagram in the morning, at different "granularity" levels. Such a feature can be used to further characterize smartphone habits, e.g., to understand behavioral routines are linked to different contextual situations, e.g., the morning in different locations, or if they are characteristic of a specific cue, only, e.g., the home location. Run-time implementations of the data analytic methodology, in particular, can exploit the ability to extract routines at different levels of granularity in several ways: in our Socialize app (see Section 5), for instance specific rules like R3 override more generic rules, e.g., R2.

Two other closely related habits are represented by R4 and R5, an App-Context and a Context Habit, respectively. They describe how U34 uses her smartphone between 12 and 02 PM when she is on a vehicle: she checks Instagram and listens to some music from Spotify. As the same user confirmed during the user validation reported in the next section, this is an habitual behavior she performs when she comes back home from school by bus. The same user also demonstrates other habits related to messaging, social, and gaming applications. R6, R7, and R8 confirm that, as for the majority of the users, also U34 is susceptible to Messaging-Social habits in which she uses messaging services and social networks in the same phone sessions. R6, in particular, is an

Table 5. The 10 most promising association rules extracted for the 4 clusters of U34.

Id	Antecedent	Consequent	Cluster	Category	Type	Lift	Supp	Conf
R1	04-06 AM home still	Instagram	1	Social	Context	1.37	0.02	0.40
R2	06-08 AM	Instagram	1	Social	Context	1.41	0.04	0.41
R3	06-08 AM home still	Instagram	1	Social	Context	1.41	0.02	0.41
R4	12-02 PM on vehicle Spotify	Instagram	2	Music-Social	App-Context	2.40	0.02	0.70
R5	12-02 PM on vehicle	Spotify	2	Music-Social	Context	7.30	0.02	0.46
R6	WhatsApp	Instagram	3	Messaging-Social	App	1.31	0.10	0.38
R7	home still	WhatsApp Instagram	3	Messaging-Social	Context	1.60	0.03	0.18
R8	12-02 PM Instagram	WhatsApp	3	Messaging-Social	App-Context	1.80	0.02	0.51
R9	still	Gangstar 4	4	Gaming	Context	1.17	0.03	0.05
R10	home still	Clash Royal	4	Gaming	Context	1.34	0.02	0.10

App Habit that is a typical example of a checking habit: the usage of WhatsApp, e.g., to check an incoming notification, often triggers the user in checking Instagram, also. Finally, R9 and R10 characterize two Context Habits of U34 related to gaming: U34 typically plays Gangstar 4 and Clash Royal when she is still, especially at home.

4.3 Follow-up Interviews

After analyzing the collected data, we contacted the 12 users who agreed to further discuss their smartphone habits in a subsequent user study. We were able to arrange an appointment and conduct a follow-up interview with 10 of them. Our aim was to validate, directly with users, our approach for modeling and detecting smartphone habits. The recruited participants (6 male and 4 females) were on average 20.82 years old (SD = 3.84), and had different occupations: 5 were college students, 3 were high school students, and 2 were professional workers.

The study was conducted in the form of a semi-structured interview that lasted about 30 minutes. For each user, we selected 10 promising association rules, i.e., habits, from her personal data, on the basis of their lift, support, and confidence. In the selection, we paid attention in picking rules from different clusters, if possible. We then showed the rules to the user one by one on a sheet of paper (Figure 6).

For each proposed habit, we collected 4 different measures related to habitual smartphone use: a) the *familiarity* of the user with the behavior, b) the user's perceived *habitualness* of the behavior, c) the overall *perception* of the user, i.e., whether the behavior is positively or negatively considered,

Fig. 6. An example of a habit shown to a participant in the user validation.

and d) the user's desire to *avoid* the behavior. To collect the measures, we used the following Likert-scale questions:

- **Familiarity.** How much this behavior is *familiar* to you? From **(1)** not familiar at all to **(7)** very familiar.
- **Habitualness.** How much this behavior is *habitual* to you? From **(1)** not habitual at all to **(7)** very habitual.
- **Perception.** How do you *consider* this behavior? From **(1)** very negative at all to **(7)** very positive.
- **Avoiding.** Would you like to *avoid* such a behavior? From **(1)** absolutely not to **(7)** absolutely yes.

We concluded the interview with a debriefing session, by asking participants if they had any comments on the evaluated habits.

4.3.1 Results. Table 6 reports the average results for all the collected metrics. Overall, all the users found the evaluated behaviors both *familiar* ($M = 5.30$, $SD = 1.23$) and *habitual* ($M = 5.18$, $SD = 1.21$), thus confirming the effectiveness of our data analytic methodology in discovering smartphone habits. Participants *perceived* such behaviors negatively, mainly ($M = 3.17$, $SD = 1.33$), and, on average, they demonstrated their willingness to *avoid* them ($M = 4.81$, $SD = 1.48$). This might confirms that, differently from intentional use, habitual smartphone use is perceived as meaningless [49]. Despite this tendency, not all the smartphone habits are perceived as negative. Indeed, by further investigating how participants perceived the evaluated association rules, we found some differences concerning the applications involved in the modeled behaviors. We found that 18 out of the 30 habits more negatively perceived, i.e., those that received a score lower than 3 for the *perception* metric, included Instagram as the rule consequent. Instead, the (rare) habits that were positively perceived, i.e., with a *perception* metric greater than 5, typically involved applications that are commonly associated to an intentional use of the phone, e.g., WhatsApp and Google Maps.

By analyzing the collected answers, we found that the perception of a habit and the willingness to avoid it were negatively correlated ($r = -0.83$, $p < 0.05$). As shown in Figure 7, where we plotted the *perception* and the *avoiding* metrics for all the 100 habits evaluated during all the interviews, the less a habit is positively perceived (lower *perception* value), the more the user would like to avoid it (higher *avoiding* value). This further demonstrates the need of new tools able to assist users in controlling their smartphone use and avoid meaningless smartphone habits.

As reported in Table 6, differences also emerged when considering the different habit types. App-Context Habits, in which both contextual cues and used apps are present in the rule antecedent, were rated on average as the most *familiar* ($M = 5.76$, $SD = 0.85$) and *habitual* ($M = 5.48$, $SD = 0.85$) behaviors. Instead, App Habits modeling interactions between apps, only, received lower values both for the *familiarity* ($M = 5.04$, $SD = 1.46$) and the *habitualness* ($M = 4.82$, $SD = 1.37$) metrics. This seems to suggest that the more precise are the cues that trigger a habitual behavior, the more

Table 6. Average results for all the metrics collected during the followup interviews. Besides showing the overall results, the table also reports the results for each type of habit, i.e., App, App-Context, and Context. Gray cells indicate the most significant results. App-Context Habits were the most familiar and habitual behavior (higher *familiarity* and *habitualness* metrics). Context Habits, instead, were perceived more negatively (lower *perception* metric), and they were more often considered as behaviors to be avoided by the participants (higher *avoiding* metric).

	App Habits	App-Context Habits	Context Habits	All
Familiarity	5.04 (1.46)	5.76 (0.85)	5.17 (1.23)	5.30 (1.23)
Habitualness	4.82 (1.37)	5.48 (0.85)	5.19 (1.30)	5.18 (1.21)
Perception	3.41 (1.53)	3.34 (4.59)	2.98 (1.32)	3.17 (1.33)
Changing	4.36 (1.49)	4.59 (1.42)	5.13 (1.42)	4.81 (1.48)

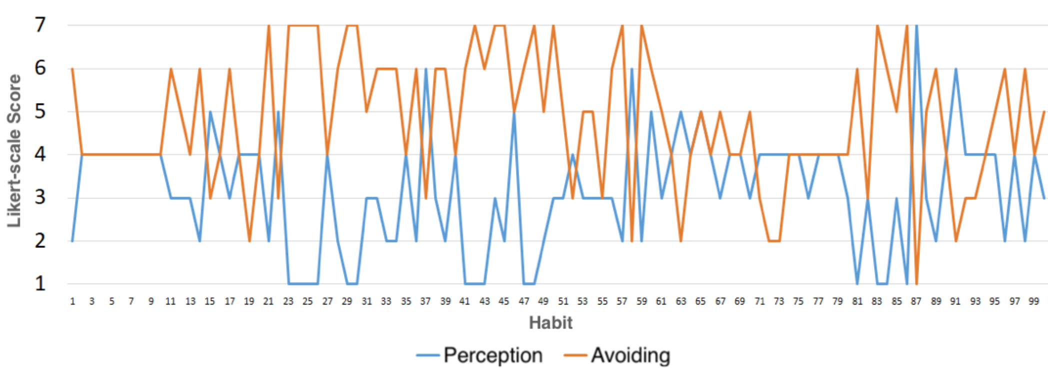


Fig. 7. Perception and avoiding metrics for the 100 habits evaluated during all the interviews. The less a habit is positively perceived (lower *perception* value), the more the user would like to avoid it (higher *avoiding* value).

the behavior is recognized as a habit. Furthermore, as suggested by the answers for Context habits, behaviors triggered by contextual cues are more likely to be considered as negative ($M = 2.98$, $SD = 1.32$): they were more often considered as behaviors to be avoided ($M = 5.13$, $SD = 1.42$) with respect to App and App-Context habits.

In the debriefing sessions, participants provided some useful feedback that allowed us to further asses the extracted habits. The majority of the participants confirmed what they stated in the Likert-scale questions, and said that the evaluation of the proposed habits made them reflect on their everyday smartphone use. U12, for example, found the evaluated habits very accurate, especially in specific (time) contexts:

> *"The majority of the behaviors I saw were familiar to me, especially the ones I typically perform in the morning or before going to sleep. They were very accurate! (U12)"*

Also U34, a high school student, provided a similar feedback. In discussing 2 habits regarding the afternoon usage of Instagram and Spotify on a vehicle[8], she said:

> *"This is exactly what I do every afternoon when I come back home by bus." (U34)*

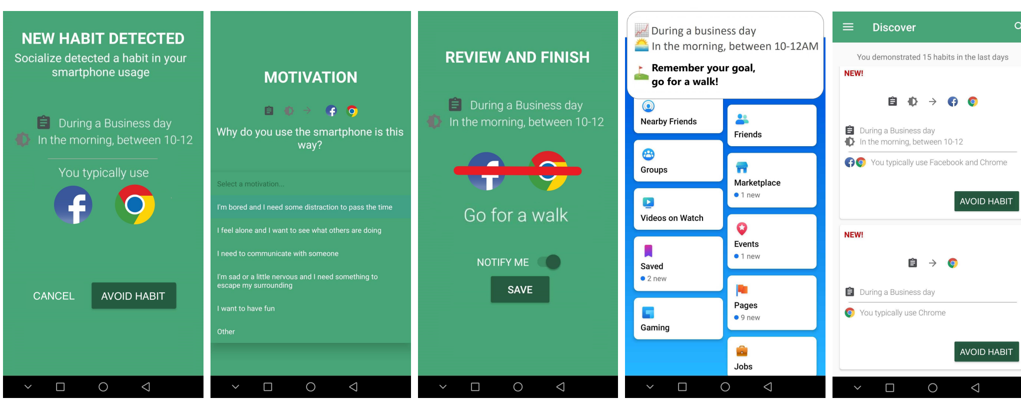
Finally, U6 confirmed the benefits of considering contextual cues in detecting habits:

[8] see Table 5 for the full list of rules evaluated by U34.

> *"I think that being alerted when one falls into the trap of some specific habits would be very useful. I found behaviors like 'in the evening, when I am still, I use Instagram' or 'when I am walking I use Whatsapp' really interesting. Actually, these are the behaviors I would like to change. I found behaviors that included times, activities, or positions far more interesting than behaviors including apps, only." (U6)*

5 MITIGATING SMARTPHONE HABITS: THE SOCIALIZE APP

We applied the proposed methodology in Socialize, a digital wellbeing mobile app that assists users to avoid the smartphone habits they consider as meaningless. We consider digital wellbeing as a natural application of our data analytic methodology for discovering smartphone habits: helping users to mitigate the disruptive effects of their habitual behaviors with the smartphone could promote meaningful experiences with mobile devices, as called for by recent studies [49, 78].



(a) Habit Detection (b) Reflection (c) Intention (d) Just-in-time Reminder (e) Dashboard

Fig. 8. When Socialize detects that the smartphone is used in a habitual way, it proactively notifies the behavior (a). If the user considers the behavior as meaningless, she can use Socialize to reflect on the motivation that drives her habitual behavior (b), and to define an alternative intention, e.g., "go for a walk" (c). To recall the intention and assisting the user in avoiding the identified meaningless behavior, the application sends a just-in-time reminder every time the smartphone habit is again detected (d). Through different dashboards, e.g., (f), the user can also see their calculated smartphone habits in any time.

Socialize is designed as an Android application[9]. The app uses the methodology described in Section 3 to discover smartphone habits. Given the (relatively) small computational capacity of smartphones, and the need of implementing the methodology automatically, i.e., without any human intervention nor analysis, we simplified it by removing the "Phone Sessions Clustering" phase: all the smartphone usage sessions of the user are directly aggregated with contextual information and used to mine association rules, i.e., smartphone habits, as if all the sessions were grouped in in a single, very large cluster. To be consistent with the original data-analytic methodology, Socialize discards association rules that exclusively involve apps whose Google Play Store category is *productivity* or *tools*: the underlying behavior modeled by such rules, indeed, typically represents a goal-oriented interaction rather than an unconscious habit. Smartphone habits are recalculated

[9]The source code of Socialize is available at https://git.elite.polito.it/public-projects/socialize-v2, last visited on January 2, 2021

on a daily base by considering a time-window of the previous 7 days. Habits representing the same routine at different levels of granularity, e.g., with and without a given location, are merged together to generate a habit that is as specific as possible.

5.1 App Walk-Through

Figure 8 exemplifies how Socialize assists a user in avoiding the smartphone habit she considers as meaningless. In any time, the user can exploit different dashboards to visualize her smartphone use statistics, including the list of smartphone habits she demonstrated in the last days (Figure 8e). By using the calculated habits and by monitoring smartphone usage and current context in real-time, Socialize detects when the smartphone is being used in a habitual way. When this happens, the application proactively notifies the habit to the user (Figure 8a). If the user considers a habit as meaningless, she can click on the "Avoid Habit" button. If this happens, Socialize first helps the user in reflecting on the motivation that drives her habitual behavior (Figure 8b). The app proposes 5 possible alternatives:

- *"I'm bored and I need some distraction to pass the time;"*
- *"I feel alone and I want to see what others are doing;"*
- *"I need to communicate with someone;"*
- *"I'm sad or a little nervous and I need something to escape my surrounding;"*
- *"I want to have fun."*

We derived the proposed motivations from the work of Lukoff et al. [49], in which the authors used a Uses and Gratifications (U&G) perspective to investigate how users make sense of their habitual use of smartphones. We defined the proposed alternatives around the type of smartphone usage (*U&G types*) and the underlying motivations (*U&G motivations*) that participants of the study associated to a meaningless use of the smartphone. Through different interviews and the experience sample method, in particular, Lukoff et al. found that entertainment and communication apps like social networks are often associated to meaningless habits. Furthermore, they also found that users habitually check their smartphones to escape from negative feelings like boredom, loneliness, and sadness. While these "micro escapes" can sometimes be useful, e.g., for emotional self-regulation, their constant and habitual repetition can become a problem, e.g., when replacing a work-related task. Besides selecting a predefined alternative, the user can also decide to specify her own motivation.

This reflection process helps users define an alternative intention, i.e., an alternative behavior to be performed instead of the smartphone habit (Figure 8c). In this case, the user is free to type her own alternative (and desirable) behavior, without any constraint or suggested option. Every time the identified meaningless habit happens again, Socialize encourages the user to avoid the behavior, by recalling the alternative intention specified by the same user (Figure 8d). Just-in-time reminders can be defined as direct, specific behavioral suggestions delivered at the expected point of enactment [61]. By guiding participants in reflecting on their habitual behaviors and defining their own alternative intentions, the just-in-time reminders adopted by Socialize aim at overcoming the "ironic effects" that may result from using such a strategy in a negative form [16]: paradoxically, indeed, warning users not to use Facebook could have the opposite effect. If the user is no longer satisfied with an activated just-in-time reminder, she can disable it.

6 EVALUATION II: IN-THE-WILD EXPERIMENT

To understand whether Socialize can effectively assist users, especially young adults, in better controlling their smartphone use through the mitigation of meaningless smartphone habits, we devised an in-the-wild study.

6.1 Method

6.1.1 Participants & Procedure . We recruited participants by exploiting mailing lists of different universities and by placing advertisements in our campus in the month of April, 2019. At the end of July, we closed the study by downloading the data collected through Socialize for all the users that used the application for *at least* three consecutive weeks. At the time of analysis, 67 users had installed and used Socialize. We excluded 22 users since they installed Socialize in the last 2 weeks of July, only, thus not providing at least 3 weeks of data. Of the remaining 45 users, we also excluded 25 participants due to missing or wrong collected data, e.g., because the user deactivated the GPS and the app could no longer monitor the user's location.

Overall, we analyzed the data of 20 users (13 male and 7 female) that were on average 22.30 years old (range = $19-31$, $SD = 2.70$). All the participants were students characterized by different educational levels: 10 of them were undergraduate students, 9 were master's degree students, and one was a PhD student. At the time of analysis, the 20 participants had used Socialize for a minimum of 21 days to a maximum of 113 days ($M = 36.80$ days, $SD = 20.59$ days). The experiment was designed as follows. In the first week (*collection phase*), Socialize ran in the background by silently logging usage data. After 7 days, participants received a notification that alerted them about the start of the *intervention phase*. From that moment, Socialize started to calculate and notify smartphone habits, and participants were able to activate just-in-time reminders for as many smartphone habits as they want. After closing the study, we sent to the 20 participants a final questionnaire to gain qualitative feedback on the evaluated app.

6.1.2 Metrics. To investigate whether Socialize makes users reduce the time spent on the smartphone habits they consider as meaningless, we calculated the following aggregated metrics:

Time Spent on Meaningless Habits (TSMH). The TSMH metric represents the average time spent by a given participant on the smartphone habits she considers as meaningless. For each user, in particular, we average the time spent on the mobile apps that a) characterize a behavioral routine of a smartphone habit for which the user defined an implementation intention, and b) are used in the presence of the specific contextual cues characterizing the given habitual behavior.

Time Spent on Contexts (TSC). The TSC metric represents the average time spent by a given participant on her smartphone, in general, in the presence of the contextual cues characterizing her meaningless smartphone habits. For each user, in particular, we average the time spent on *any* mobile apps when they are used in the contexts characterizing the user's implementation intentions. We used such a metric to understand whether the time saved on unwanted habits was actually saved from the smartphone, or if it was just redirected to other mobile apps.

We collected subjective feedback thanks to the final questionnaire. We asked participants to evaluate a) whether the notified smartphone habits were appropriate, and b) whether their perceived smartphone use changed after using Socialize. Finally, we also encouraged participants to leave any open comment on their experience with the application.

6.2 Usage Overview

We collected 234,865 phone usage sessions that resulted in 1,428,495 different app executions and more than 6,900 hours of smartphone use. Since our approach takes into account the habitual nature of using smartphones, only, participants experienced a limited number of interventions, but specifically targeted to their smartphone usage, context, and preferences. Overall, participants were notified (Figure 8a) 94 times about an habitual behavior with their devices. In total, 17 out of

20 participants (75%) used Socialize to activate just-in-time reminders for at least a notified habit: on average, each participant wanted to avoid 2.00 smartphone habits (SD = 1.64), with only 3 participants (15%) that used the application without activating any reminder. On the 94 notified habits, in particular, participants activated 40 just-in-time reminders, i.e., the 42.55% of notified habits were considered as meaningless smartphone habits worth to be avoided. In the remaining 54 cases (57.45%), participants ignored the notified habit either by clicking on the "Cancel" button (Figure 8a, 21 times) or by simply closing the app (33 times).

At the time of analysis, 32 of the 40 just-in-time reminders (80%) were *active*, i.e., participants still continued to receive them (Figure 8d). On average, such reminders were active for 32.39 days (SD = 30.53 days), with a minimum of 8 days and a maximum of 102 days. In the remaining 8 cases (20%), 5 different participants left the reminder active for 1 to 25 days (M = 11.46 days, SD = 11.34 days) and then *disabled* it. Participants defined all the intentions in their first intervention week.

6.2.1 Meaningless Smartphone Habits. The 40 smartphone habits considered as meaningless by the participants, i.e., those for which participants activated a just-in-time reminder, involved different contextual cues and mobile apps. The smartphone habits participants wished to avoid were more common:

- in business days (24, 60%);
- when participants were still (30, 75%), e.g., at their desks or in classroom.

Such a distribution reflects the population involved in the study, i.e., students. For what concerns the existing routines, 29 meaningless habits (72.50%) involved the usage of a single mobile app. The remaining 11 habits (27.50%), instead, involved the usage of 2 mobile apps at the same time. As reported in Table 7, meaningless habits were of different categories.

Table 7. The categorization of the Meaningless Smartphone Habits (MSH), i.e., the habits for which participants activated a just-in-time reminder, on the basis of the mobile apps involved in the related behavioral routines.

Habit Category	**Examples**	**# MSH**
Social	Facebook, Instagram	24
Messaging & calls	WhatsApp, Telegram, Skype	16
Web & video	Chrome, YouTube	6

The majority of them (24, 60%) included apps like Instagram or Facebok (*social* category), thus confirming that using social networks, especially in a passive way [82], is often associated with meaningless experiences [49]. Furthermore, 16 (40%) unwanted habits included a messaging or calling app such as WhatsApp or Skype (*messaging & video calls* category), while 6 (15%) intentions were defined to avoid the usage of apps like Chrome and YouTube (*web & video category*). This suggests that, besides being used intentionally [49], communication services and apps to browse the web and watch videos may also be associated to meaningless habits.

6.2.2 Motivations. In activating just-in-time reminders, Socialize guided participants in reflecting on the motivation that drove their habitual behaviors (Figure 8b). As reported in Table 8, participants stated that the majority of their meaningless smartphone habits were a distraction to escape from boring situations (24, 60.78%), e.g., studying. Instead, 6 just-in-time reminders (15%) were activated to avoid habits resulting from loneliness feelings. In such cases, participants used social networks and messaging apps, mainly, to see what others were doing, e.g., by browsing Facebook's posts. In line with previous works, e.g., [49], participants also acknowledged that they sometimes habitually used their smartphones to escape from negative emotions, e.g., when they were sad or nervous (4, 10%). Other motivations for habitually using the smartphone included the need of communication (3, 7.50%) and fun (3, 7.50%).

Table 8. The motivations that drove the smartphone habit-loops for which participants defined an Implementation Intention (II).

Motivation	**# II**
I'm bored and I need some distraction to pass the time	24
I feel alone and I want to see what others are doing	6
I'm sad or nervous and I need something to escape my surrounding	4
I need to communicate with someone	3
I want to have fun	3

6.2.3 Intentions. By reflecting on the motivations that drove their smartphone habits, participants defined different intentions to be encouraged, through the just-in-time reminders, to avoid the habitual behaviors (Figure 8c). As reported in Table 9, a large number of intentions focuses on studying or working (16, 40%), or performing a specific physical activity instead of using the smartphone (14, 35%), e.g., sleeping (7) or walking (2). Other intentions included a generic *"do something useful"* statement (4, 10%), or were defined in a negative form to motivate the user not to use a particular mobile app in a given context (4, 10%), e.g., *"do not use Facebook at work."*. Finally, participants defined 2 intentions (5%) to call a friend instead of contact her through instant messages.

Table 9. The alternative intentions participants defined after reflecting on the motivations that drove their smartphone habits.

Intention	**#**
Study/Work	16
Perform a specific activity, e.g., sleeping or reading a book	14
Do something useful	4
Don't use it	4
Call a friend	2

6.3 Socialize Effectiveness

To analyze the effectiveness of Socialize, we conducted different Wilcoxon Signed-Ranks tests on the TSMH and TSC measures to explore the impact of the just-in-time reminders on the habits participants wished to avoid (Table 10 and Figure 9). The reason for choosing a non-parametric test that does not assume a normal data distribution was due to the high-variability in the data under analysis. Indeed, participants used their smartphone very differently, and the habits for which participants activated just-in-time reminders had different duration: some users habitually checked Instagram for less than 10 seconds, while others habitually used YouTube for more than 30 minutes in a row. To avoid biases towards users who used Socilize for a longer period of time, we run the analysis by considering the first 21 days of data of each user, only, i.e., the collection phase (1 week) and 2 weeks of interventions.

6.3.1 Meaningless Smartphone Habits Reduction. By investigating the effect of all the defined just-in-time reminders, either still *active* or *disabled*, we found that 28 reminders (70%) had been *successful*, i.e., they resulted in a reduction, even just minimum, of the time spent on the corresponding smartphone habit.

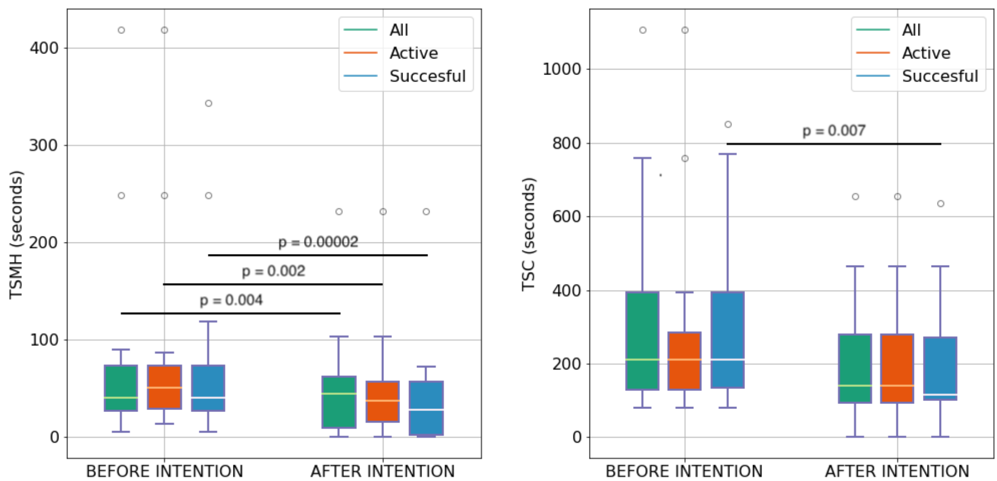
Overall (Table 10, left columns), participants significantly reduced ($p < 0.01$) the time spent on the habits they considered as meaningless by 28.69 seconds on average: the average time spent on meaningless habits was 76.84 seconds (SD = 104.18) before using Socialize to avoid them, and 48.15 seconds (SD = 56.03) after the activation of the corresponding just-in-time reminders. This difference Δ becomes even more significant by considering the just-in-time reminders that were still *active* at the 21st day, only, with a significant reduction of the TSMH metric of 37.81 seconds on average ($p < 0.01$): this further confirms that receiving just-in-time reminders has an effect on encouraging users to avoid meaningless smartphone habits. Not surprisingly, the difference Δ between the TSMH metric before and after the activation of a just-in-time reminder is also highly significant ($p < 0.01$) when considering *successful* reminders, only: when successful, intentions assisted participants in reducing the time spent on meaningless smartphone habits from 73.94 seconds (SD = 90.38) to 38.53 seconds (SD = 55.95).

Table 10. Wilcoxon Signed-Ranks tests on the Time Spent on Meaningless Habits (TSMH) and the Time Spent on Context (TSC) metrics before and after the activation of a just-in-time reminder. The analysis was repeated by considering a) *all* the defined reminders, b) the reminders still *active* at the 21st day, and c) the *successful* reminders.

Intentions group	TSMH (sec)				TSC (sec)			
	Before M (SD)	After M (SD)	Δ	p	Pre M (SD)	Post M (SD)	Δ	p
All	76.84 (104.18)	48.15 (56.03)	28.69	**.004**	312.88 (283.22)	201.60 (171.22)	111.28	.064
Active	89.92 (115.56)	52.11 (61.28)	37.81	**.002**	230.77 (293.70)	160.24 (181.31)	70.53	.100
Successful	73.94 (90.38)	38.53 (55.95)	35.41	**.000**	310.64 (261.38)	197.35 (173.33)	113.29	**.007**

To further confirm the effectiveness of Socialize in assisting young adults in avoiding meaningless smartphone habits, we also analyzed whether the time saved on the behavioral routines of the given habits was actually saved from the smartphone, e.g., to respect the defined alternative intention, or if it was just redirected to other mobile apps. For this purpose, we repeated the same Wilcoxon Signed-Ranks tests by considering the TSC metric (Table 10, right columns). We found that the overall smartphone use of each participant decreased, although not significantly, in the contexts related to the defined implementation intentions: on average, participants reduced their smartphone use from 312.88 seconds (SD = 283.22) to 201.60 seconds (SD = 171.22). A similar trend was found for *active* intentions (Δ = 70.53 seconds). As Table 10 shows, such a reduction becomes statistically significant when considering *successful* reminders (Δ = 113.29 seconds, $p < 0.01$). This further confirms that Socialize effectively helped participants to avoid the smartphone habits they considered as meaningless, and suggests that reducing meaningless smartphone habits helps users reduce the overall smartphone usage, too.

6.3.2 Habit Category and Socialize Effectiveness. While the majority of the activated just-in-time reminders successfully assisted participants in avoiding the smartphone habits they considered as



(a) TSMH

(b) TSC

Fig. 9. Box-plots representing the Time Spent on Meaningless Habits (TSMH) (a) and the Time Spent on Context (TSC) metrics before and after the activation of a just-in-time reminder for *all*, *active*, and *successful* reminders. Socialize assisted participants to significantly reduce the time spent on meaningless smartphone habits while reducing overall smartphone use, especially for successful reminders.

meaningless, some of them (12, 30%) did not produce the desired result. To better understand why some reminders were more effective than others, we conducted a series of Wilcoxon Signed-Ranks tests to investigate their impact for each of the habit categories reported in Table 7, i.e., *social*, *messaging & call*, and *web & video*, on the TSMH metric.

Table 11. Wilcoxon Signed-Ranks tests investigating the impact of the habit category on the effectiveness of the activated just-in-time reminders (TSMH).

Habit-loop category	**TSMH (sec)**			
	Before M (SD)	**After M (SD)**	**Δ**	**p**
Web & video	29.00 (85.92)	9.23 (26.10)	19.77	.079
Social	96.29 (187.27)	52.35 (60.27)	43.94	**.025**
Messaging & calls	38.82 (65.87)	33.29 (62.39)	5.53	.066

As reported in Table 11, results clearly highlight that the most effective reminders were the ones activated to avoid *social* smartphone habits. On average, such reminders assisted users in reducing the time spent on behavioral routines involving apps like Facebook and Instagram from 96.29 seconds (SD = 187.27) to 52.35 seconds (SD = 60.27), a statistically significant difference of $\Delta = 43.94$ seconds ($p < 0.05$). Also reminders for *web & social* meaningless habits resulted in a reduction of the TSMH metric, although with a less pronounced and not significant effect: in the given contexts, the usage of apps like Chrome and YouTube dropped on average from 29.00 seconds ($SD = 85.92$) to 9.23 seconds ($SD = 26.10$), with a difference of $\Delta = 19.77$ seconds. Instead, just-in-time reminders did not have a measurable effect when they were defined to avoid *messaging & video calls* habits: on average, the TSMH remained roughly the same before ($M = 38.82$ seconds, $SD = 65.87$) and after ($M = 33.29$ seconds, $SD = 62.39$) activating reminders for apps like WhatsApp and Telegram. This analysis suggests that just-in-time reminders are effective with apps that are mainly used passively, e.g., social media, while they have little impact on the use of communication apps. Indeed, apps like WhatsApp and Telegram are typically used intentionally [49]: even if we can experience the need of reducing the usage of such apps, the effectiveness of just-in-time reminders is limited when we need to actively communicate with someone.

6.4 Residual Effects

We further investigated the collected data by focusing on the 8 just-in-time reminders that participants disabled during the study. Our aim was to investigate whether disabled reminders had a residual effect, in the medium or long term, on participants' behavior. To this end, we focused on the 5 participants that disabled at least one reminder, by considering *all* their available data, i.e., without reducing the analysis to 21 days. The selected participants used Socialize for 33.80 days on average ($SD = 5.54$, range = $27 - 42$). Specifically, the average period between the deactivation of one of their reminder and their most recent available data was 14.48 days ($SD = 13.07$ days).

As shown in Figure 10, the TSMH metric of a user after the deactivation of her reminders ($M = 22.77$ seconds, $SD = 25.30$) was still lower, on average, than TSMH metric calculated before the activation of the same reminders ($M = 36.30$ seconds, $SD = 32.25$). Although not significant ($p > 0.05$), this difference may suggest that reminders are able to continue to influence participants' behavior even after their deactivation. Consequently, just-in-time reminders seem to be a promising approach: as advocated by previous work [61], encouraging people to repeat a wanted behavior in a stable context may effectively promote the formation of new habits. Habit-formation approaches, in particular, could play an important role in digital wellbeing apps, supporting behavior change towards a more conscious use of technology, and ensuring the long-term effects of the new behavior [38, 50, 54].

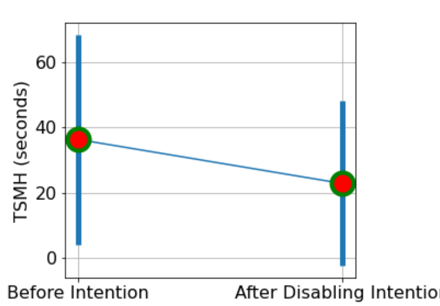


Fig. 10. Analysis of the TSMH metric for the just-in-time reminders that participants disabled during the study.

6.5 Subjective Feedback

On a Likert-scale from 1 (not appropriate at all) to 5 (very appropriate), all the participants stated that the notifications they received about their smartphone habits were appropriate or very appropriate ($M = 4$, $SD = 0.53$). In the open comments, P12 said that almost all the displayed habits were accurate, while P3 asserted that the notified habits reflected *"exactly"* her typical behaviors with the smartphone. Furthermore, P6 and P8 noted that being notified about their habits made them reflect on their behaviors with the smartphone, and allowed them to better monitor their device usage. Obviously, not all smartphone habits can be considered as negative behaviors to be avoided. The 3 participants that did not activate any just-in-time reminders, for example, agreed that they were not interested in changing their behavior with the smartphone. Surprisingly, the usage of Socialize did not influence the perception participants had of their smartphone use. On a Likert-scale from 1 (absolutely no) to 5 (absolutely yes), they declared that their smartphone use remained roughly the same even after activating a just-in-time reminder ($M = 2.5$, $SD = 0.50$). Participants, in particular, were convinced that receiving just-in-time reminders, only, was not sufficient to avoid a smartphone habit. P7 and P9, in particular, stated that a notification can always be ignored, while P12 suggested the usage of *"engaging intentions harder to ignore."* As reported in this section, however, the participants perception is not reflected by the quantitative data. Indeed, participants actually reduced their smartphone habits. This suggests that monitoring and notifying smartphone habits, despite being less restrictive and intrusive than a locking mechanism, is an effective strategy to allow users to control their smartphone use.

7 DISCUSSION

Different previous studies [9, 24, 66, 81] discovered that one of the reasons that contributes to smartphone overuse, especially in young populations [44, 85], is the *habitual* use of the device. Habits, in particular, makes smartphone use more meaningless [49], and researchers and professionals should focus on designing solutions that promote meaningful experiences with mobile devices [78].

Our understanding on how to discover, and mitigate meaningless smartphone habits is, however, in its early stage. The majority of previous studies in this field either do not explicitly target complex habitual behaviors, e.g., by exploring simple usage patterns such as checking [56] or revisitation [31], or they compare application usage across all users [69]. Furthermore, studies that explicitly analyze smartphone usage under the lens of habits typically make use of qualitative methods such as interviews or surveys, as in[49, 78].

To close this gap, we started our work by investigating how to characterize smartphone habits (Section 2), with the aim of supporting a data analytic methodology to automatically discover them (Section 3). By reviewing previous works on habitual smartphone use, we showed that some cues, be they specific contexts or user's internal states, unconsciously spur the user in performing an automatic behavioral routine with the smartphone, exactly as it happens with any other habitual behaviors. When the routine ends, the user can experience a reward that, over the time, transforms the link between the cues and the performed smartphone routine into an automatic response. To automatically discover smartphone habits from smartphone usage data, we selected a set of contextual cues, e.g., performed activities and current location, that can be linked to behavioral smartphone routines, i.e., phone sessions that include the consecutive usage of one or more mobile apps.

Stemming from the smartphone habits characterization, we devised a habit-discovery methodology based on clustering and association rules mining. The assessment of the methodology with real-world data of users aged between 16 and 33, i.e., a target population highly susceptible to smartphone overuse [44], showed evidence that smartphone use of young adults can be characterized by various types of links between contextual situations and usage sessions, which are highly diversified across users. Context Habits, for example, represent strong correlations between contextual cues and mobile apps in which the period, the time slot, the user activity and/or the user location, along with the reception of a notification trigger the usage of one or more mobile apps. In App Habits, instead, the usage of a mobile app spurs the usage of other applications, as already described for checking behaviors [56]. Finally, App-Context Habits model the relationship between an application used in a given context and the usage of other mobile apps. Besides validating the methodology, a follow up interview with 10 users confirms that habitual smartphone use is often perceived as a negative and meaningless behavior [49, 78]: the less a habit is positively perceived, in particular, the more the user would like to avoid it.

A natural implication is the need of providing users with effective tools to control and personalize their smartphone usage. Being able to automatically assess habitual smartphone use, in particular, might have different applications, including the design of better digital wellbeing solutions. Indeed, the digital wellbeing apps that are nowadays used by million of users, e.g., QualityTime [29] and Forest [68], rarely take into account habits [50], but they often adopt pure self-monitoring strategies. Such an approach has been already criticized in terms of efficacy and users' acceptance [54]: users need to be constantly motivated to effectively use statistics, timers, and locking mechanisms, and when the motivation decreases, their behavior quickly reverts to pre-interventions levels [34].

We therefore applied our habit-discovery methodology in Socialize, a digital wellbeing mobile app that assists users to avoid the smartphone habits they consider as meaningless. Socialize constantly monitors the user's behavior with her mobile devices, and it proactively notifies the detected smartphone habits in real-time. If the user considers a notified habit as meaningless, she can activate custom just-in-time reminders to be encouraged to avoid the identified behavior when it happens again. To the best of our knowledge, this digital wellbeing tool is the first example of a mobile app that monitors and notifies smartphone habitual behaviors in real-time. Results of an in-the-wild evaluation with 20 students (age 19-31) are promising. In the majority of cases, our participants avoided the smartphone habits they considered as meaningless by activating a just-in-time reminder. Besides reducing the time spent on the mobile apps which characterized unwanted habits, in particular, participants significantly reduced their overall smartphone use in the given contexts. This means that the time saved was not redirected to other applications, as sometimes happens for digital wellbeing apps adopting simpler strategies (e.g., [33]).

Some measurable effects of just-in-time reminders persisted even after their deactivation. Furthermore, participants avoided their meaningless habits even without being aware of their choice: in the final questionnaire, they stated that their behavior with the smartphone did not change after activating a just-in-time reminders. The fact that participants did not perceive any improvements in their usage habits after using Socialize represents a shortcoming of the app, since it could potentially lead to high abandonment rates. Providing users with more detailed statistics about the defined reminders could allow users to gain awareness of their improvements, therefore encouraging them to continue using the app. That being said, participants' unawareness and the residual effects of the deactivated just-in-time reminders suggest that encouraging users to "replace" meaningless smartphone habits with alternative intentions is a promising habit-formation approach, i.e., to transform the conscious definition of an alternative routine into an automatic habit that is executed non-consciously [17]. Habit-formation approaches could play an important role in digital wellbeing apps [50, 54], supporting behavior change towards a more conscious use of technology, and ensuring the long-term effects of the new behavior [38].

7.1 Limitations and Future Work

Our work has potential limitations. In the reported in-the-wild evaluation (Section 6), we analyzed participants' usage data without and with Socialize (collection phase *vs.* intervention phase, respectively), but we did not include a control group. Therefore, we must acknowledge that some reduction effects of Socialize may have been circumstantial. More controlled experiments manipulating the different features of the Socialize app, for instance, would allow researchers to further assess the relative effectiveness of the different adopted strategies, e.g., habit detection *vs.* habit detection and just-in-time reminders.

Furthermore, the in-the-wild study and the assessment of our data-analytic methodology (Section 4) involved two relatively small samples of young adults, only. This limits the generalizability of the results. Future works would need to further asses the data-analytic methodology and the Socialize app by involving larger and diverse populations: older generations, for instance, might have different smartphone habits, and they might respond differently to the strategies implemented by Socialize.

Finally, more longer-term studies are needed to investigate the habit-forming nature of encouraging users to avoid meaningless smartphone habits and performing alternative routines. Habit-forming strategies, indeed, may take time to become established [61]: experiments [39] demonstrated that a new behavior needs from a few weeks to almost an year of repetition to become automatic, with substantial variation at individual level.

8 CONCLUSIONS

In this paper, we investigated how to characterize, discover, and mitigate habitual usage of smartphones, with a particular focus on young adults. To this end, we first reviewed previous works on habitual smartphone use to gain an initial understanding on smartphone habits. Then, we defined a data analytic methodology based on clustering and association rules mining to automatically discover complex smartphone habits from mobile usage data. We assessed the methodology over more than 130,000 phone usage sessions collected from users aged between 16 and 33. Furthermore, we applied it in Socialize, a digital wellbeing app that monitor habitual smartphone behaviors in real time, and uses proactive notifications and just-in-time reminders to encourage users to avoid the smartphone habits they consider as meaningless. We demonstrated that smartphone use of young adults can be characterized by various types of links between contextual situations and usage sessions, which are highly diversified and differently perceived across users. Furthermore, the in-the-wild evaluation of Socialize demonstrates that Socialize can effectively assist users, especially students, in better controlling their smartphone usage, with a reduction of their unwanted smartphone habits. Despite the need for further evaluations, our work opens the way for a new type of habit-forming digital wellbeing tools to assist users in replacing unwanted smartphone behaviors with more desirable activities.

A LITERATURE REVIEW PROTOCOL

This Appendix details the procedures we followed to review previous studies that talk about smartphone use under the lens of habits (Section 2). Despite the adopted rigorous method, we must acknowledge the analysis did not follow the full process of a systematic literature review.

A.1 Search 1

We performed a first search on January 13, 2020, to investigate *what* smartphone habits are and *why* they form (Section 2.1 and Section 2.2, respectively). We searched Google Scholar and the ACM Digital Library for papers published since 2010 with the following queries:

- {("mobile phone addiction" OR "smartphone addiction")}
- {("app overload" OR "mobile phone overload" OR "smartphone overload")}
- {("smartphone habits" OR "mobile phone habits" OR "habitual smartphone use" OR "app usage habits" OR "app launching habits")}

From the initial corpus, we first removed duplicates. Then, we screened the retrieved papers by removing non-academic manuscripts, limited research reports or abstracts, manuscripts that did not target smartphones, or papers that used the term "habit" superficially, i.e., without contextualizing its meaning. The following criteria were finally used to determine relevant papers:

- papers exploring the characteristics of habitual behaviors with smartphones;
- papers exploring the negative aspects, e.g., addiction, of performing habitual behaviors with smartphones;
- papers exploring interventions to mitigate habitual smartphone behaviors.

A.2 Search 2

We performed a second search on October 10, 2020, to investigate *when* smartphone habitual use occurs and can be predicted (Section 2.3). We searched Google Scholar and the ACM Digital Library for papers published since 2010 with the following queries:

- {("smartphone behavior" OR "mobile phone behavior" OR "app usage behavior")}
- {("app usage prediction" OR "mobile usage prediction")}

As in the first search, we removed duplicates, and we excluded non-academic manuscripts, limited research reports or abstracts, and manuscripts that did not target smartphones. We finally used these criteria to determine relevant papers:

- papers that present a model describing how users habitually use their smartphone;
- papers that present algorithms to predict the next interaction of the user with her smartphone.

REFERENCES

[1] 2018. Our commitment to Digital Wellbeing. https://wellbeing.google/ Accessed: 2019-06-20.

[2] Henk Aarts, Theo Paulussen, and Herman Schaalma. 1997. Physical Exercise Habit: On the Conceptualization and Formation of Habitual Health Behaviours. *Health education research* 12 (10 1997), 363–74. https://doi.org/10.1093/her/12.3.363

[3] Rakesh Agrawal, Tomasz Imieliński, and Arun Swami. 1993. Mining Association Rules Between Sets of Items in Large Databases. In *Proceedings of the 1993 ACM SIGMOD International Conference on Management of Data (SIGMOD '93)*. ACM, New York, NY, USA, 207–216. https://doi.org/10.1145/170035.170072

[4] Rakesh Agrawal and Ramakrishnan Srikant. 1994. Fast Algorithms for Mining Association Rules in Large Databases. In *Proceedings of the 20th International Conference on Very Large Data Bases (VLDB '94)*. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 487–499.

[5] Morgan G. Ames. 2013. Managing Mobile Multitasking: The Culture of iPhones on Stanford Campus. In *Proceedings of the 2013 Conference on Computer Supported Cooperative Work (CSCW '13)*. ACM, New York, NY, USA, 1487–1498. https://doi.org/10.1145/2441776.2441945

[6] Ricardo Baeza-Yates, Di Jiang, Fabrizio Silvestri, and Beverly Harrison. 2015. Predicting The Next App That You Are Going To Use. In *Proceedings of the Eighth ACM International Conference on Web Search and Data Mining (WSDM '15)*. Association for Computing Machinery, New York, NY, USA, 285–294. https://doi.org/10.1145/2684822.2685302

[7] Nikola Banovic, Christina Brant, Jennifer Mankoff, and Anind Dey. 2014. ProactiveTasks: The Short of Mobile Device Use Sessions. In *Proceedings of the 16th International Conference on Human-computer Interaction with Mobile Devices & Services (MobileHCI '14)*. ACM, New York, NY, USA, 243–252. https://doi.org/10.1145/2628363.2628380

[8] Joseph B. Bayer and Scott W. Campbell. 2012. Texting while driving on automatic: Considering the frequency-independent side of habit. *Computers in Human Behavior* 28, 6 (2012), 2083 – 2090. https://doi.org/10.1016/j.chb.2012.06.012

[9] Adriana Bianchi and James G. Phillips. 2005. Psychological Predictors of Problem Mobile Phone Use. *Cyberpsychology & behavior: the impact of the Internet, multimedia and virtual reality on behavior and society* 8 1 (2005), 39–51.

[10] Matthias Böhmer, Brent Hecht, Johannes Schöning, Antonio Krüger, and Gernot Bauer. 2011. Falling Asleep with Angry Birds, Facebook and Kindle: A Large Scale Study on Mobile Application Usage. In *Proceedings of the 13th International Conference on Human Computer Interaction with Mobile Devices and Services (MobileHCI '11)*. ACM, New York, NY, USA, 47–56. https://doi.org/10.1145/2037373.2037383

[11] Juan Pablo Carrascal and Karen Church. 2015. An In-Situ Study of Mobile App & Mobile Search Interactions. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15)*. Association for Computing Machinery, New York, NY, USA, 2739–2748. https://doi.org/10.1145/2702123.2702486

[12] Rory Cellan-Jones. 2018. Confessions of a smartphone addict. https://www.bbc.com/news/technology-44972913 Retrieved January 25, 2019.

[13] Chen Chongyang, Kem Zhang, and Sesia J. Zhao. 2015. Examining the Effects of Perceived Enjoyment and Habit on Smartphone Addiction: The Role of User Type. *Lecture Notes in Business Information Processing* 209, 224–235. https://doi.org/10.1007/978-3-319-17957-5_15

[14] Laura Dabbish, Gloria Mark, and Víctor M. González. 2011. Why Do I Keep Interrupting Myself?: Environment, Habit and Self-interruption. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11)*. ACM, New York, NY, USA, 3127–3130. https://doi.org/10.1145/1978942.1979405

[15] Tilman Dingler, Dominik Weber, Martin Pielot, Jennifer Cooper, Chung-Cheng Chang, and Niels Henze. 2017. Language Learning On-the-Go: Opportune Moments and Design of Mobile Microlearning Sessions. In *Proceedings of the 19th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '17)*. Association for Computing Machinery, New York, NY, USA, Article 28, 12 pages. https://doi.org/10.1145/3098279.3098565

[16] Brian D. Earp, Brendan Dill, Jennifer L. Harris, Joshua M. Ackerman, and John A. Bargh. 2013. No sign of quitting: incidental exposure to "no smoking" signs ironically boosts cigarette-approach tendencies in smokers. *Journal of Applied Social Psychology* 43, 10 (2013), 2158–2162. https://doi.org/10.1111/jasp.12202

[17] Gilles Einstein and Mark Mcdaniel. 2005. Prospective Memory: Multiple Retrieval Processes. *Current Directions in Psychological Science* 14 (12 2005). https://doi.org/10.1111/j.0963-7214.2005.00382.x

[18] Martin Ester, Hans-Peter Kriegel, Jörg Sander, and Xiaowei Xu. 1996. A Density-based Algorithm for Discovering Clusters a Density-based Algorithm for Discovering Clusters in Large Spatial Databases with Noise. In *Proceedings of the Second International Conference on Knowledge Discovery and Data Mining (KDD'96)*. AAAI Press, 226–231.

[19] Denzil Ferreira, Jorge Goncalves, Vassilis Kostakos, Louise Barkhuus, and Anind K. Dey. 2014. Contextual Experience Sampling of Mobile Application Micro-usage. In *Proceedings of the 16th International Conference on Human-computer Interaction with Mobile Devices & Services (MobileHCI '14)*. ACM, New York, NY, USA, 91–100. https://doi.org/10.1145/2628363.2628367

[20] Benjamin Gardner. 2015. A review and analysis of the use of "habit" in understanding, predicting and influencing health-related behaviour. *Health Psychology Review* 9, 3 (2015), 277–295. https://doi.org/10.1080/17437199.2013.876238

[21] Victor M. González, Gloria Mark, and Gloria Mark. 2004. "Constant, Constant, Multi-tasking Craziness": Managing Multiple Working Spheres. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '04)*. ACM, New York, NY, USA, 113–120. https://doi.org/10.1145/985692.985707

[22] Alina Hang, Alexander De Luca, Jonas Hartmann, and Heinrich Hussmann. 2013. Oh App, Where Art Thou?: On App Launching Habits of Smartphone Users. In *Proceedings of the 15th International Conference on Human-computer Interaction with Mobile Devices and Services (MobileHCI '13)*. ACM, New York, NY, USA, 392–395. https://doi.org/10.1145/2493190.2493219

[23] Ellie Harmon and Melissa Mazmanian. 2013. Stories of the Smartphone in Everyday Discourse: Conflict, Tension & Instability. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '13)*. ACM, New York, NY, USA, 1051–1060. https://doi.org/10.1145/2470654.2466134

[24] Joshua Harwood, Julian J. Dooley, Adrian J. Scott, and Richard Joiner. 2014. Constantly connected – The effects of smart-devices on mental health. *Computers in Human Behavior* 34 (2014), 267 – 272. https://doi.org/10.1016/j.chb.2014.02.006

[25] Alexis Hiniker, Sungsoo (Ray) Hong, Tadayoshi Kohno, and Julie A. Kientz. 2016. MyTime: Designing and Evaluating an Intervention for Smartphone Non-Use. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, New York, NY, USA, 4746–4757. https://doi.org/10.1145/2858036.2858403

[26] Alexis Hiniker, Shwetak N. Patel, Tadayoshi Kohno, and Julie A. Kientz. 2016. Why Would You Do That? Predicting the Uses and Gratifications behind Smartphone-Usage Behaviors. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '16)*. Association for Computing Machinery, New York, NY, USA, 634–645. https://doi.org/10.1145/2971648.2971762

[27] Daniel Hintze, Philipp Hintze, Rainhard D. Findling, and René Mayrhofer. 2017. A Large-Scale, Long-Term Analysis of Mobile Device Usage Characteristics. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 2, Article 13 (June 2017), 21 pages. https://doi.org/10.1145/3090078

[28] Ke Huang, Chunhui Zhang, Xiaoxiao Ma, and Guanling Chen. 2012. Predicting Mobile Application Usage Using Contextual Information. In *Proceedings of the 2012 ACM Conference on Ubiquitous Computing (UbiComp '12)*. ACM,

New York, NY, USA, 1059–1065. https://doi.org/10.1145/2370216.2370442

[29] NComputing Global Inc. 2019. QualityTime: Discover Your Smartphone Habits. Manage Your Digital Diet. http://www.qualitytimeapp.com/ Accessed: 2019-06-20.

[30] Alexander J Rothman, Paschal Sheeran, and Wendy Wood. 2009. Reflective and Automatic Processes in the Initiation and Maintenance of Dietary Change. *Annals of behavioral medicine : a publication of the Society of Behavioral Medicine* 38 Suppl 1 (09 2009), S4–17. https://doi.org/10.1007/s12160-009-9118-3

[31] Simon L. Jones, Denzil Ferreira, Simo Hosio, Jorge Goncalves, and Vassilis Kostakos. 2015. Revisitation Analysis of Smartphone App Use. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '15)*. ACM, New York, NY, USA, 1197–1208. https://doi.org/10.1145/2750858.2807542

[32] L. Kaufman and P.J. Rousseeuw. 1990. *Finding Groups in Data: an introduction to cluster analysis*. Wiley.

[33] Jaejeung Kim, Joonyoung Park, Hyunsoo Lee, Minsam Ko, and Uichin Lee. 2019. LocknType: Lockout Task Intervention for Discouraging Smartphone App Use. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. ACM, New York, NY, USA, Article 697, 12 pages. https://doi.org/10.1145/3290605.3300927

[34] Predrag Klasnja, Sunny Consolvo, and Wanda Pratt. 2011. How to Evaluate Technologies for Health Behavior Change in HCI Research. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11)*. Association for Computing Machinery, New York, NY, USA, 3063–3072. https://doi.org/10.1145/1978942.1979396

[35] Christian A. Klöckner. 2013. A comprehensive model of the psychology of environmental behaviour—A meta-analysis. *Global Environmental Change* 23, 5 (2013), 1028 – 1038. https://doi.org/10.1016/j.gloenvcha.2013.05.014

[36] Minsam Ko, Seungwoo Choi, Koji Yatani, and Uichin Lee. 2016. Lock N' LoL: Group-based Limiting Assistance App to Mitigate Smartphone Distractions in Group Activities. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, New York, NY, USA, 998–1010. https://doi.org/10.1145/2858036.2858568

[37] Minsam Ko, Subin Yang, Joonwon Lee, Christian Heizmann, Jinyoung Jeong, Uichin Lee, Daehee Shin, Koji Yatani, Junehwa Song, and Kyong-Mee Chung. 2015. NUGU: A Group-based Intervention App for Improving Self-Regulation of Limiting Smartphone Use. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing (CSCW '15)*. ACM, New York, NY, USA, 1235–1245. https://doi.org/10.1145/2675133.2675244

[38] Phillippa Lally and Benjamin Gardner. 2013. Promoting habit formation. *Health Psychology Review* 7, sup1 (2013), S137–S158. https://doi.org/10.1080/17437199.2011.603640

[39] Phillippa Lally, Cornelia H. M. van Jaarsveld, Henry W. W. Potts, and Jane Wardle. 2010. How are habits formed: Modelling habit formation in the real world. *European Journal of Social Psychology* 40, 6 (2010), 998–1009. https://doi.org/10.1002/ejsp.674

[40] Simone Lanette, Phoebe K. Chua, Gillian Hayes, and Melissa Mazmanian. 2018. How Much is 'Too Much'?: The Role of a Smartphone Addiction Narrative in Individuals' Experience of Use. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW, Article 101 (Nov. 2018), 22 pages. https://doi.org/10.1145/3274370

[41] Simone Lanette and Melissa Mazmanian. 2018. The Smartphone "Addiction" Narrative is Compelling, but Largely Unfounded. In *Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems (CHI EA '18)*. Association for Computing Machinery, New York, NY, USA, Article Paper LBW023, 6 pages. https://doi.org/10.1145/3170427.3188584

[42] Robert Larose, Jung-Hyun Kim, and Wei Peng. 2011. *Social Networking: Addictive, Compulsive, Problematic or Just Another Media Habit?* 59–81.

[43] J. K. Laurila, Daniel Gatica-Perez, I. Aad, Blom J., Olivier Bornet, Trinh-Minh-Tri Do, O. Dousse, J. Eberle, and M. Miettinen. 2012. The Mobile Data Challenge: Big Data for Mobile Computing Research. (2012). http://infoscience.epfl.ch/record/192489

[44] Uichin Lee, Joonwon Lee, Minsam Ko, Changhun Lee, Yuhwan Kim, Subin Yang, Koji Yatani, Gahgene Gweon, Kyong-Mee Chung, and Junehwa Song. 2014. Hooked on Smartphones: An Exploratory Study on Smartphone Overuse Among College Students. In *Proceedings of the 32Nd Annual ACM Conference on Human Factors in Computing Systems (CHI '14)*. ACM, New York, NY, USA, 2327–2336. https://doi.org/10.1145/2556288.2557366

[45] Yu-Kang Lee, Chun-Tuan Chang, You Lin, and Zhao-Hong Cheng. 2014. The dark side of smartphone usage: Psychological traits, compulsive behavior and technostress. *Computers in Human Behavior* 31 (2014), 373 – 383. https://doi.org/10.1016/j.chb.2013.10.047

[46] Robert LiKamWa, Yunxin Liu, Nicholas D. Lane, and Lin Zhong. 2013. MoodScope: Building a Mood Sensor from Smartphone Usage Patterns. In *Proceeding of the 11th Annual International Conference on Mobile Systems, Applications, and Services (MobiSys '13)*. Association for Computing Machinery, New York, NY, USA, 389–402. https://doi.org/10.1145/2462456.2464449

[47] Moez Limayem, Sabine Gabriele Hirt, and Christy M. K. Cheung. 2007. How Habit Limits the Predictive Power of Intention: The Case of Information Systems Continuance. *MIS Quarterly* 31, 4 (2007), 705–737.

[48] Xi Lu, Junko Watanabe, Qingbo Liu, Masayo Uji, Masahiro Shono, and Toshinori Kitamura. 2011. Internet and mobile phone text-messaging dependency: Factor structure and correlation with dysphoric mood among Japanese

adults. *Computers in Human Behavior* 27, 5 (2011), 1702 – 1709. https://doi.org/10.1016/j.chb.2011.02.009 2009 Fifth International Conference on Intelligent Computing.

[49] Kai Lukoff, Cissy Yu, Julie Kientz, and Alexis Hiniker. 2018. What Makes Smartphone Use Meaningful or Meaningless? *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 1, Article 22 (March 2018), 26 pages. https://doi.org/10.1145/3191754

[50] Ulrik Lyngs, Kai Lukoff, Petr Slovak, Reuben Binns, Adam Slack, Michael Inzlicht, Max Van Kleek, and Nigel Shadbolt. 2019. Self-Control in Cyberspace: Applying Dual Systems Theory to a Review of Digital Self-Control Tools. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. ACM, New York, NY, USA, Article 131, 18 pages. https://doi.org/10.1145/3290605.3300361

[51] Christopher D. Manning, Prabhakar Raghavan, and Hinrich Schütze. 2008. *Introduction to Information Retrieval*. Cambridge University Press, New York, NY, USA.

[52] John G. McHaffie, Terrence R. Stanford, Barry E. Stein, Veronique Coizet, and Peter Redgrave. 2005. Subcortical loops through the basal ganglia. *Trends in Neurosciences* 28, 8 (2005), 401 – 407. https://doi.org/10.1016/j.tins.2005.06.006

[53] Abhinav Mehrotra, Sandrine R. Müller, Gabriella M. Harari, Samuel D. Gosling, Cecilia Mascolo, Mirco Musolesi, and Peter J. Rentfrow. 2017. Understanding the Role of Places and Activities on Mobile Phone Interaction and Usage Patterns. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 3, Article 84 (Sept. 2017), 22 pages. https://doi.org/10.1145/3131901

[54] Alberto Monge Roffarello and Luigi De Russis. 2019. The Race Towards Digital Wellbeing: Issues and Opportunities. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. ACM, New York, NY, USA, Article 386, 14 pages. https://doi.org/10.1145/3290605.3300616

[55] Sheina Orbell and Bas Verplanken. 2010. The Automatic Component of Habit in Health Behavior: Habit as Cue-Contingent Automaticity. *Health psychology : official journal of the Division of Health Psychology, American Psychological Association* 29 (07 2010), 374–83. https://doi.org/10.1037/a0019596

[56] Antti Oulasvirta, Tye Rattenbury, Lingyi Ma, and Eeva Raita. 2012. Habits make smartphone use more pervasive. *Personal and Ubiquitous Computing* 16, 1 (01 Jan 2012), 105–114. https://doi.org/10.1007/s00779-011-0412-2

[57] Abhinav Parate, Matthias Böhmer, David Chu, Deepak Ganesan, and Benjamin M. Marlin. 2013. Practical Prediction and Prefetch for Faster Access to Applications on Mobile Phones. In *Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '13)*. Association for Computing Machinery, New York, NY, USA, 275–284. https://doi.org/10.1145/2493432.2493490

[58] Woong Ki Park. 2005. *Mobile Phone Addiction*. Springer London, London, 253–272. https://doi.org/10.1007/1-84628-248-9_17

[59] Martin Pielot, Bruno Cardoso, Kleomenis Katevas, Joan Serrà, Aleksandar Matic, and Nuria Oliver. 2017. Beyond Interruptibility: Predicting Opportune Moments to Engage Mobile Phone Users. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 3, Article 91 (Sept. 2017), 25 pages. https://doi.org/10.1145/3130956

[60] Martin Pielot, Tilman Dingler, Jose San Pedro, and Nuria Oliver. 2015. When Attention is Not Scarce - Detecting Boredom from Mobile Phone Usage. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '15)*. Association for Computing Machinery, New York, NY, USA, 825–836. https://doi.org/10.1145/2750858.2804252

[61] Charlie Pinder, Jo Vermeulen, Benjamin R. Cowan, and Russell Beale. 2018. Digital Behaviour Change Interventions to Break and Form Habits. *ACM Transaction on Computer-Human Interaction* 25, 3, Article 15 (June 2018), 66 pages. https://doi.org/10.1145/3196830

[62] Adam Popescu. 2018. Keep Your Head Up: How Smartphone Addiction Kills Manners and Moods. https://www.nytimes.com/2018/01/25/smarter-living/bad-text-posture-neckpain-mood.html Retrieved January 25, 2019.

[63] Amanda Rebar, James Dimmock, Ben Jackson, Ryan Rhodes, Andrew Kates, Jade Starling, and Corneel Vandelanotte. 2016. A Systematic Review of the Effects of Non-Conscious Regulatory Processes in Physical Activity. *Health Psychology Review* 10 (04 2016), 1–86. https://doi.org/10.1080/17437199.2016.1183505

[64] Eric Robinson, Paul Aveyard, Amanda Daley, Kate Jolly, A Lewis, Deborah Lycett, and Suzanne Higgs. 2013. Eating attentively: A systematic review and meta-analysis of the effect of food intake memory and awareness on eating. *The American journal of clinical nutrition* 97 (02 2013). https://doi.org/10.3945/ajcn.112.045245

[65] Larry D. Rosen, L. Mark Carrier, and Nancy A. Cheever. 2013. Facebook and Texting Made Me Do It: Media-induced Task-switching While Studying. *Computers in Human Behavior* 29, 3 (May 2013), 948–958. https://doi.org/10.1016/j.chb.2012.12.001

[66] Mohammad Salehan and Arash Negahban. 2013. Social Networking on Smartphones: When Mobile Phones Become Addictive. *Comput. Hum. Behav.* 29, 6 (Nov. 2013), 2632–2639. https://doi.org/10.1016/j.chb.2013.07.003

[67] G. Salton, A. Wong, and C. S. Yang. 1975. A Vector Space Model for Automatic Indexing. *Commun. ACM* 18, 11 (Nov. 1975), 613–620. https://doi.org/10.1145/361219.361220

[68] Seekrtech. 2019. Forest - Stay focused, be present. https://www.forestapp.cc/ Accessed: 2019-06-20.

[69] Choonsung Shin and Anind K. Dey. 2013. Automatically Detecting Problematic Use of Smartphones. In *Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '13)*. ACM, New York, NY, USA, 335–344. https://doi.org/10.1145/2493432.2493443

[70] Choonsung Shin, Jin-Hyuk Hong, and Anind K. Dey. 2012. Understanding and Prediction of Mobile Application Usage for Smart Phones. In *Proceedings of the 2012 ACM Conference on Ubiquitous Computing (UbiComp '12)*. ACM, New York, NY, USA, 173–182. https://doi.org/10.1145/2370216.2370243

[71] Manya Sleeper, Alessandro Acquisti, Lorrie Faith Cranor, Patrick Gage Kelley, Sean A. Munson, and Norman Sadeh. 2015. I Would Like To..., I Shouldn'T..., I Wish I...: Exploring Behavior-Change Goals for Social Networking Sites. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing (CSCW '15)*. ACM, New York, NY, USA, 1058–1069. https://doi.org/10.1145/2675133.2675193

[72] A. David Smith and J. Paul Bolam. 1990. The neural network of the basal ganglia as revealed by the study of synaptic connections of identified neurones. *Trends in Neurosciences* 13, 7 (1990), 259 – 265. https://doi.org/10.1016/0166-2236(90)90106-K

[73] Michael Steinbach, George Karypis, and Vipin Kumar. 2000. A Comparison of Document Clustering Techniques. *Proceedings of the International KDD Workshop on Text Mining* (06 2000).

[74] Chen Sun, Jun Zheng, Huiping Yao, Yang Wang, and D. Frank Hsu. 2013. AppRush: Using Dynamic Shortcuts to Facilitate Application Launching on Mobile Devices. *Procedia Computer Science* 19 (2013), 445 – 452. https://doi.org/10.1016/j.procs.2013.06.060 The 4th International Conference on Ambient Systems, Networks and Technologies (ANT 2013), the 3rd International Conference on Sustainable Energy Information Technology (SEIT-2013).

[75] Pang-Ning Tan, Michael Steinbach, and Vipin Kumar. 2005. *Introduction to Data Mining, (First Edition)*. Addison-Wesley Longman Publishing Co., Inc., Boston, MA, USA.

[76] Virginia Thomas, Margarita Azmitia, and Steve Whittaker. 2016. Unplugged: Exploring the costs and benefits of constant connection. *Computers in Human Behavior* 63 (2016), 540 – 548. https://doi.org/10.1016/j.chb.2016.05.078

[77] Chad Tossell, Philip Kortum, Ahmad Rahmati, Clayton Shepard, and Lin Zhong. 2012. Characterizing Web Use on Smartphones. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '12)*. ACM, New York, NY, USA, 2769–2778. https://doi.org/10.1145/2207676.2208676

[78] Jonathan A. Tran, Katie S. Yang, Katie Davis, and Alexis Hiniker. 2019. Modeling the Engagement-Disengagement Cycle of Compulsive Phone Use. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. ACM, New York, NY, USA, Article 312, 14 pages. https://doi.org/10.1145/3290605.3300542

[79] Patti Valkenburg and Jochen Peter. 2007. Preadolescents' and Adolescents' Online Communication and Their Closeness to Friends. *Developmental psychology* 43 (04 2007), 267–77. https://doi.org/10.1037/0012-1649.43.2.267

[80] Niels van Berkel, Chu Luo, Theodoros Anagnostopoulos, Denzil Ferreira, Jorge Goncalves, Simo Hosio, and Vassilis Kostakos. 2016. A Systematic Assessment of Smartphone Usage Gaps. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. Association for Computing Machinery, New York, NY, USA, 4711–4721. https://doi.org/10.1145/2858036.2858348

[81] Alexander J.A.M. van Deursen, Colin L. Bolle, Sabrina M. Hegner, and Piet A.M. Kommers. 2015. Modeling habitual and addictive smartphone behavior: The role of smartphone usage types, emotional intelligence, social stress, self-regulation, age, and gender. *Computers in Human Behavior* 45 (2015), 411 – 420. https://doi.org/10.1016/j.chb.2014.12.039

[82] Philippe Verduyn, David Lee, Jiyoung Park, Holly Shablack, Ariana Orvell, Joseph Bayer, Oscar Ybarra, John Jonides, and Ethan Kross. 2015. Passive Facebook Usage Undermines Affective Well-Being: Experimental and Longitudinal Evidence. *Journal of Experimental Psychology General* (02 2015). https://doi.org/10.1037/xge0000057

[83] Tingxin Yan, David Chu, Deepak Ganesan, Aman Kansal, and Jie Liu. 2012. Fast App Launching for Mobile Devices Using Predictive User Context. In *Proceedings of the 10th International Conference on Mobile Systems, Applications, and Services (MobiSys '12)*. ACM, New York, NY, USA, 113–126. https://doi.org/10.1145/2307636.2307648

[84] Sha Zhao, Julian Ramos, Jianrong Tao, Ziwen Jiang, Shijian Li, Zhaohui Wu, Gang Pan, and Anind K. Dey. 2016. Discovering Different Kinds of Smartphone Users Through Their Application Usage Behaviors. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '16)*. ACM, New York, NY, USA, 498–509. https://doi.org/10.1145/2971648.2971696

[85] Maayan Zhitomirsky-Geffet and Maya Blau. 2016. Cross-generational analysis of predictive factors of addictive behavior in smartphone usage. *Computers in Human Behavior* 64 (2016), 682 – 693. https://doi.org/10.1016/j.chb.2016.07.061

Received ; revised ; accepted