The Race Towards Digital Wellbeing: Issues and Opportunities

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ABSTRACT

As smartphone use increases dramatically, so do studies about technology overuse. Many different mobile apps for breaking "smartphone addiction" and achieving "digital wellbeing" are available. However, it is still not clear whether and how such solutions work. Which functionality do they have? Are they effective and appreciated? Do they have a relevant impact on users' behavior? To answer these questions, *(i)* we reviewed the features of 42 digital wellbeing apps, *(ii)* we performed a thematic analysis on 1,128 user reviews of such apps, and *(iii)* we conducted a 3-week-long in-the-wild study of Socialize, an app that includes the most common digital wellbeing features, with 38 participants. We discovered that digital wellbeing apps are appreciated and useful for some specific situations. However, they do not promote the formation of new habits and they are perceived as not restrictive enough, thus not effectively helping users to change their behavior with smartphones.

CCS CONCEPTS

• **Human-centered computing → Smartphones**; *Empirical studies in ubiquitous and mobile computing*; Field studies.

KEYWORDS

Smartphone Addiction, Digital Wellbeing, Self-Monitoring, Habit Formation

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1 INTRODUCTION

Smartphones have become an integral part of our daily lives. Through smartphones, users can nowadays perform many different tasks such as browsing the web, reading emails, and using social networks. As smartphone use increases dramatically [39], however, so do studies about the negative impact of overusing technology. Smartphones, in particular, have been found to be a source of distraction [3], and their excessive use can be a problem for mental health [27] and social interaction [31]. Furthermore, smartphones serve as a gateway for a variety of mobile applications that can result in addictive behaviors [11], e.g., constantly checking social networks. As a consequence, HCI researchers started to pay more attention to the field of intentional "non-use" of technology [5, 40, 48], and the term "smartphone addiction" has gained interest both in the literature and in mainstream media [29]. Many different mobile apps can currently be used as tools for changing users' behavior with smartphones, and even Google and Apple recently announced new tools for monitoring, understanding, and limiting technology use in their operating systems, with the aim of promoting a more conscious use of the smartphone. Google, in particular, summarized its commitment with the term "digital wellbeing":

> *"We're committed to giving everyone the tools they need to develop their own sense of digital wellbeing. So that life, not the technology in it, stays front and center."* [1]

Despite the growing popularity, contemporary digital wellbeing apps have not been extensively evaluated by researchers, yet, and it is still not clear how effective they are. Which functionality do they have? Are they effective and appreciated? Do they have a relevant impact on users' behavior? Answering these questions is fundamental to improve our knowledge of the problem and to design better digital wellbeing solutions.

In this paper, we report on the results of 3 different studies with the aim of providing an overall perspective of contemporary mobile apps for digital wellbeing, and identifying possible issues and opportunities to improve such solutions.

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First, we conducted a functionality review of the 42 most popular digital wellbeing apps available in the Google Play Store[1], by highlighting which features are more common, and how such apps support a more conscious use of technology. Second, we extracted 1,128 reviews left by users for these 42 apps, and we conducted a thematic analysis to gain insight about the users' experience with digital wellbeing apps and their features. Third, we designed and implemented Socialize, our own digital wellbeing app, by integrating the most common digital wellbeing features extracted during our functionality review. We conducted a three-week in-the-wild study of Socialize with 38 participants. Our aim was to gain a quantitative insight into the findings stemming from the first 2 qualitative studies, thus assessing whether the features that contemporary digital wellbeing solutions share are effective for changing behavior and promoting a more conscious use of the smartphone. The main contribution of our work is threefold:

- We highlight that contemporary digital wellbeing apps are mainly focused on supporting self-monitoring, i.e., tracking user's behavior and receiving feedback, but are not grounded in habit formation nor social support literature. Habit formation, 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 [26].
- Thanks to the qualitative reviews' analysis and the quantitative data extracted from the Socialize evaluation, we show that contemporary digital wellbeing apps are liked by users and useful for some specific use cases, but they are not sufficient for effectively changing users' behavior with smartphones. By using self-monitoring functionality, in particular, such apps are effective for temporary breaking some unhealthy behaviors, e.g., the excessive use of social networks, but they fail in other circumstances. For example, by offering functionality that can be easily bypassed, they do not prevent users from constantly checking their devices.
- We discuss the results and we propose a series of insights to inform future works and go beyond self-monitoring techniques. Promising areas to be explored include the design of digital wellbeing apps that support the formation of new habits and promote self-regulation through social support.

[1]https://play.google.com/, last visited on August 24, 2018

2 RELATED WORK AND BACKGROUND

Technology Overuse

Due to their accessibility and functionality, smartphones have become an integral part of our daily lives and their use increased dramatically in the last few years [39]. Smartphones, in particular, serve as a gateway to many different mobile apps and online services, giving the users a world of possibility, such as browsing the web, messaging, and checking social networks. Unfortunately, despite many advantages and increasing opportunities for social support [44], the excessive usage of smartphones and online services often exhibits negative effects on mental health [27] and social interaction [31]. Mobile device use can sometimes disrupt the introspective processes that accompany in-person social interaction [22], preventing one from understanding the psychological states of others and thereby empathizing with them [20]. This can affect the quality of face-to-face conversations [45], resulting in a shift from vertical relationships that require long-term effort and commitment, to horizontal relationships that indicate an expanded network of shallow relationships [14]. Furthermore, several studies demonstrate that smartphones are a source of distractions that interferes with daily activities and ongoing tasks such as studying, working, and driving [3, 16]. Distractions can be caused by external stimuli, e.g., notifications, but also by internal stimuli [10], e.g., users that interrupt themselves by frequently checking emails [39]. Users that experience frequent and unpredictable external or internal interruptions, in particular, tend to feel less productive [35] and more stressed [36]. As a result, the term "smartphone addiction" has become popular in research studies [7, 11, 29]. Technology-related addictions can be classified as behavioral addictions [8]: interactive devices induce and reinforce features that may promote addictive tendencies [33]. Even if the addiction framing may not be appropriate for widespread and everyday behaviors like mobile devices use [28], people often perceive their excessive smartphone use as problematic [23, 42], and they are willing to adopt different strategies to mitigate such a behavior [23]. Problematic smartphone use, in particular, can be identified through self-reported questionnaires [6, 37] or through computational methods [30, 42].

Our work stems from the technology overuse research with the aim of exploring and understanding how contemporary solutions for changing users' behavior with smartphones work, whether they are sufficient, and how we could improve them.

Mobile Apps for Digital Wellbeing

In response to technology overuse, HCI researchers started to pay more attention on the field of intentional "non-use" of technology [5, 40, 48]. These works reveal that many users feel conflicted about the time they spend with digital technologies [23]. In addition, many different mobile apps are currently available in the Google Play Store to help people limit and improve their smartphone use, e.g, QualityTime and Forest. Moreover, Google and Apple recently announced their commitment in designing technology truly helpful for everyone, with the introduction in their mobile operating systems of tools for monitoring, understanding, and limiting technology use [1].

Our understanding of how to design for self-regulation of technology use, however, is still in its early days [47]. Apps for digital wellbeing have not been extensively evaluated by researchers and it is yet not clear how effective they are. Only a limited number of previous works [9, 34] analyze commercially available tools, by focusing on productivity, mainly. Furthermore, the tools proposed in the literature against smartphone addiction are designed for evaluating specific use cases [17, 22, 23, 32]. Hiniker et al. [17], for example, propose MyTime, an intervention app to support people in achieving goals related to smartphone non-use. With AppDetox [32], instead, users can define simple rules to block the usage of certain apps. Ko et al. [22] developed Lock n' LoL, a mobile app that helps students focus on their group activities by allowing group members to limit their smartphone usage together. In another mobile app, called NUGU, Ko et al. [23] demonstrate that self-regulation can be improved by leveraging social support, i.e., groups of people that limit their use together by sharing their limiting information.

Despite a growing interest on the topic, previous work fails in providing a comprehensive view of existing digital wellbeing apps and their features, and open questions still remain. Little is known, for example, about whether contemporary digital wellbeing apps are capable of supporting the formation of new habits. A habit is defined as a consistent repetition of a behavior in the presence of stable contextual cues that increases the automaticity of that behavior [26]. With smartphones, habits can be defined as automated smartphone usage sessions associated with explicit contexts such as location, performed activity, and emotional state [39]. Habit formation techniques could play an important role in digital wellbeing apps, supporting behavior change and ensuring its long-term effects [26]. Such techniques, in particular, could help users in forming new habits a) that promote a meaningful smartphone use, e.g, using an educational app to learn something new in the evening, or b) that discourage smartphone use in a given situation, e.g, going for a walk in the leisure time instead of playing Candy Crush.

In our work we would like to close this gap, by trying to understand issues and opportunities for this "race" towards digital wellbeing. To reach our goal, we review the most common features offered by contemporary commercial digital wellbeing apps, we analyze a consistent number of users' reviews, and we quantitatively evaluate such solutions with an in-the-wild study.

3 CHARACTERIZING DIGITAL WELLBEING APPS

Hundreds of apps that can be classified as "digital wellbeing assistants" can be downloaded and installed on our smartphones and tablets with a single click. Despite a growing interest in topics like smartphone addiction and technology overuse, little is known about the effectiveness or theoretical grounding of existing digital wellbeing apps. Therefore, we conducted an exploratory study to investigate which features such apps offer, and how they support a more conscious use of technology.

	Category	**Features**
Self Monitoring	Tracking	Phone Unlocks, Phone Time, App Time, App Checking
	Data Presentation	Phone Summary, App Summary, Charts, Daily/Widget Recap, Social Comparison
Interventions	Phone Interventions	Phone Timers, Phone Blockers, Take a Break, Redesign UI
	App Interventions	App Timers, App Blockers, Notification Blockers
	Extra Features	Motivational Quotes, Rewards, Automatic Interventions

Table 1: Features offered by digital wellbeing apps (N=42).

Method

To define an exhaustive and representative list of digital wellbeing apps, we searched for mobile apps in the Google Play Store by using the following keywords: *"digital diet," "smartphone addiction," "avoid distractions," "screen time," "app usage tracker,"* and *"phone usage tracker."* The search included both free and selling apps, and was conducted in July, 2018. We decided to focus on the Google Play Store, rather than Apple's App Store, since iOS is typically more restrictive than Android and it does not allow developers to access sensitive information such as phone usage statistics.

Results were scanned to identify apps specifically designed for changing behavior and promoting a more conscious use of smarphones. Furthermore, we excluded from the results beta apps, apps with less that 1,000 downloads, and apps with less than 50 reviews. In the end, 42 apps were selected as relevant. By analyzing the descriptions of each app, we extracted a set of 19 offered features. Other supported features such as data export or backups were also noted, but were excluded from the analysis as they were not directly related to digital wellbeing. Table 1 reports all the extracted features, while Figure 1 shows their distribution through the analyzed digital wellbeing apps.

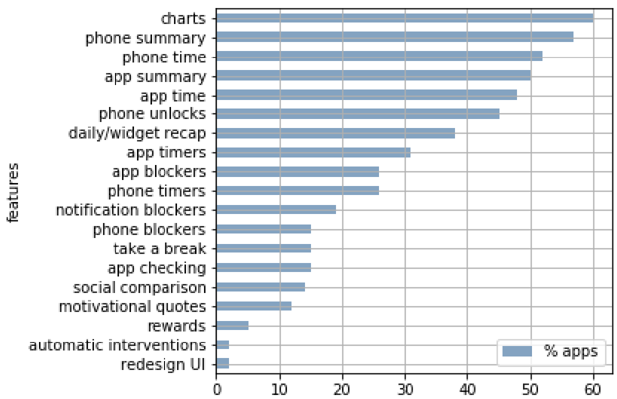


Figure 1: Distribution of features offered by digital wellbeing apps (N=42).

Findings

Tracking and Visualizing Data. The most popular features across all the 42 apps are related to tracking usage data and presenting them to the users. In total, 15 apps track and visualize data related to the phone, only (*phone-level apps*). Instead, 12 other apps are developed with the aim of monitoring the usage of other apps (*app-level apps*). The remaining 15 apps include both phone and app-level statistics.

More in detail, 57% of the apps offer a *phone summary*, i.e., one or more windows visualizing statistics about how long the phone has been used (*phone time*, 52%), or checked (*unlocks*, 27%). Furthermore, 50% of the apps offer an *app summary*, i.e., one or more windows visualizing statistics about how long the various apps have been used (*app time*, 48%), or checked/opened (*app checking*, 15%). In visualizing data, digital wellbeing apps typically adopt *charts* (60%), and use home-screen widgets and daily e-mail summaries to draw user attention (*daily/widget recap*, 38%). Finally, they can offer the users the possibility to compare their own statistics with other users (*social comparison*, 14%).

Reducing Addiction Through Interventions. Beside tracking and visualizing data, wellbeing apps also offer various interventions to mitigate addictive usage of phone and apps. At the app-level, users can typically instantiate *app timers*, to be notified when they are using an app for too long (31%); *app-blockers*, to block the usage of a given app (26%); or *notification blockers*, to disable notifications (19%). Users can also instantiate phone-level timers (26%) and blockers (15%), to limit the usage of the entire phone. Furthermore, they can *take a break* (15%) from their devices, by silencing and locking them to completely avoid distractions.

As extra-features, some apps support users through *motivational quotes* (12%), and reward them if they succeed in some "digital wellbeing challenge" (*rewards*, 10%).

In addition to the most common features, there are some interesting but rarely adopted features. A few apps (2%) are able to instantiate *automatic interventions* by reasoning on user data, while other apps (2%) can be used to dynamically *redesign the phone UI*, e.g., to randomize the location of the most addictive apps to prevent unconscious opening and usage.

4 REVIEWS' ANALYSIS

To gain insights about the experience of users with digital wellbeing apps and their features, we conducted a second exploratory study based on online reviews of the 42 previous apps. Analyzing user reviews is a common practice to understand users' opinion [13]. Even if reviews are often bimodal and represent extreme viewpoints [19], they provide a crowd-sourced indication of app-quality [46].

Method

For each of the 42 apps selected for the first study, we used the ParseHub[2] web scraping tool to scrape the first 50 publicly available reviews on the Google Play Store. To ensure a mix of positive, negative, new and old reviews was included, all reviews were sorted by "Helpfulness" during the data collection phase. From the results, we excluded non-English reviews. We also excluded short reviews, i.e., less than 3 words, that provided limited information, e.g.,"good app" or "doesn't work". In the end, our final dataset included 1,128 reviews posted between 2015 and 2018 with the following distribution: 3% in 2015, 8% in 2016, 25% in 2017, and 64% in 2018. On average, they are 153 characters long (SD = 96), and have a rating of 3.79 out of 5 (SD = 1.45). In total, 175 of them (16%) are anonymous, i.e., with "A Google User" as username.

We conducted a thematic content analysis to characterize the rationale for why users liked or disliked digital wellbeing apps. We leveraged a hybrid approach [12] based on inductive and deductive codes. Deductive codes were informed by the reported related work on digital wellbeing and technology overuse, while inductive codes were added upon reviewing the data. We used a multi-phase process to ensure coding reliability [18]. First, a researcher built an initial codebook by reading all the reviews in depth. Then, the researcher that created the initial codebook and another researcher coded 20 randomly selected reviews, discussed

[2]https://www.parsehub.com/, last visited on August 9, 2018

disagreements, and refined the codebook. After the first coding process, the same 2 researchers independently coded other 40 randomly selected reviews by reaching a consensus (Cohen's kappa = 0.95, SD = 0.08). Finally, one researcher coded all the reviews using the refined codebook. We allowed multiple codes to apply to each review. Table 2 summarizes our final codebook with which we coded all the reviews. In the remainder of this section, we describe the reviews' characteristics, and we present the themes emerging from the thematic analysis.

	Main Themes	**Codes**
Liked	Generic Liking & Proposed Improvements	Good Idea, Useful, Accurate, Easy To Use, Feeling Better, Add Features, Detailing, Other Devices
	Use Cases	Studying, Working, Sleeping, Parental Control, Free Time
	Preferred Features	Statistics, Timers & Blockers, Rewards & Motivation, Metaphor & Gamification, Restrictive
	Control Unhealthy Behaviours	Impulse Control, Productivity, Focus, Awareness, Unplug, Break Habits, Time Management, Addiction, Self-Monitoring
Disliked	Generic Disliking & Usability Issues	Performance, Design Flaws, Bugs, Price
	Insufficiently Restrictive	Bypassable, Permissive, Ignorable, Unrestrictive
	Privacy Invasive	Privacy, Irritating, Intrusive

Table 2: Codes used in the review analysis.

Why Users Like Digital Wellbeing Apps

Users Are Fascinated and Propose Improvements. In terms of overall tone, the majority of the review comments are positive (N = 619, 55%), while 9% are neutral (N = 96) and 37% (N = 413) are negative. Users like the idea of having a digital wellbeing assistant (N = 67, 6%), and find it useful (N = 49, 4%) for breaking phone addiction. 17 reviews (2%), in particular, explicitly mention that digital wellbeing apps have the potential to make users feeling better:

> *"I've been using this for three hours now. I can already tell it's going to stay on my phone. In just the last few hours, I've been made aware of how often I reach for my phone and then cycle through the same five apps looking for hits. Instant relief. (R309)"*

Reviews suggest that digital wellbeing apps are easy to use (N = 34, 3%), and they are the more useful the more they are accurate in tracking information such as screen time, unlocks, or time (N = 8, 1%).

Furthermore, some users ask whether the apps are also available for other devices (N = 7, 1%). Users are also likely to propose improvements, ranging from adding new features (N = 173, 15%) to detailing existing ones (N = 19, 2%).

Not surprisingly [11], a few reviews also point out that focusing on the phone-level, only, is not enough:

> *"The entire phone gets locked..i just wanted to block specific apps for specific time." (R67)*

Digitall Wellbeing Apps Are Useful for Many Use Cases. Users exploit digital wellbeing apps in different contexts and for different use cases. The most common tasks emerging from the reviews are studying (N = 46, 4%) and working (N = 20, 2%):

> *"An easy way to get off from distraction during studies. A must-app for students who are addicted to social world." (R619)*

> *"Great tool to focus and get down to your work. Made me more aware of how I am really working and how much I "think" I was working." (R897)*

Users also feel that digital wellbeing apps could be useful as parental control tools (N = 11, 1%). By installing such applications on their kids' devices, in fact, parents could control how their kids use smartphones, limiting the usage of any dangerous or addictive application:

> *"This app is amazing. I discovered it while reading the book Glow Kids. It's a great way to reduce screen time for yourself and your kiddos!" (R234)*

Other mentioned use cases include sleeping (N = 10, 1%) and free time (N = 4, <1%). For sleeping, in particular, digital wellbeing apps provide more information than ordinary sleep-tracker apps:

> *"I use this every day to track my sleep, oddly enough (sleep apps don't accomplish what I need). This consistently shows exactly what I need to be sure I was asleep." (R709)*

Users Like Different Features. For what concerns the features offered by digital wellbeing apps, users perceive some of them as particularly important. 99 reviews (9%), in particular, mention the possibility to view statistics, while timers and blockers are mentioned in 59 reviews (5%), making them the most appreciated interventions for limiting excessive smartphone use.

As interventions, restrictive solutions are useful to control unhealthy behaviors (N = 11, 1%):

> *"Wonderful. The strict mode feature is really strict. Really prevents you from going on an app you locked until the set time has expired." (R274)*

Statistics, instead, help to identify usage patterns, and can be used as motivational tools:

> *"I greatly appreciate this app. It helps encourage me to stay off my phone, as I always want to beat my lowest record." (R987)*

Motivation can also come through motivational quotes, metaphors and gamification principles, and rewards (N = 17, 15%). By describing Forest, a mobile app in which the life of one or more trees depends on the smartphone use, a user say:

> *"Excellent for me, since I have a very kind heart to trees. So I wouldn't open any other app while studying to kill that tree! Love it, thanks to the developer :)" (R71)*

Users Can Control Unhealthy Behaviours. Several reviews associate digital wellbeing apps as a remedy to addictive behaviors (N = 72, 6%), and as tools for time management (N = 66, 6%). Such apps, in fact, are useful to increase productivity (N = 37, 3%), and to allow users to focus (N = 51, 5%) on their primary tasks:

> *"A very simple yet useful application. It helps me to track my time using smartphone and this app actually helped me to reconsider my time and spend it on other productivity task." (R11)*

Users, in particular, mention that they are able to "unplug" from their smartphones (N = 35, 3%), and control the impulse of constantly checking their devices (N = 33, 3%):

> *"Wonderful idea! Really helps in keeping me from randomly looking for something to do on my phone." (R298)*

Users also describe digital wellbeing apps as self-monitoring tools (N = 90, 8%) that can be used to discover and understand how they use their smartphone, thus increasing their awareness of potential addictive behaviors (N = 40, 4%):

> *"Great app that gives you the inconvenient truth." (R123)*

Through self-monitoring tools, users can break unhealthy habits (N = 15, 1%), and they can learn how to use the mobile phone in a more conscious way (N = 8, 1%):

> *"I have found value in this app since installing it a few weeks ago. I am hoping that after a few months of use, I will no longer need the app to remind me to be more deliberate in the use of my phone." (R98)*

Why Users Dislike Digital Wellbeing Apps

Bugs Affects Usefulness and Usability. Many negative reviews are actually reports of bugs (N = 323, 29%) or design flaws (N = 39, 3%). Most of the highlighted bugs are related to an erroneous data tracking (N = 209, 19%) that affects the accuracy of the visualized statistics:

> *"Unfortunately the app includes background time in its records. For instance, according to the app I spent over 14 hours yesterday in Messaging. I can assure you I did not! A nice idea but..."(R33)*

Accuracy, in particular, highly affects how the users perceive the applications. With accuracy bugs, in fact, people find digital wellbeing apps useless:

> *"The first day data was precise, consistent, and illuminating. The second day provided no data whatsoever. This seems like a bug which would be fixed soon. But for now the app is useless to me." (R983)*

Bugs are often difficult to be detected, and design flaws affect the apps' usability:

> *"Complicated. The apps that I want to track are not shown on the list. It basically tracks the usage of the own app. Maybe I'm terribly mistaken.. which proves the app is not intuitive." (R54)*

Furthermore, 29 users (3%) complain about the price of the apps, and the differences between the free and the paid versions. Finally, in some reviews (N = 12, 1%) user also mention that the installed apps resulted in a worsening of the devices' performances in terms of memory and battery duration.

Unrestrictive Solutions are Useless To Reduce Addiction. Another interesting theme that emerges from the reviews is that users want restrictive solutions, since permissive, ignorable, and unrestrictive tools are useless to reduce phone addiction (N = 11, 1%). A considerable number of users, in particular, (N = 76, 7%), point out that digital wellbeing apps are often *bypassable* in some ways:

> *"The app is good but it is not able to stop me to open the apps I am addicted to...I can just simply uninstall this app if I want to use the restricted apps." (R54)*

As reported for "why users like digital wellbeing apps", restriction can be seen as an advantage: users are willing to provide any permission, and they devise "self-made" strategies to make digital wellbeing apps more difficult to be circumvented:

> *"Absolutely Fabulous Fantastic Futuristic!!! Please add mobile data and WiFi restrictions because phone without internet is too much LESS distracting. I know it's difficult to implement. But what if I give u root permission? I think then it's possible, right?" (R1054)*

> *"The password to this app is with my wife, every third day I'm asking her to lock this is like an annoying experience." (R679)*

Privacy is important. The last theme that emerges from a small number of reviews concerns *privacy* ($N = 8$, 1%). Sometimes, in fact, users perceive digital wellbeing apps as *irritating* and *intrusive*:

> *"Just another data-stealing greedy app!! Hate greedy data-stealing apps, Robbery! Deleted" (R856)*

> *"Keeps coming up when I am navigating in the car. Infuriating. Uninstall. It needs to be smarter." (R1004)*

5 DIGITAL WELLBEING IN THE WILD

To further explore and analyze the findings retrieved thanks to the two qualitative studies, we devised an in-the-wild study. Our aim was to *quantitatively* assess contemporary digital wellbeing solutions in helping users to change their behavior with the smarphone. For this purpose, we designed our own digital wellbeing app, named Socialize, by implementing some of the most common features identified in our first exploratory study, and we deployed it to 38 participants.

Socialize

Figure 2 shows some screenshots of Socialize. We designed it as an Android application, by implementing the most common features identified in our first exploratory study, i.e., those available at least in 15% of the reviewed apps (see Table 3 for the list of the implemented features). Socialize works both at the phone and the app-level, by providing tools for self-monitoring as well as interventions. We excluded *notification blockers* since the Android SDK does not allow developers to directly update notification settings.

Category	Features
Tracking	Phone Unlocks, Phone Time, App Time, App Checking
Data Presentation	Phone Summary, App Summary, Charts, Daily/Widget Recap
Phone Interventions	Phone Timers, Phone Blockers, Take a Break
App Interventions	App Timers, App Blockers
Extra Features	Contextual-Based Interventions

Table 3: The features implemented in Socialize.

Self-Monitoring. Socialize provides users with statistics both at the phone and the app-level. The application has 2 main type of windows: the main dashboard, and the detailed views.

Through the main dashboard (Figure 2a), users can monitor phone-level statistics such as number of daily unlocks, number of received notifications during the day, and total daily time spent with the device. Furthermore, the dashboard includes per-app daily information, by showing the time spent per-app, the number of times such apps have been checked, and the number of app notifications.

By clicking on the phone-level information, users can access a more detailed view of their smartphone usage, with hourly charts displaying time spent, unlocks, and notifications hour by hour (Figure 2b). The same detailed view is provided also for each specific app (Figure 2c).

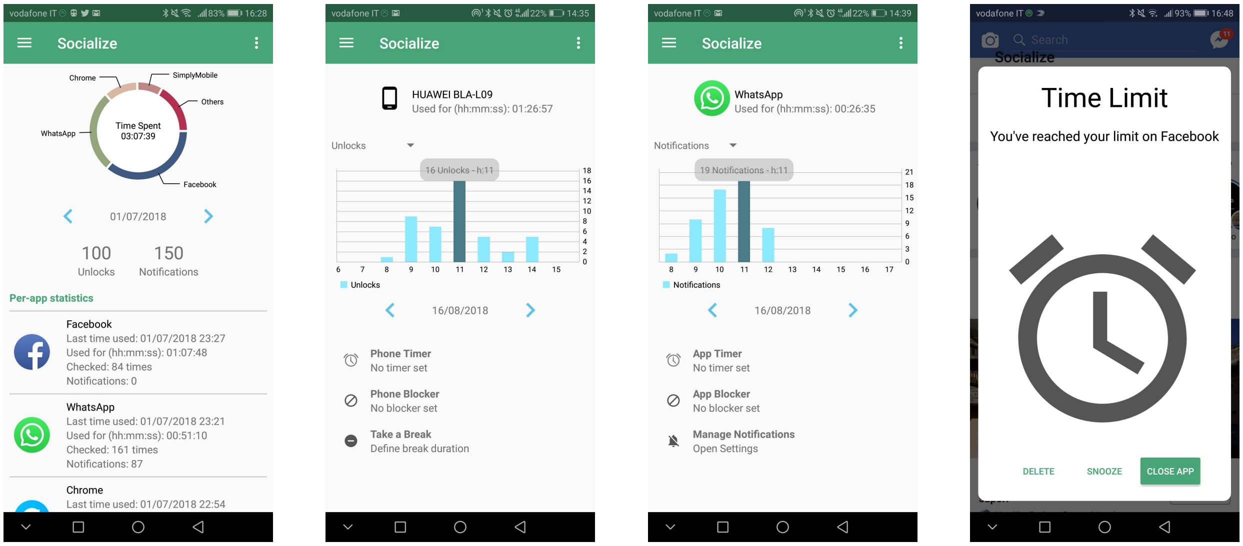
As widget recap, Socialize constantly shows a notification that displays some basic information, and acts as a shortcut to the main dashboard.

Interventions. From the detailed views, users can set up interventions both at the phone and the app-level. For limiting the usage of the entire phone, users can set up a) phone timers to be notified when they are using the phone for too long, b) phone blockers to block the usage of the phone, and c) phone breaks to take a break from the devices by silencing and locking it. At the app-level, users can set up app timers and app-blockers. When interventions trigger, a pop-up window opens on top of any other currently used application (Figure 2d): users have the possibility to i) respect the intervention, i.e., by closing the blocked app/locking the phone; ii) snooze the intervention, i.e., by resetting the timer; or iii) delete the intervention. Beside the duration, all timers and blockers are customizable in terms of context: users can optionally specify an activity (still, walking, running, cycling, on vehicle) and a location to make the interventions valid in a given context, only.

Socialize Evaluation: Participants, Method, and Metrics

To study Socialize in-the-wild, we uploaded it into the Google Play Store and we set up a within-subject experiments. We recruited participants by sending emails to students enrolled in different university courses and private messages to our social circles. In the month of July, 2018, 69 users responded to the announcement and installed Socialize. Of the 69 users, 38 (24 male and 14 female) completed the study and their data were used in our experimental analysis. Participants were on average 22.5 years old ($SD = 4.46$), and had different occupations: 5 were high school students, 18 were college students, 5 were Ph.D. students, and 10 were professional workers.

The initial recruitment message described the main steps of the experiment, and contained a link to an initial questionnaire that we used to collect demographic information, and to measure a) the level of problematic smartphone use (*problematic use*), and b) the participants self-efficacy of self-regulation of smartphone use (*self-regulation*). For measuring the problematic use, we used the Short Version of the Smartphone Addiction Scale (SAS-SV [24]), a specialization of the Smartphone Addiction Scale [25] for young adults.



(a) Main Dashboard (b) Phone-Level Details (c) App-Level Details (d) App-Timer Exceeded

Figure 2: User interface of Socialize.

The SAS-SV scale comprises 10 six-point Likert scale questions. The higher the SAS score is, the more addicted the user is to her smartphone. For measuring self-regulation we customized the Korean version of the General Self-Efficacy Scale (GSE [41]) to our context of self-regulation of smartphone use, as in [23]. Participants declared different scores about their perceived level of problematic use ($M = 30.44$, $SD = 9.71$, *range:* $17 - 55$) and self-regulation ($M = 30.03$, $SD = 4.53$, *range:* $19 - 38$).

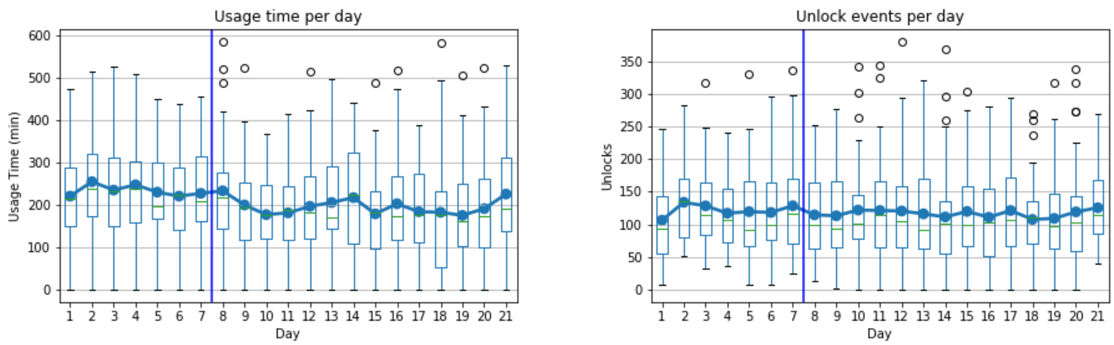
After filling in the initial survey, we asked the participants to install Socialize from the Google Play Store. The experiment lasted three weeks for each participant. In the first week (*collection phase*), Socialize ran in the background by silently logging usage data. In particular, we collected the *usage time*, both for the entire phone and for the different apps, the number of smartphone *unlocks*, the number of *app executions*, and the number of *used apps*. After 7 days, participants received a notification that alerted them about the end of the *collection phase* and the start of the *intervention phase*, i.e., 2 weeks in which participants could use all the functionality offered by Socialize. When clicking on the notification, a tutorial introduced participants to the Socialize's features. The usage data collection continued during the entire study. In the *intervention phase*, we also logged all the interactions of the users with Socialize, e.g., which interventions were defined, respected, snoozed, etc. At the end of the study, we asked participants to complete an exit survey. We asked them about the features they liked and disliked of Socialize, and whether they would use Socialize in the future. Furthermore, we measured *problematic use* and *self-regulation* a second time. All the collected data were properly anonymized.

Socialize Evaluation: Results

Metric	CP - M (SD)	IP - M (SD)	p (t)
SAS-SV	3.04 (0.97)	2.92 (0.78)	1.000 (0.51)
GSE	3.01 (0.21)	3.07 (0.24)	1.000 (0.62)
Usage (min)	233.59 (114.16)	196.50 (124.72)	.000 (3.96)
Unlocks	121.84 (66.64)	116.64 (77.78)	1.000 (0.92)
App Exec.	630.66 (269.33)	581.67 (276.06)	.223 (2.09)
Used Apps	23.86 (6.41)	22.39 (7.17)	.003 (2.84)

Table 4: Independent *t*-test with Bonferroni correction for the collected metrics in the Collection Phase (CP) and Intervention Phase (IP). Gray cells indicate statistically significant differences (p < 0.05).

Metrics Analysis. Figure 3 and Figure 4 show the daily values of the measured metrics. The figures highlight a positive effect of Socialize on the smartphone usage time, while such an effect is less pronounced for the other 3 metrics, i.e., phone unlocks, app executions, and used apps. To better understand and analyze these findings, we conducted a series of independent t-tests with Bonferroni correction on the collected metrics between the collection phase and the intervention phase (Table 4). The tests confirmed that the smartphone usage time decreased significantly ($p < 0.05$). Furthermore, also the number of used apps was different in the two phases,



(a) Daily Usage Time

(b) Daily Unlocks

Figure 3: Changes in smartphone usage time and smartphone unlocks over the duration of the study. The long vertical line indicates the start of the Intervention Phase.

with participants using significantly less apps in the intervention phase. As reported in Table 4, however, we did not find any significant difference in the number of app executions and phone unlocks between the collection phase and the intervention phase: even by using Socialize, participants continued to constantly check their smartphones. At the same time, we we did not find a significant difference in the self-reported questionnaires about problematic use (SAS-SV scale) and self-regulation (GSE scale) before and after the study.

To further analyze whether and how Socialize impacted the smartphone use, we extracted other information from the large amount of collected data. We first tried to understand whether there were differences in how participants used their smartphones during the study. In particular, we analyzed the daily average number of times participants used their smartphones very frequently, i.e., with phone sessions at a distance of less than a minute, thus demonstrating a compulsive phone checking behavior. Also in this case, we did not find significant differences: participants behaved similarly in the collection phase ($M = 49.70$, $SD = 36.91$) and in the intervention phase ($M = 52.45$, $SD = 42.91$, $p > 0.05$).

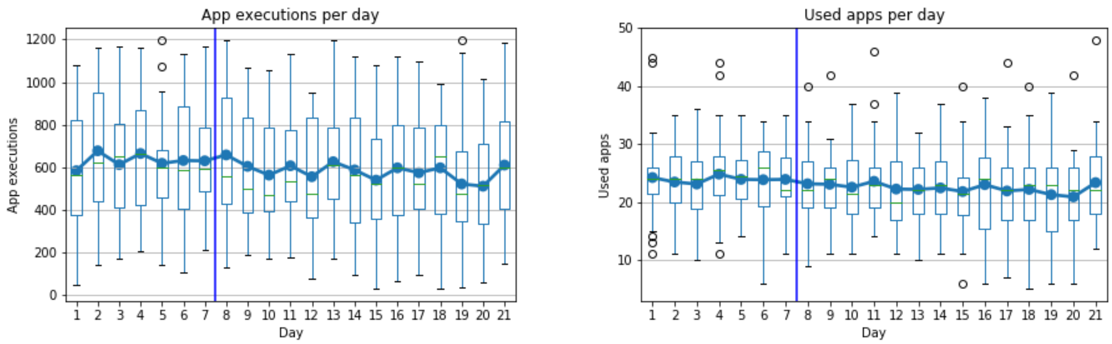
We also tried to understand whether Socialize impacted the usage of specific apps. For this purpose, we separately analyzed the data related to messaging apps (e.g., WhatsApp and Telegram) and social networks (e.g., Facebook and Instagram). We found that participants significantly reduced the time spent on social networks by using Socialize ($M = 33.15$, $SD = 30.16$) with respect to the collection phase ($M = 37.97$, $SD = 27.99$, $p < 0.05$). On the contrary, we did not find significant differences for messaging apps ($M = 26.47$, $SD = 35.65$ in the collection phase *vs.* $M = 25.35$, $SD = 32.46$ in the intervention phase, $p > 0.05$).

Interventions	#	Trigger	Respected	Snoozed	Del
Phone Timers	6	91	2	89	3
App Timers	11	0	-	-	4
Phone Blockers	7	5	0	5	7
App Blockers	16	245	115	130	16
Phone Breaks	1	1	0	-	-

Table 5: Study results about interventions. The table reports how many interventions have been defined, how many times interventions were triggered, and how many times interventions were respected, snoozed, or deleted.

Interventions Analysis. Table 5 reports the data about the usage of interventions. During the intervention phase, participants set up 41 interventions in total: 6 phone timers, 11 app timers, 7 phone blockers, 16 app blockers, and 1 phone break. Users demonstrated to prefer blockers (23) with respect to timers (17). Furthermore, intervention data suggest that participants were more interested in acting at the *app-level*, rather than setting interventions at the *phone-level*: by considering the interventions available for both levels, i.e., timers and blockers, participants set up 27 app-level interventions (67.50%), while only 13 (32.50%) were set up at the phone level. Participants, in particular, defined the majority of app-level interventions for limiting the usage of social networks: 10 of them were defined for Facebook, 14 for Instagram. Since we found that participants significantly reduced the time spent on social networks during the intervention phase, we may conclude that app-level interventions are effective in limiting the usage of this type of apps.

Differences also emerged when analyzing whether interventions were respected, snoozed, or deleted. Participants deleted 3 of the 6 defined timers (50.00%) before the end of the intervention phase. The 6 timers were triggered 91 times in



(a) App Executions

(b) Used Apps

Figure 4: Changes in app executions and used apps over the duration of the study. The long vertical line indicates the start of the Intervention Phase.

total: in only 2 cases (2.19%) timers were respected, while in 89 cases (97.81%) timers were snoozed. On the contrary, only 4 app timers out of 11 (36.37%) were deleted before the end of the intervention phase, but none of them were triggered during the study. For what concerns the 7 phone blockers, participants always snoozed them (i.e., in 5 cases out of 5). The 16 app blockers, instead, were triggered 245 times: in 115 cases (46.94%) participants respected the blocker, while in 130 cases (54.06%) participants snoozed the blocker. All the phone and app blockers were deleted by the participants before the end of the collection phase. Phone breaks were the less used and considered interventions: only one participant decided to take a break from her smartphone, but she ignored it by unlocking the phone before the end of the break.

Qualitative Results. In the exit survey, all the 38 participants asserted that they would use Socialize in the future. Furthermore, by describing what they liked of Socialize, they provided feedback in line with our reviews' analysis. Many participants (17, 44.74%), in particular, were enthusiastic of seeing their smartphone usage statistics, even if most of them were shocked to see how many time they spent on their devices. P9, for example, said:

> *"I liked the possibility to see how much time I waste on the smarphone, but at the same time this shocked me. I could not imagine such a thing."*

Furthermore, 8 participants asserted that they used Socialize to effectively improve their smartphone usage through interventions, by limiting the time they spent on different apps.

By describing what they disliked, a few participants (3) highlighted the high battery consumption with Socialize, while another participant asserted that Socialize impacted the performance of her smartphone. The remaining comments were actually constructive feedback, e.g., the possibility to customize interventions for different times of the day. Finally, the participants' answers confirm the necessity of improving digital wellbeing apps with more restrictive and motivational solutions, e.g., by inserting penalties when interventions are snoozed/deleted and by making the challenge of respecting interventions as a sort of game (P11). We also analyzed whether and how participants customized timers and blockers in terms of context. Surprisingly, only 9 of them (22.50%) included a contextual customization. In particular, 1 intervention was defined for a specific location, while 8 for a specific activity.

6 DISCUSSION

In this section, we first discuss the results of our three studies by highlighting that the features offered by contemporary digital wellbeing apps are often not sufficient to effectively help users in changing their behavior with the smartphone. Then, we try to better understand such a problem by discussing to what extent digital wellbeing apps are grounded in research backgrounds such as behavior change and habit formation. Finally, we summarize the discussion by presenting suggestions to be explored in future work regarding the design of digital wellbeing solutions.

Digital Wellbeing Features and Their Effectiveness

People are making use of digital wellbeing apps and they like the idea of having a digital wellbeing assistant that alerts them in case of any addictive behavior. Despite the overall positive tone of the analyzed reviews and Socialize's users, however, challenges still arose, and users are often aware that such solutions are sometimes not sufficient:

> *"I love this app. Makes breaking my addiction to the cell phone much easier. Although I still need strong will of my own." (R93)*

Apps such as Socialize are liked by users, and can be useful to reduce the time spent on smartphones, especially for some specific use cases. Statistics, in particular, are helpful to understand the time wasted on smartphones, and interventions are effective to limit the smartphone use, especially at the app-level: participants of our in-the-wild study, for example, significantly reduced the time spent on social networks by defining interventions for Facebook and Instagram. The same participants, however, rarely set up interventions, and in most of the cases they snoozed and deleted them. Thus, they continued to frequently check their smartphones, and the usage of Socialize did not change how they perceived their problematic smartphone use and their self-regulation skills. Moreover, we found many proposed improvements and suggestions for new features in the analyzed users' reviews. Digital wellbeing apps, for instance, should be more "intelligent", e.g., by adding context to existing interventions:

> *"Nice app but I'd like to see some additional features, for example if like the app to automatically detect when in a moving vehicle and activate." (R500)*

Furthermore, users often ask for the possibility of setting goals, and for introducing the possibility of interacting with other users, thus confirming the need of including more social support:

> *"Can you show avg stats of all the people? To see if you are way above the normal people in phone usage." (R222)*

The data collected during the in-the-wild study allowed us to further understand which features are appreciated. Participants, in particular, set up more blockers than timers, thus confirming a preference towards restrictive solutions. Furthermore, as reported for the reviews' analysis, the in-the-wild results suggest that users are more interested in controlling specific apps, rather than the entire phone. Finally, results show that allowing users to customize interventions in terms of performed activity and current location does not add much value: participants used the contextual customization in a limited number of cases. This seems to suggest that users consider their behaviors problematic independently of their contextual situation.

Self Monitoring vs. Habit Formation

Similarly to what happens for habit-formation mobile apps [43], our work shows that also digital wellbeing apps are mainly focused on supporting self-monitoring, i.e., tracking own behavior and receiving feedback. While self-tracking plays an important role in the behavior change process [4], it does not support the formation of new habits, and it strongly depends on the monitoring behavior: once the monitoring stops, e.g., because the app does not work or because users get bored, the behavior can revert to pre-interventions levels [21]. Habit formation could play an important role in digital wellbeing apps, by supporting behavior change towards a more conscious use of technology, and ensuring the long-term effects of the new behavior [26].

As reported in our first study, the only, rarely adopted features that supports habit formation in contemporary digital wellbeing apps are *motivational quotes* and *rewards*, which can be seen as positive reinforcement techniques. Through such techniques, users experience the feeling of success, a fundamental aspect to strengthen new habits [2]. Satisfaction can trigger the feeling of being in control, thus motivating the users and reinforcing the need to repeat the action in the future [2]. Unfortunately, this cannot work in the long term, since the role of motivation decreases as the behavior becomes automatic [38]. Our second study confirms this finding, showing that contemporary digital wellbeing apps are mainly designed to *break existing habits*, instead of *developing new habits*. Breaking habits, however, is frustrating, and users need to be continuously motivated in continuing the monitoring behavior to effectively use such apps. Contemporary digital wellbeing apps totally lack other fundamental aspects of the habit formation process, such as providing cues and trigger events [43]: new habits linked with some routines, e.g., turn off the phone when I am having lunch, are generally easier to remember, and each repetition reinforces that association, which increases the automaticity of the behavior [15]. In addition, despite previous studies demonstrated that social support can increase self-regulation of smartphone usage [23], existing digital wellbeing apps do not seem to be designed with a focus on promoting self-regulation through social support. The possibility of comparing statistics with other users, for example, is rarely introduced. According to the Social Cognitive Theory (SCT) [4], however, learning occurs in a social context and much of what is learned is gained through observation: through social learning, people can have better awareness of normative behaviors and can also be motivated to self-regulate.

Designing for Digital Wellbeing

Our findings point to different promising areas that could be explored in future work regarding the design of digital wellbeing solutions. First, our results highlight that contemporary digital wellbeing apps do not support the formation of new habits, but they are mainly designed for breaking existing "unhealthy" habits through self-monitoring. We argue that digital wellbeing apps should be more grounded in habit formation research, by adopting tools and methodologies to form and make "healthy" behaviors persistent, e.g., by increasing the usage of positive reinforcement techniques [2], and by providing cues and trigger events [43]. By exploiting the contextual-awareness functionality of smartphones, for example, a digital wellbeing app could dynamically suggest new habits, e.g., "go for a walk in the evening", to revert some existing behaviors, e.g., browsing Facebook.

Furthermore, contemporary digital wellbeing apps rarely take into account social-supporting techniques. For example, only a limited number of apps allow users to compare their own statistics with the statistics of other users. This limitation is also highlighted by the same users, that frequently ask for introducing the possibility to interact with other users in their reviews. As in previous studies, e.g., [23], we claim that digital wellbeing apps should promote self-regulation through social support, and should be more grounded in the Social Cognitive Theory (SCT) [4]. Beside comparing statistics, many different solutions could be adopted. As requested by some users in our studies, users could interact through "social games", with the possibility of setting goals, rewarding mechanism in case of success, and penalties in case of failures.

Perhaps the most interesting result of our work is that users want restrictive solutions to limit their excessive smartphone use. Users feel that unrestrictive and bypassable solutions are not enough for changing their behaviors with the smartphone, and this is especially confirmed by the results of our in-the-wild study: interventions are often snoozed or deleted, and digital wellbeing apps fail in preventing addictive behaviors, e.g., the compulsive checking of the smartphone. As a result, future work in this field should explore the adoption of restrictive interventions, difficult to be bypassed, that penalize users when they do not respect an intervention.

Finally, results of our studies suggest that digital wellbeing apps should be focused at the app-level rather than phone-level, and they should provide users with accurate and explainable statistics. In line with previous work [11], indeed, participants of our in-the-wild study significantly set up and respected more interventions for limiting the usage of specific apps, while users' reviews often point out that focusing on the phone-level is not enough. Furthermore, reviews suggest that bugs, especially those related to the accuracy of the visualized statistics, highly affect the usefulness and the usability of digital wellbeing apps. Indeed, such bugs are difficult to detect, and users are often not able to distinguish if high usage data are due to an addictive behavior or an application bug.

7 LIMITATIONS

There are some major limitations to be considered. First, it is worth noticing that any claims arising from users' reviews can be influenced by the bi-modal and extreme viewpoints that users typically insert in their comments [19]. Furthermore, our in-the-wild study was conducted over a short time of three weeks, and involved a limited number of participants (n = 38). Moreover, the three weeks overlapped with the exam period for college students. As a result, such participants were subjected to different levels of work and stress. Finally, we did not take into account other forms of technology overuse regarding other devices such as tablets and personal computers.

8 CONCLUSIONS AND FUTURE WORK

Terms such as "technology overuse" and "smartphone addiction" have recently gained interest. In this paper, we have presented the results of 3 different studies with the aim of providing the first overall perspective of existing mobile apps for changing users' behavior with smartphone. Results show that despite contemporary digital wellbeing apps can be used to reduce some addictive behaviors, e.g., using social networks, the road for effectively helping users in changing their behaviors with smartphones and promoting a more conscious technology use is still long. For closing this gap, we have proposed suggestions to be explored in future work: we are currently exploring digital wellbeing solutions that are more grounded in habit formation and social support theories, with the aim of overcoming the drawbacks of pure self-monitoring techniques.

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