

POLITECNICO DI TORINO

Master's Degree In Computer Engineering



Master's Thesis

Towards Designing Multi-Device Digital Self-Control Tools

Supervisors

Luigi DE RUSSIS

Alberto MONGE ROFFARELLO

Candidate

Elia BRAVO

October 2020

Summary

Developers, tech industries and researchers are designing and creating software for achieving “digital wellbeing”. Recent studies define “digital wellbeing” as a “degree to which users perceive their digital device usage to be well-aligned with personal, long-term goals”, suggesting that the self-control of the user over their devices is central to this topic. The majority of Digital-Self Control Tools (DSCTs) are typically implemented for a single device, providing self-tracking statistics integrated with access blockers, timers, launches limits, goal reminders and other features. In the modern multi-device world, people typically own more than one device and they often use them in a concurrent way, or sequentially, performing the same task or for multi-tasking purposes. The lack of DSCTs that deal with our global technology usage points out the need of investigating digital wellbeing in a multi-device context. The goals of this thesis are:

- To define, through a literature analysis, which self-control strategies can be adopted in a multi-device context, with a focus on the digital habits.
- To develop a software tool to implement some of these strategies in a few dedicated multi-device settings.
- To evaluate the developed tool with an user study.

Digital habits and habit forming approach Some studies point out the effectiveness of habit forming approaches like the Digital Behaviour Change Interventions (DBCIs) in the design of digital wellbeing tools. According to cognitive psychology theories, a “habit” is a human behaviour with a high frequency, a high level of automaticity and a consistent link with the individual and social context that triggers the behaviour. The habit formation phases can belong to non-conscious and implicit processes of our mind (impulses), or to deliberative, explicit and conscious processes (intentions). Most of the cited studies related to digital wellbeing identify the habit formation approaches as crucial for long-time behaviour change. The time and launches limits, the redirections of user activity, associated with a context, are the most effective features implemented in DSCTs

with the aim to bridge the gap between intentions and impulses, scaffolding the formation of new habits. The previous definition of digital habits, as well as the features of DSCTs, look easily suitable for an adaptation to a multi-device world.

FeelHabits design I tried to extend the concept of digital habits in a multi-device environment composed of the PC and the smartphone, in the design of FeelHabits, a first prototype of multi-device DSCT. To achieve this goal, I defined the “multi-device sessions” as usage sessions composed of the websites on PC browser or the apps on smartphone that are visited when the other device is active or was active in the last minute. Then, I introduced the concept of “multi-device app” as the pair composed of smartphone application and the analogous website (supposed to be visited through the PC browser). For instance: “WhatsApp” for smartphone, “web.whatsapp.com” on PC browser. Finally, a multi-device habit can belong to one of the three following categories:

- *Multi-device context habit*: it is a strong correlation between a contextual cue that involves itself the usage of a device, and a consequent interaction with a app/website of another device (in a common multi-device session). For instance: at work, in the morning, while using PC, the user frequently launches Instagram with the smartphone.
- *Multi-device app habit*: when a user habitually visits a multi-device app both with the smartphone and the PC browser, even if these two habits occur in different contexts. Together, they belong to a “multi-device app habit” category. For instance, a student during the day may be used to watching a TV series on Netflix with the smartphone, while performing another task (not necessarily technology related). At night, the same student may prefer to watch Netflix with the PC.
- *Multi-device app-context habits*: a hybrid form, where the usage of a specific app/website in a given context, with a given device, spurs the usage of a second app/website (even not related) with a different device (in a common multi-device session). For example: the usage of web.whatsapp.com with PC browser, in the morning, during working days, is frequently followed by a visit of Facebook with the PC.

To implement the habit forming features, the user can select among 3 intention categories:

- *Multi-device apps*. It is the option for the users who want to mitigate a habit that consist of visiting too often or for too long a multi-device app.

- *Smartphone at PC*. This intention aims to mitigate habits that involve a excessive usage of a smartphone app while using PC. (Multi-device context Habit)
- *Screen time*. To form the good habit to make a break after a long multi-device session, and to control the overall daily screen time.

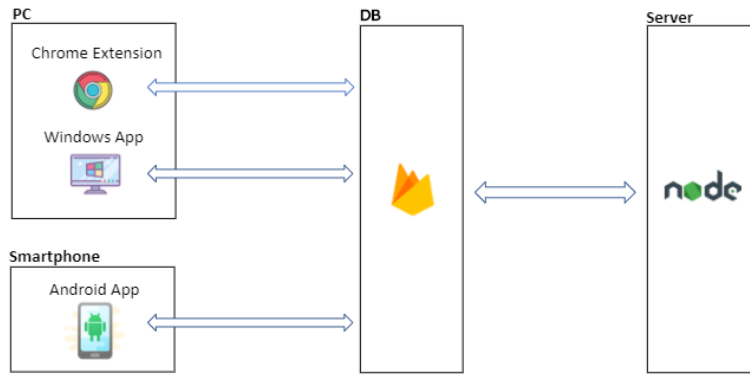
These intention are associated with a daily temporal context, where the possible options are: working days and/or holidays, morning/afternoon/night.

FeelHabits FeelHabits is the resulting prototype of multi-device Digital-Self Control Tool, composed of a Chrome Extension, smartphone Android app and a PC desktop app that work synchronously, communicating with one another through a Cloud database (Figure 1(a)). The user can define the previously mentioned context-related intentions by applying to them time limits (for all the intention categories), or limits of launches (for the “multi-device apps” and “smartphone at PC” categories). Then, the user can choose the severity of the system intervention in case of reach of a limit: it can be a simple notification, or a blocker. In case of blocker (Figure 1(b)), the user can accept the restriction or refuse it for the current day.

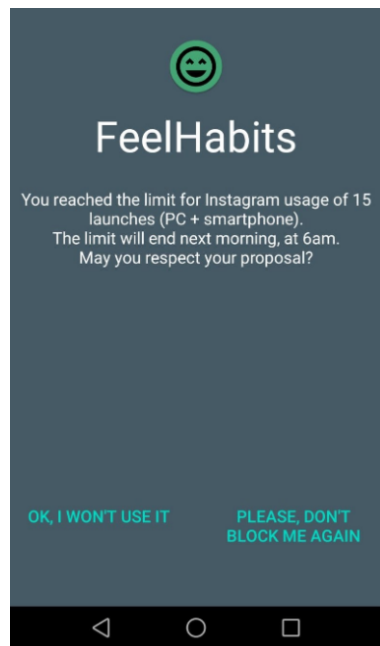
Moreover, the FeelHabits system collects data about multi-device sessions for statistical purposes.

Evaluation FeelHabits has been used in a two weeks test study performed with 7 participants with the aim of discovering the users behaviour towards the defined intentions, exploring the users multi-device habits, and evaluating the effectiveness of the implemented features. Users had a preference for the intentions at app-level: just 2 of them defined a non-stop session usage limit. The most common category for app choice is social networks (Instagram and Facebook) followed by communication (WhatsApp and Telegram), and video (Twitch, Prime Video, Netflix, YouTube). Users behaviours are significantly varied. Among them, 2 users tended to reach the limits almost everyday, with a opposite reaction towards blocker: one of them tried always to respect the limit, the other one always refused it. Other users defined less restrictive limits of usage time, reaching them few times. Generally, users deleted intentions to substitute them with new ones, when they realized that the associated limits were too strict, re-defining their personal goals. In general, the FeelHabits app received positive feedback for the effectiveness in reducing some app-related digital interactions.

Analysing the multi-device session data, the findings suggest that the users are not fully aware of their digital usage, and sometimes the limits look inconsistent with the actual interaction. With regard to multi-device context habits, I deeply explored the smartphone apps usage in front of the PC: the “smartphone at PC”



(a) Architecture



(b) Smartphone block example

Figure 1: FeelHabits

intention looks as the most effective and universal one. In fact, in this context both the “messaging” and “social network” categories belong to the top 3 launched apps for all the users. About multi-device digital habits, not all the users showed a habitual interaction with multi-device apps. Differently, the extracted data about multi-device app-context habits reveal some context-related correlations that include the apps targeted as source of bad habits. This observation suggests a potentiality for the automatic modeling of this category of multi-device habits.

Conclusions The results of this work provide a further proof for the need to evaluate digital wellbeing on the basis of the multi-device ownership. In my opinion, the road for future work should begin from a improvement in the features for the PC, followed by the involvement of other devices (smartwatch, tablet, smart TV).

Acknowledgements

It is a great pleasure to acknowledge my gratitude to Prof. Luigi De Russis and Alberto Monge Roffarello, for their kind and punctual supervision, their encouragement to accomplish this thesis and the precious teachings that I will take with me in my future experience.

I would like to thank the persons who participated to the test conducted in this work, for their availability and patience.

To my loving family and friends: you are the first reason of my enthusiasm.

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Acronyms

DSCT

Digital-Self Control Tool

XDI

Cross-Device Interaction

TPB

Theory of Planned Behaviour

DBCI

Digital Behaviour Change Intervention

HAM

Habit Alteration Model

Chapter 1

Introduction

Developers, tech industries, and researchers are designing and creating software for achieving “digital wellbeing”. A recent study defines “digital wellbeing” as a “degree to which users perceive their digital device usage to be well-aligned with personal, long-term goals”, suggesting that the self-control of the user over their devices is central to this topic [1]. However, the majority of the Digital-Self Control Tools (DSCTs), designed to monitor and show personal usage statistics and trying to mitigate bad habits, are typically implemented for a single device. The relative features, such as usage patterns representations, timers and automatic blockers, provide the user with an instrument to regulate his/her behaviour with the smartphone or with the PC, without any consideration on the aggregate user-technology interaction. In the modern multi-device world, people typically own more than one device (e.g, PC, tablet, smartwatch), and they often use them in a concurrent way, or sequentially, performing the same task, or for multi-tasking purposes. The lack of DSCTs that deal with our global technology usage points out the need of investigating digital wellbeing in a multi-device setting. Understanding how to design multi-device DSCTs, in particular, may allow users to enhance their digital wellbeing in a comprehensive way: with different devices, in different places, contexts, and with different goals.

The main goals of the present thesis are:

- To define, through a literature analysis, which self-control strategies can be adopted in a multi-device environment, with a focus on the digital habits.
- To develop a software tool to implement some of these strategies in a few dedicated multi-device settings.
- To evaluate the developed tool with an user study.

I start by exploring the multitude of multi-device usage patterns and reporting the related works referred to multi-device and cross-device environments, with an

attention on the most habitual scenarios and the related risks for digital wellbeing. In literature, the definitions of “digital habit” are based on cognitive psychology theories and argue that a habit is a behaviour with a high frequency, a high level of automaticity and a consistent link with the individual and social context that triggers the behaviour [2][3]. These characteristics are fully suitable for the multi-device context: starting from them, I try to define in an exhaustive way the concept of “multi-device habits”. With the support of two preliminary definitions of “multi-device sessions” and “multi-device apps”, I get into the identification of 3 categories for multi-device habits: “multi-device app habits”, “multi-device context habits” and “multi-device app-context habits”.

Then, I provide an overview of the digital wellbeing tools and their main features. I introduce the self-control strategies that can be applied in a multi-device setting composed of a smartphone and a PC. I implemented these strategies in “FeelHabits”, a multi-device Digital-Self Control Tool, designed for mitigating or avoiding the negative multi-device digital habits that involve the PC and the smartphone, through 3 user-defined daily intentions:

- “Multi-device Apps”: to mitigate the habits where the user visits too often or for too long an application on smartphone and/or the respective website with the PC browser.
- “Smartphone at PC”: to mitigate habits that involve an excessive usage of a smartphone app while using PC.
- “Screen time”: to control the overall daily screen time and to form the good habit to make a break after a long multi-device session.

The associated interventions are blockers/notifications that appear when the user reaches a limit in terms of duration or frequency of usage. After providing a detailed description of the design, the interface and the functionalities of FeelHabits, I present the results of a 2 weeks user test study of the system performed with 7 participants, with the aim of discovering the users behaviour towards the defined intentions, exploring the users multi-device habits, and evaluating the effectiveness of the implemented features.

Users behaviours are significantly varied: they have a preference for the intentions at app-level, where the most common category for app choice is social networks (Instagram and Facebook) followed by communication (WhatsApp and Telegram), and video (Twitch, Prime Video, Netflix, YouTube). Two users tended to reach the limits almost everyday, with an opposite reaction towards blocker: one of them tried always to respect the limit, the other one always refused it. Other users defined less restrictive limits of usage time, reaching them few times. In general, the FeelHabits app received positive feedback for the effectiveness in reducing some app-related digital interactions.

Analysing the multi-device session data, the findings suggest that the users are not fully aware of their digital usage, and sometimes the limits look inconsistent with the actual interaction. The “smartphone at PC” intention looks as the most effective and universal one, since all users perform a frequent smartphone apps usage in front of the PC. Moreover, I find many sequential correlations between apps of different devices suggesting a potentiality for the automatic modeling of multi-device app context habits, better explained in the thesis.

The results of this work provide a further proof for the need to evaluate digital wellbeing on the basis of the multi-device ownership, beginning from a improvement in the features for the PC, followed by the involvement of other devices (smartwatch, tablet, smart TV).

Chapter 2

Multi-device patterns

In this chapter, through a analysis of previous literature, I explore the multi-device world, introducing the concept of “cross-device”, investigating other sequential and parallel multi-device patterns. Referring to some user-diaries and surveys about human interaction with multiple devices, I focus on the most frequently used devices in relation with the context and the potential risks for digital wellbeing. The introduction of tablet enhance our multi-device interactions, especially at home. Differently, workers and students typically use the PC and the smartphone, performing multi-tasking activity and dealing with the phenomenon of digital interruptions and micro usage, forming new “checking habits”.

2.1 What is Cross Device

In literature there are many references to “cross-device” as a particular kind of multi-device interaction. But what does it mean?

Florian Scharf et al. [4] formalize for the first time a definition of Cross Device Interaction (XDI). They start from some preliminary classifications about human-technology interaction patterns. First of all, they make a distinction among the roles of the devices. They can be:

- Input device: it takes any form of user input.
- Output device, that renders and presents any kind of information, in any form that human senses are able to perceive.
- Mixed device, that incorporates both input as well as output, within one device.

Another important factor for XDI settings is the ownership of the devices: I mainly focus on “personal” devices, that belong to a specific user and are configured and

used only by him or her. Moreover, the authors distinguish the forms of access to the device: in this work I refer to the “private” access patterns, where a device is controlled by and displays for exactly one person. The authors finally get into the definition of “XDI” as a user-device interaction, where a person interacts with several, input and output devices. The input devices are used to manipulate content on output devices that are within an activity space. Moreover, the output devices provide an immediate feedback to the user.

It is obvious that, in the present study, all the involved devices belong to the category of mixed device. Nevertheless, we know that in a typical XDI scenario, one device is exploited as input device, used to manipulate content on a second device, that in this case works as output device.

Thus, cross-device interaction figures as a subset of the multi-device ecosystem, where an interaction between devices is characterised by a common user-defined task. In terms of digital wellbeing, referring to the previous taxonomy, I am interested in all the the digital devices that we deal with habitually. I try to explore the links between the multi-device world and the digital habits, with a eye towards the XDI scenarios.

Lascau et al. [5] point out the need to evaluate cross-device ecosystem as a starting point for designing the new digital wellbeing applications, focusing the attention on two main topics: cross-device tracking, and cross-device notifications. According to them, the first aim for designing a digital wellbeing application consists in avoiding a trivial productivity overview that can just provoke anxiety to the users about their screen time.

Taking into considerations these suggestions, in the design of FeelHabits I mainly focus on the “tracking” aspect of cross-device interactions, introducing the concept of “multi-device session”.

2.2 Multi-device usage patterns

The ways we deal with our multi-device environment are significantly varied. Jokela et. al [6] analyse 123 user-reported cases of multi-device use in everyday life. They identified the main usage patterns, defining a set of practical use cases for each category. These are:

- Sequential Use: when the user switches from one device to another, doing the same task. The reason, for about 1 out of 3 cases is a technological impediment, e.g. when the user is not able to open an attachment from a email read on the smartphone, and he/she switches to the PC.
- Resource Lending: the activity primarily focuses on one single device, and

this device borrows some resources from other devices. For instance, when the user exploits the hotspot feature on his/her phone to connect the laptop to the Internet.

- Related Parallel Use: when the user is working on a single task using two or more devices together. An example can be: searching for a tutorial on the PC for an operation executed on the smartphone.
- Unrelated Parallel Use: i.e. multiple tasks, multiple devices: the user is working simultaneously on more than one device, performing a different task for each of them. A common example can be a phone call when using the PC.

I would like to find, among those patterns, the cases associated to an idea of “digital habit”. What makes these behaviours habitual is the frequency of these actions, repeated in the same context. Thus, referring again to the previous categories and to the Jokela’s study, I extract a use case hypothesis for each category:

- Sequential Use: switching from the smartphone to the PC while watching a video.
- Resource Lending: connecting the PC to the TV with a HD cable, for watching a movie. This can be an example of potential digital habit.
- Unrelated Parallel Use: listening to music played with the smartphone, or watching TV while studying or working at the PC. I discuss later about the topic of multi-tasking, distractions and interruptions during worktime, that is linked with this usage pattern.
- Related Parallel Use: among the examples provided by the authors, none of them look related to digital habits. As a matter of fact it seems harder to find a habitual use case belonging to the category of bad habits.

2.3 The tablet in a multi-device context

Müller et al. [7] point out the modern tendency to multi-device ownership and the consequent need for technological solutions that support transitions between devices and their concurrent use. By analysing smartphone and tablet usage patterns through a diary study, they observe that the most frequent secondary activity while using smartphone or tablet is watching TV. Moreover, they find that the total usage time for participants who own both smartphone and tablet is greater than the total usage time for users that own only the smartphone. This aspect suggests that, in this case, the introduction of a tablet may increase the user’s daily technology usage. Finley et al. [8] confirm this hypothesis in their work on

a multi-device panel that include smartphone, tablet and PC. They suggest that users primarily perform different types of task on smartphones and tablets, while only around 17% of a user’s total mobile apps are used on both devices. Differently, the tablet seems to be used in substitution of the PC, for performing some tasks that would be otherwise fulfilled on PC.

A further study by Finley et al. [9] on multi-device usage patterns that involve smartphone and tablet usage is of particular interest for the present thesis, especially for the definition of “multi-device sessions”, that will be one of the starting point for the design of FeelHabits. Their findings about smartphone and tablet usage, under a multi-device point of view, are:

- The case of operating on a single app on a device, followed by the transition to a single app in another device, is very rare: the typical usage patterns deal with more than a applications for each device.
- The 2 most frequent usage patterns represent a primarily usage of a single device along with the sparse usage of a second device. In general, multi-device interactions lasts about 10 times longer than a single interaction with a unique device.
- Users who own both smartphone and tablet have a higher overall time spending on digital life (as argued in [6]), but reducing the time spent on the smartphone. The productivity and video categories indicate potential novel usage on tablet.
- 90% of tablet interaction time is associated with multi-device usage.

These data demonstrate that the introduction of a new device in our life doesn’t introduce just novel activities: for some tasks, a device can be used in substitution of another one, but the overall screen time tends to increase. A limitation in studies of tablet usage is due to the fact that in some cases, the ownership of this device is shared, typically in family contexts [10]. Moreover, a small portion of users deal with tablets for work related tasks: tablets are typically used for personal aims, and not everyday [11]. For these reasons, in the FeelHabits project, we decide to give priority to other devices that are most commonly used everyday, in order to collect some useful data even in a short-term field study.

2.4 Interruptions and cyberloafing

A common case of multi-device usage is the workplace at desk and studies point out that the risks for digital wellbeing, in this context, are several. Typically, the involved devices are the PC and the smartphone. There are many stimuli and motivations that make the workers interact with technology for work or other

purposes, as there are many consequent positive and negative effects. Most of these behaviours fall into the category of “interruptions” and “cyberloafing” and are associated to “workplace breaks”.

In general, workplace breaks range from physical breaks (e.g., going to the bathroom, or drinking something) to short digital breaks (e.g. answering to personal emails, visiting a social network, or catching up on the news) and consist of an interruption of a task. Interruptions in workplace can be classified in “external interruptions” and “self-interruptions” [12]:

- The external interruptions include physical breaks, such as getting a coffee or going for a walk during a break time, but also all the distractions caused by notifications coming from our digital environment, mostly received from the smartphone.
- Self-interruptions refer to the off-task activities during worktime such as visiting social networks or web browsing.

Self-interruptions account for 40% of interruptions [13] and may be more disruptive than external interruptions [14]. Additionally, external interruptions experienced in a certain time can have an incidence on the next self interruption. But workers seem to self-interrupt also to switch to solitary work. This motivation suggests a potential positive aspect of self-interruption, that is the fulfillment of the key work task.

The term “cyberloafing” or “cyberslacking” describes the voluntarily use, at work, of digital technologies using the company Internet access for non-work purposes [15]. Such behaviour can provide a benefit against work-stress and may have a positive psychological influence on the worker. For instance, it can be a palliative against negative workplace experiences, related to stress, burnout, boredom. [16] [17]. But when it turns in an abuse, these distractions actually represent a bad habit [18][19].

According to Kelly Garrett et al., approximately 80% of information workers reported cyberloafing behaviors during work hours [20]. The proliferation of ICT in the workplace is furtherly enhancing cyberloafing [21], providing more opportunities for breaks and personal activities, especially when workers are unhappy with their employers [22]. Thus, originally the work distractions arise from the web browser at the PC, as more and more work and personal activities take place online.

Other studies confirm that cyberloafing activities cover a large amount of working time: Lim et al. [15] confirm a common habit to use internet at work for personal purposes, with workers reporting spending on average 51 minutes in a workday. Moreover, they point out that the most frequent actions of cyberloafing are browsing and not work related emailing activities, and some findings suggest that men

cyberloafing activities are more frequent and longer than women. The effect of cyberloafing on user's feelings seems to change with the type of activity. In fact, emailing for no work purposes is correlated with negative emotions, while web browsing is significantly related to positive affect.

The risk of the abuse of distraction is not limited to the sources of distraction, but also on the consequences. In fact, many workers express a difficulty to switch back to the main task after an external or self interruption, when returning to their desk. [23], [24], especially if they do not feel ready to work [17]. In [25], the users reported that they need, on average, 8 minutes. Tseng et al. [19] show that a automatic system that temporarily blocks the access to cyberloafing activities during these "transitions points", can reduce digital distractions and stress without losing workers' sense of control.

To summarize, the reasons that drive workers to assume cyberloafing activities can be divided into 2 main categories:

- Individual: they depend on the psychological aspect of the worker in term of personality, self-regulation and other personal characteristics [26]. The most common triggers are feelings of boredom or stress.
- Social: they depend on the cultural aspects of the place they live [27], but also on the dynamics of the company, that has a influence on the individual behaviour, and on the generational habits [28].

Cyberloafing is not only a behaviour of workers but also a common activity in academic settings [29]. Both for workers and students, cyberloafing has been successfully modeled by the Theory of Planned Behaviour (TPB). [30] According to TPB [31], the proximal predictor for a behaviour is the intention. The intention is caused by 3 key factors:

- Attitude towards the behaviour.
- Social Norms.
- Perceived Behavioural Control.

If we apply the TPB to cyberloafing, the perceptions of other students/workers cyberloafing behaviors enhance or reduce the formation of intentions to cyberloaf. For this reason, a digital tool that controls the individual abuses of distracting activity for users who habitually work in a shared office will consequently contribute on a improvement of general behaviour in the social context.

In this work, I focus on the main two digital sources of interruptions: the PC and the smartphone, trying to mitigate the cyberloafing behaviours, without preventing users from taking breaks. The adopted approach for mitigating cyberloafing will

be defined by the user and will consist of setting some apps/URLs usage limit on their smartphone/PC browser, and it is better explained in chapter 5.

2.5 Micro Usage, multitasking and smartwatch

Denzil Ferreira et. al [32] show that about approximately 40% of smartphone application launches last less than 15 seconds and happen most frequently when the user is at home and alone. Considering routine and focusing on mobile phone users' habits, Oulasvirta et al. [2] suggest that mobile phones are "habit-forming" devices. The "checking habit", defined as a "brief, repetitive inspection of dynamic content quickly accessible on the device", characterise a large part of smartphone usage.

This behaviour, that falls into category of "Application Micro Usage" [32] doesn't consist only of the quick interaction with a application on the smartphone, but involves other devices and it is strictly connected with the multitasking behaviours and the interruptions (both external and self)[33]. In fact, multitasking patterns commonly involve the desktop PC in the work environment. Desktop users focus on a main goal, embedded with a set of secondary goals that need the management of multiple tasks. More precisely, multi-tasking is commonly defined as "performing multiple tasks at the same time", but typically it consist of performing multiple tasks sequentially and in quick succession [34]. Generally, the PC desktop often takes place over longer time periods, while the use of mobile phone tends to be more intermittent. For this reason, exploring the characteristics of micro-usage means mainly focusing on the smartphone interactions, especially for habitual computer users. A field study on the smartphone usage [32] suggests that micro-usage is more frequent when users are alone.

But the micro usage affects even more the smartwatch. Aku Visuri et al. [35] analysed the smartwatch usage. They found that, compared with smartphones, smartwatches are used more briefly and more frequently throughout the day, with half the sessions lasting less than 5 seconds, making a distinction between the user-initiated sessions (proactive use, 80%) and the notification initiated ones (reactive use, 20%). More than half of them (65%) are peeks: whether for timekeeping, or for checking notifications, that if are relevant for the user, lead to consume its information on the smartphone. A consideration on how these factors affect our habits comes naturally.

According to Marta E. Cecchinato et al. [36][25], the introduction of the smartwatches in our daily lives causes more benefits than disadvantages in terms of digital wellbeing. In fact it creates a microboundary from the multitude of notifications coming from the smartphone [32], keeping us up to date with messages with minimal disruption to our current task. Feeling a control over the digital information, with

a filter of the most urgent ones, results in a slower response to the minor priority notifications and reduces the more distracting gesture of checking the phone.

Chapter 3

Digital Self-Control Tools

In this chapter, I better analyse the digital wellbeing tools and their implemented strategies, with a particular attention on the multi-device approaches. Developers implemented many tools for smartphone, desktop PC, or PC browser, while the cases of multi-device tools are very rare. Roffarello et al. [37] conduct a study over the most popular digital wellbeing applications for Android smartphone. They analyse 42 apps and classify 19 different offered features. Furthermore, they collect the most relevant user reviews, to extract the general opinion of digital wellbeing applications. The most common feature of these apps consists of tracking usage data and presenting them by a chart. The visualizations can be:

- “phone level”, to monitor data about phone usage, for instance counting the phone time and the number of unlocks.
- “app level”, i.e. they show data related to the usage of other apps, with statistics about “app-time” (usage time), “app-checking” (number of times they’re launched).

Some apps offer a “social comparison” opportunity to compare the own statistics with other users. Beside showing tracking statistics, a second feature of the digital wellbeing apps on the market is an intervention to reduce digital addiction. Typically they are “timers” that let the user know when they use a specific app for too long. The severity of the intervention can be a notification when the limit is reached, or a real “blocker” to block the access to part or all the phone resources. As before, the interventions can be “phone-level”, to limit the usage of the entire phone, or “app level”, to be warned when a specific app is used for too long. Few apps provide motivational quotes to stimulate the user to perform positive behaviours in terms of digital wellbeing.

Lyngs et al. [38] review 367 apps and browser extensions from the Google Play, Chrome Web, and Apple App stores. They analyse all the features offered by these

tools, classifying them in 4 macro-categories. In order from the most common, they are:

- “Block/removal”: this category includes the resources blocks (apps, websites), but also the time/launches limits.
- “Self-tracking”: all the usage statistics available to the user.
- “Goal advancement”: such as goal reminders and motivational quotes.
- “Reward/punish” They include the gamification approaches such as gaining points or unlocking new application features.

Among all the analysed the tools, 65% of them include interventions belonging to just one of these categories, 32% of them contain features belonging to 2 categories.

3.1 Multi-Device tools

In this section, I report the digital wellbeing tools that include functionalities for more than one device.

3.1.1 ScreenLife

Rooksby et al. [10] underline the potential positive effects of screen time personal tracking: reducing device use, becoming productive, monitoring devices, keeping record of everyday life. Anyway, they assert that tracking of screen time is less meaningful on shared devices. In fact, not all devices are necessarily personal, and so the data generated from these is not necessarily personal (e.g. the tablet). They create ScreenLife [10], a multi-device tool for tracking our digital lives, implemented for iPhones, iPads, Android phones, Android tablets, Mac computers, and Windows computers. A logger monitors and records each device use, with an interface that provides to users a visual representation of screen time across their logged devices. The limitation of Screenlife is in the absence of an implementation for monitoring the specific usage of a device.

3.1.2 PomodoLock

Jaejeung et al. [12] develop Pomodolock, a tool for mitigating usage, that involves both the company provided devices (PC) and the personal ones (smartphone), to improve productivity. It is inspired from the Pomodoro Technique [39], a time management strategy based on giving self-assessment and intrinsic rewards, to improve productivity. The technique is based on the repetition of 4 steps:

1. Choosing a task to be performed.
2. Setting a timer (the Pomodoro timer, typically of 25 minutes).
3. Working on the planned task until the end of the timer.
4. Taking a break of 3-5 minutes.

After 4 pomodoro timers, the user can take a longer break (15-30 minutes).

PomodoLock includes a timer for applying this strategy through a Chrome browser, a Windows application and an Android application that work synchronously. During the 25 minutes work-sessions self-initiated by the user, the tool encourages to resist from the interruptions, silencing the notification sources from the smartphone, forbidding some website accessed by the PC with the Chrome extension, blocking the access to Windows applications that are on the blocklist.

3.1.3 UpTime

Tseng et al. [19] take inspiration from PomodoLock and develop a new application, UpTime, composed of a Chrome extension, a Slack chatbot, and a web-server back-end.

UpTime focuses on the transitioning from break to work when the user is particularly vulnerable to self distractions, through a conversational interaction approach that encourage the worker to focus on the main task and make him/her aware of the risks of too many distractions. The Chrome extension works similarly, with a blacklist of distracting websites and a blocking system activated during work sessions. It is integrated with the chatbot, that communicates with the user with proactive alerts when an unproductive behaviour or a transition to computer work is detected. A node.js back-end server manages all chat communications and maintains a record of each user's blocking state.

However, UpTime doesn't take into account the multi-device features introduced by Pomodolock, that deals with the problem of smartphone dependency at work [18] and clears the way to more complete analysis of digital habits during worktime.

3.1.4 Freedom

Freedom [40] is a example of multi-device system. A large section of the website has been dedicated to explain the modern needs in a digital wellbeing tool. In the following paragraphs, I resume the key concepts extracted from the website articles. The first consideration is about the screentime features, that can be a way to fight against digital addiction. But digital addiction is not the unique step for wellness. The ubiquity of devices represent a risk for losing control of technology,

reduce concentration and productivity. After this consideration, the article on “freedom.com” claims the need that a company like Apple creates an API for digital wellbeing, so that third-party developers can build innovative tools, complementing the offerings in the operating systems.

Making a comparison with the era when cars didn’t have safety tools, smartphones are labelled as “new technology with few safeguards”. In the implementation of a system to reduce technology related risks, we must consider the high level of customization of the smartphone, that makes this device deeply personal. Since the usage patterns are several, the digital wellbeing approaches need to be differentiated to every social and cultural modes of use.

To effectively build an API for Digital Wellbeing, it’s not enough to make a set of on/off switches for apps. Maintaining a positive relationship with technology is an “embodied” experience, involving technology, social and emotional wellbeing, physical state, location, stress, and a host of other elements. Our devices track and make available much of this data, and it can be combined with other third-party sources [...]. To build innovative tools for digital wellbeing, it is important that we’re able to leverage multiple sources of data.

Freedom’s designer point out three key concepts to an API for Digital Wellbeing.

- Insight. Insights are the signals about our activity levels, physical state, our habits and routines, our technology use, that paint a picture of our state when using technology.
 - Technology Use. It represents the individual’s area of use and overuse of technology. The apps that keep track of the screentime and the number of unlocks provide a measure of device use, but this is only a part of the digital wellbeing scenario.
 - Place. The information about where we use our device is informative, and our usage habits change based on place. It is a critical component for designing a digital wellbeing tool.
 - Routine. Our device behaviors are highly routinized, and the routine is what in the previous analysis we called “habits”. Providing insight into routine help understand the ways to deviate from it and produce new habits.
 - Physical State. Our physical state, how we feel, the hours of sleep, our level of hunger are factors that affect the quality of our interaction with technology. Vice versa, our device use can influence our physical state. A digital wellbeing system must consider this aspect and contribute to improve our health through recommendations.
 - Emotional State. Apps and website can convey emotions of happiness, unease, relief or stress. Even if we cannot measure our emotional state,

but understanding how apps contribute on it would be crucial for digital wellness designing.

- Activity. Understanding the achievements of our activity, especially with productivity related ones, is important to improve the quality of our technology usage.
- Actions. Actions are the control of the technology enabled by the digital wellbeing tool. For instance, the ability to turn off apps and messaging, to silence notifications, to reduce overuse.
 - Controls. The screentime blocker is a classical example of control. The variety of forms of control make the digital wellbeing app more robust. The forms of control can be more or less strong.
 - Strength. As just mentioned, the strength represents the severity of the intervention adopted by the digital wellbeing tool. The strength level, if chosen by the user, represents his/her willpower to mitigate a digital behaviour.

Another aspect of a digital wellbeing system is the privacy protection. The design must grant appropriate privacy safeguards, since it processes confidential data. Freedom supports Mac, Windows, Android, iOS, and Chrome devices, and the main offered features are:

- Websites and Apps blocker: the user can define a list of websites on PC browser and smartphone apps to block during a session.
- Internet Blocker: when the user needs a break from all the pieces of information of the Internet for a while.

The system is multi-device and the data are synchronized. The user can define in a flexible way the temporal sessions when the limits are supposed to be applied. The user can check the details of the sessions, track the personal progress and share the information about productivity with other users.

3.1.5 Cold Turkey

Cold turkey [41] works as a website, app, internet blocker, and it is designed to improve productivity. It includes a customisable websites blacklist, and the block page shows a motivational quote to stimulate the user to work. The tool provides the possibility to block just a specific page (for instance “facebook.com/username”) and allow the access to the rest of the domain.

Moreover, the user can block the entire internet, or just have a white list (and block all the other websites). Another peculiar feature is the Google searches block,

defining the forbidden keywords.

The Cold Turkey system is multi-device because it includes a Desktop app for blocking other applications on PC. The websites/apps blocking strategies are several. The user can:

- set a usage timer, and block the resource at the end.
- lock resources with a password, and unlock them when typed.
- schedule a daily period for the blocks.
- block until a PC restart.

Finally, the interface shows the statistics about usage data.

Chapter 4

Digital habits and multi-device sessions

The introduction of a multitude of devices in our digital lives changes our habits, but not necessarily with a negative influence on our digital wellbeing. The causes that bring us to acquire habits in terms of technology use differ in relation with the individual and social contexts. In chapter 2, I explored the multi-device scenarios in working and studying environments, where the aim is to enhance productivity fighting against stress. In other contexts, devices are used for entertainment or socialization purposes.

In this chapter, I would like to define the concept of digital habits, with the aim to extend it to the multi-device world. To achieve this goal, I refer to a definition of usage pattern that is independent from the contextual characteristics: the concept of “multi-device session”.

4.1 Digital habits

So far, I analysed a lot of typical single and multi-device digital behaviours, and I described many cases of repetitive actions. I already referred to “digital habits” on smartphone as “checking habits”: repetitive and quick device inspection.

In chapter 1 I introduced that, according to cognitive psychology theories, a “habit” is a behavior that has 3 main features:

- It is repeated frequently.
- It has a high degree of automaticity.
- It is cued by a context.

Orbell et. al [3] after pointing out this aspect, add that in health behaviour it is important to consider the automatic component of habits and the little conscious awareness. Wood et al. [26] show that people are more likely to label their actions as habitual if they did not require much thought to perform.

Moving into the digital scenario, Oulasvirta et al. [2] deal with the smartphone habits, defining a “habit” as an automatic behavior triggered by stable, situational cues (e.g. places, people, and preceding actions). According to them, the study of habits in the smartphone usage context must focus on the study of two interrelated things:

1. Automatized behaviors relating to smartphone use.
2. The cues that trigger these behaviours.

The cues that trigger these behaviours are not just related to the current situation. A lack of stimulation perceived by the user, or more simply, the presence of the phone on the table when the user is at desk, are some motivations to perform a technology interaction. This reaction can be felt as a potential psychological “reward”.

Moreover, Oulasvirta et al. [2] define the “habit strength” in the smartphone use as the frequency of application usage in a particular context. However, a frequent action must not be confused with habits: habits are a subset of frequent behaviours, and they are consistently related to a contextual cue that triggers them. Wood et al. [26] propose two forms in which the context cuing of habits arises:

1. A direct form: a cognitive association between context cues and response behaviour.
2. A motivated form: the repeated context when people feel a sense of reward for performing a behaviour.

The second form can be characterised by the absence of a concrete goal in the relationship between context and response action. This is the case when the habit originally was formed by repetition of a action with the aim to achieve a concrete goal. Once a habit is formed, the routine behaviour can arise even without the mediation of the goal to pursue, but just as a automatic, sometimes non-conscious action.

Similarly, Monge Roffarello et al. [37] [42] refer to the psychological theories that define a “habit” as a consistent repetition of a behaviour in the presence of stable contextual cues that increase the automaticity of that behaviour. Generally, a habit arises when our mind is waiting for contextual cues (1), that lead to routine behaviours (2). The temporary distraction from a routine is represented by the technology usage, that conveys a reward (3). When rewarded, for our brain the routine acquires importance and gives us a sense of craving (4).

4.1.1 Digital Behaviour Change Interventions

Moreover, Monge Roffarello et al. [42] assert that recent literature about digital wellbeing shows a poor use of habit forming approaches such as Digital Behaviour Change Interventions [43], described below. The “habit forming approach” applied in this context, consists of breaking an existing usage pattern (once detected), trying to let the user change it with the insertion of a more healthy routine that substitutes the old one, delivering the same reward. The Digital Behaviour Change Interventions (DBCIs) has been deeply analysed by Pinder et al. [43], who took into account the theoretical approaches in DBCI research (one of them is the Theory of Planned Behaviour, cited in section 2.4) and highlighted three theories that refer to intervention for habitual behaviours. These are:

- “Dual Process Theory”. It argues that behaviour arises from two distinct sets of processes:
 - Broadly automatic: the non-conscious habits belong to this category (labelled as “type 1”)
 - Broadly conscious: the behavioural intentions (labelled as “type 2”)
- “Goal Setting Theory”. The theory asserts that to be effective, the proposed goals must be accepted by the users, and it is important to provide feedback about their progress. In general, specific goals are more effective than vague ones.
- “Modern habit theory” It includes both stimulus-response behaviourist theories and goal-directed ones.

Synthesising these three theories, they build the “Habit Alteration Model” (HAM), a conceptual model that simplifies the habit forming process, focusing on the external and internal factors that generate them. The HAM is composed of the succession of 3 phases: “Filter”, “Prepare”, “Act”. In the “Filter” phase, our perceptions and attention processes filter the cues that form a given context. Then, in the “Prepare” phase, our memory processes match these cues to generate potential responses. This phase is strongly influenced by the emotional state. Finally, in the “Act” phase, a potential response becomes actual and the action is done. The 3 phases of a habit forming process can belong to one of the 2 categories of the Dual Process Theory: a habit is formed through implicit, non-conscious processes (type 1), or in alternative through deliberative, explicit, conscious processes (type 2). The implicit processes (type 1) generate impulses, while explicit processes generates intentions (type 2). If the “Act” phase is repeated in a stable context (Filter phase), then the habit arises. The habit formation process can be accelerated if the person receives a reward for the the response action.

The aim of a habit forming approach is to find strategies for moving a process of type 2 (intentional) to type 1 (impulsive) to enforce the automaticity of good behaviours. The strategies of HAM in digital contexts can belong to different habit-forming phases (Filter, Prepare, Act). Referring to the 3 phases, here is a brief description of the possible strategies:

1. Filter

- Alter context: adding or removing the cues to influence potential impulses and intentions. For instance, silencing notifications, or hiding the potentially distracting applications.
- Priming: providing a specific cue to form a wanted impulse in the “prepare” phase and activate wanted behaviours. Motivational quotes to perform a good behaviour can be an example.

2. Prepare

- Train context-response: train individuals to inhibit responses or reject these unwanted items, and to accept alternative wanted items.
- Implementation intentions: trying to bridge the gap between intentions (type 2) and impulses (type 1), by consciously emulating a impulsive context-response through a process that consists of a concrete if-then plan.
- Provide information: providing to the user statistics about the positive effect for a given behaviour.
- Just-in-time reminders: specific suggestions, delivered at the same point the action starts. They can be habit-forming (reminding to repeat a wanted behaviour), or habit breaking (reminding to stop a certain action).
- Train self-control: supporting the user to train to resist from a bad behaviour.

3. Act

- Self-monitoring: using information from self-tracking, and presenting them to the user to form alternative intentions to act.
- Revalue outcome: providing rewards for “correct” behaviour or punishments for “incorrect” behaviour.

Socialize [37] [42] is a habit forming smartphone app, based on these strategies. The 3 implemented strategies in this tool are: “implementation intention”, “just-in-time reminders” and “train context response”. In order to apply a habit changing technique, the first step must consist of modeling the habit and detecting it. To

make this, Socialize exploits a machine learning methodology based on association rule mining to find correlations among data. These data are structured as binary vectors that represent a phone usage session. Even in this case, a session is the interval that starts when the phone screen is turned on and ends when the screen is turned off. The binary vectors contain pieces of information about the sessions: the period, the user location, the activity.

When the Socialize app detects a habit, it shows the details about the contextual cue and the consequent repetitive behaviour. If it is labelled by the user as a “bad habit”, Socialize offers the opportunity to define an alternative behaviour for that contextual cue. When, in that cue, the unwanted behaviour is detected, a notification with the alternative behaviour is shown.

In the study conducted by Lyngs et al. [38] mentioned in the previous chapter, for evaluating and classifying the design features of the DSCTs, the authors apply the “Dual Systems Theory”: a self-regulation model supporting self-control over digital devices, theory that can be compatible with the DBCIs. The core of the Dual System Theory consists in the distinction between two behavioural processes:

- Non-conscious processes, driven by environment inputs and emotional state, with a high degree of automaticity.
- Intentional, conscious processes, driven by goals and rules.

This distinction is comparable with the “type 1” and “type 2” processes described previously.

Lyngs et al. make a comparison between the Dual System Theory and the DSCTs functionalities. Non-conscious habits can be prevented by the features that block the target of habitual action, or hide the elements of the user interface that triggers the action. Usage time limits, launches limits, redirecting user activity are other strategies that influence non-conscious habits scaffolding the formation of new ones (the “Implementation Intentions”). The management of conscious goals and self-monitoring is influenced by the self tracking strategies that involve timing, recording, visualizing usage data, but also by comparing these statistics to the user’s goal and providing concrete goal reminders. The rewarding strategies such as gamification of the digital tool, or feature unlock, motivational quotes, can promote a faster formation of new habits. On the other side, implementing a time lag for resource access is an approach to break unwanted habits with a “delay”.

Among the analysed tools, the prevalence is characterised by unwanted non-conscious habits prevention features, followed by self-monitoring and goal strategies, and then by the rewarding methods. Even if the block/removal features are the most common, the strategies to bridge the gap between intentions and impulses, scaffolding the formation of new habits, are very rare, although most of the cited

studies identify the habit formation strategies as crucial for long-time behaviour change [42][43][38]. Furthermore, they make a further distinction, on the basis of previous literature, between “self-regulation” and “self-control”, asserting that:

- Self-regulation includes all the regulatory processes to achieve a behavioural goal to avoid unwanted actions, including the automatic (type 1) habits. A preventive action of putting the smartphone away, not to fall into some automatic unwanted temptations, is an example.
- Self-control, more restrictively, refers just to the deliberate control actions performed when a immediate impulse is in conflict with the planned goals. For instance, the action of “resisting” from reading a notification when the user’s planned aim is to remain focused.

The self-control approach has some limitations in:

- The limited capacity of the user working memory to guide the control of goals, that can make the user forget about the digital wellbeing goals for a while, to leave space for other ones.
- The influence of the emotional state on the self-control ability.
- The effects of the cost-benefit analysis of self-control intentions: the self-control capacity depends on the reward that the user can obtain, on the “perceived likelihood” to be able to respect a goal, and on the “delay” before the outcome of a good self-control behaviour is received.

In this work, I deal with Digital Self-Control Tools (DSCTs) trying to expand them in a multi-device environment. Nevertheless, the goals of digital wellbeing are not merely focused on forming good self-control behaviours, but the real target is to help improving the user self-regulation attitude until it acquires a automaticity level. It is intuitive to find, on the basis of the related works, that the previous definitions of “habits” and habit-forming strategies are suitable for the multi-device world. It comes naturally that in a multi-device environment, a typical daily contextual cue can easily involve itself the use of technology (e.g the use of PC at work), and a consequent routine behaviour that may arise could be a interaction with another device (typically the smartphone). Thus, I deal with the same definition of habit. Differently from Socialize, my approach does not consist of modeling the user’s digital habits in order to recognise them automatically, but I propose a system where the intentions to improve the digital habits are user-defined. To take the leap towards the designing of a multi-device tool, the first step is to define a preliminary concept for determining and classifying the multi-device usage patterns: the “multi-device sessions”.

4.2 Multi-device sessions

Oulasvirta et al. [2], in their smartphone-related habit study, adopt the concept of session as unit analysis, composed by all the user actions detected between the activation of a device from the locked mode and the next time it is locked again. In these intervals, they detect the launched application and their average duration. The criteria to identify habits among these sessions are:

- The rapidity of the sessions, that is a symptom of automaticity: a non-habitual behaviour would be slower.
- Sessions that are repeated with a certain sequentiality, following similar patterns.
- Sessions that are consistently associated with a contextual cue.

In chapter 2, I referred to the study conducted by Finley et. al [9]. My attention on their work is also due to the usage data tracking model they implement, for the definition of “sessions” and the relationships among them, that pave the way for the formalisation of the “multi-device session” presented in this thesis. According to the authors, a session can be “app session” or “device session”. A “app session” is the time interval starting with an app moving to the foreground of the device and ending with the app moving out of the foreground (either replaced by a different app or screen off). A “device session”, intended as a single device usage session, is a collection of app sessions on a single device where the time interval between two sequential app session is minor than a Maximum Timeout Value (MTV1). Moreover, to model the relationships among single device usage sessions and define “multi-device session” the authors adopted the Allen’s temporal relational model.

Allen’s Relations

Allen [42] built a temporal representation model and defined a series of relations among time intervals. They are:

- Precedes (preceded by).
- Meets (met by).
- Overlaps (overlapped by).
- Finished by (finishes).
- Encloses (enclosed by).
- Starts (started by).

Figure 4.1: Allen’s multi-device sessions relationships

precedes	meets	overlaps	finishedBy	encloses	starts	equals	startedBy	enclosedBy	finishes	overlappedBy	metBy	precededBy

- Equals.

The Allen’s relations, represented in figure 4.1 can be partly applied to better define the single device session, and fully exploited to model the multi-device usage.

Single Device Since by definition the single device sessions are sequential, in this case only 2 Allen’s relations (precedes and meet) are valid. Specifically, if two sessions meet, the sessions will always belong to the same one, while the ‘precedes’ relation is valid only with the constraint of the Maximum Timeout Value (MTV1).

Multiple Devices For multiple devices (of a single user) all of Allen’s relations are applicable. As mentioned, precedes and meet (with their respective converse relations) describe sequential usage, while the remaining relations describe (at least partly) simultaneous usage of the devices.

In general, if the time interval between the end of a single device session and the start of another one is minor than another Maximum Timeout Value (MTV2), the two sessions are merged in one. If these two sessions belong to different devices, this new session become a “multi-device session”.

In the present work, I take inspiration from this definition to model the multi-device interactions in the design of FeelHabits.

Chapter 5

FeelHabits

In the last chapter I introduced the most effective strategies of Digital Self Control Tools and I explored their links with the Digital Habit Forming approaches, considering them fully suitable for an adaptation to a multi-device prototype. Then, I referred to the multi-device sessions as a starting point for detecting and modeling the multi-device usage patterns and designing a prototype of multi-device DSCT. Here, I finally define in a rigorous way the concept of “multi-device sessions” and “multi-device habits” adopted in the design of FeelHabits. Then, I provide a detailed description of FeelHabits: a multi-device digital wellbeing tool for improving multi-device digital habits.

5.1 Design

To simplify the project, I choose to start from the analysis of two devices: the PC and the smartphone. In details, I still focus on the smartphone app usage, while for the PC I focus on the details about web use.

5.1.1 FeelHabits multi-device sessions

The definition of multi-device sessions adopted in this thesis is a simplification on the model presented at the end of the last chapter. First of all, I refer to “device session” to describe the time interval starting with a device unlock, and ending when the screen is off. This model looks suitable for smartphone, as it is commonly locked when not used, and it is the same of the one adopted by Oulasvirta et al. [2]. In the case of PC, I consider two different approaches for PC session. One is similar: it is the time interval when the PC is on, until suspension or switch off. An alternative for PC session is the interval starting with a mouse or keyboard event, and ending with the last event time, if for a period of (at least) the Maximum

Timeout Value (MTV1), none of the previously mentioned events occurs. My choice for the model of PC session is the first option. The reason is that I don't want to exclude the cases when, for instance, the user is watching a video with the PC. In this case, even if there are no mouse or keyboard inputs, the user is interacting with PC. This interaction with the PC may represent a potential contextual cue for a consequent action performed with the smartphone, thus a possible habit.

In FeelHabits, the collected data about sessions are the launched smartphone apps and the opened websites on PC browser, when the other device session is active, or it was active in the last Maximum Timeout Value (MTV2). Afterwards, if the user keeps interacting with just one device and the other one is not active for longer than the MTV2, the system stops saving the information about further opened apps/websites, since they do not belong to a multi-device session.

Therefore, a "multi-device session" focuses on the sequential and parallel multi-device usage patterns. In the rest of the thesis, every reference to "multi-device sessions" only considers the apps/websites that are visited during or immediately after a interaction with the other device. The reason for this choice is that I would like to keep track of:

- The apps/websites opened in the transitions from a device usage to another one.
- Information about the simultaneous usage of two devices. I expect to detect a primarily usage of the PC along with a more intermittent usage of the smartphone.

Moreover, the Maximum Timeout Value is an important parameter that affects the eventual interpretation of the results. The timeout value should be neither too short, in order to preserve the single usage session without fragmenting it, nor too long, to avoid merging different sessions supposed to be separate. With the simplified model of multi-device session, I am no more interested in defining the MTV1 value, because there is no need to merge sessions of the same device. For MTV2, I choose to use the same value adopted by Finley et al. [9], that is one minute ($MTV2 = 60s$).

5.1.2 FeelHabits multi-device habits

On the basis of all the previous analysis about digital habits and multi-device sessions, I define "multi-device habits" as: *a frequent, automatic, context-related behaviour that involves the interaction between the user and more than one digital device*. The context cue typically includes itself a interaction with a device, and the response action involves the usage of another digital device. In this section, I present some further ideas to go into details of multi-device habits. Monge

Roffarello et al. [37], starting from the definition of digital habit that I introduced previously, model 3 main habit categories in smartphone usage:

- Context Habits: association rules that model a strong correlation between contextual cue and mobile app. Period, Time Slot, User Activity and/or User Location trigger the activity. Example: {working day, 10-12AM, work} → {Facebook}
- App Habits: association rules that model a strong correlation between mobile apps, only when the usage of a given app spurs the usage of one or more other ones. {Whatsapp} → {Twitter, Facebook}
- App-Context habits: hybrid association rules, where the usage of a specific app in a given context spurs the usage of a second one or more other apps. {02-04 PM, work, Slack } → {Chrome, Instagram}

This classification provides insights for a broader definition of multi-device habit. As seen, in the multi-device world, a common pattern is based on performing the same task with more than one device (“Sequential Use”, section 2.2). In the multi-device context addressed in this thesis, many services can be available both with smartphone app and with the PC browser. Depending on social, practical and psychological factors that are determined by the context, a user may prefer to access a resource with a device rather than another one, and vice versa in a different context. For instance, a student during the day may be used to watching a TV series on Netflix with the smartphone, while performing another task (not necessarily technology related). At night, the same student may prefer to watch Netflix with the PC. This example has to do with habits, since it deals with two context-related and repeated behaviours. These two habits, even if are temporary separate, involve performing the same task (with 2 different devices). Moreover, when a resource represents the target for a potential unwanted digital habit, with a correlated risk of overuse, this risk may increase if the resource is accessible from more than one device. Even if this scenario doesn’t mirror the definition of “multi-device habits” presented before, actually it belongs to the category of digital habits and it is associated to more than one device. Moving the focus of the habit definition into the action triggered by a context, rather than into the involved devices, I can put in the same category the two habits that, even in different contexts, involve the access to the same service with different devices.

For this reasons I introduce the concept of “Multi-Device App” as the pair composed of smartphone application and the analogous website (supposed to be visited through the PC browser). For instance: “WhatsApp” for smartphone, “web.whatsapp.com” on PC browser. Now, inspired by the model drawn by Monge Roffarello et al. [37], and on the basis of the last considerations, I try to broaden the field of multi-device habit, by identifying the following three classifications:

- “Multi-device context Habit”: it is a strong correlation between a contextual cue that involves itself the usage of a device, and a consequent interaction with a app/website of another device. For instance: at work, in the morning, while using PC, the users frequently launches Instagram with the smartphone.
- “Multi-device app Habit”: when a user habitually visits a multi-device app both with the smartphone app and the PC browser, even if these two habits occur in different contexts. A example can be the mentioned use of Netflix with 2 devices in different daily periods. Together, they belong to a “multi-device app habit” category.
- Multi-device app-context habits: a hybrid form, where the usage of a specific app/website in a given context, with a given device, spurs the usage of a second app/website (even not related) with a different device. This category looks as a subset of the first one, where the detail about the visited app/website in the contextual cue is crucial for habit modeling.

In the present thesis, I collect data about multi-device sessions. Then, I try to recognise these categories in the collected data.

5.1.3 FeelHabits intentions

To implement the habit mitigating function of FeelHabits, I start from a simplified model of context, which is mainly temporal. The user can choose among working days and/or holidays, and among some daily periods (morning, afternoon, night). Then, in relation with the chosen context, the user can select among 3 intention categories for mitigating multi-device digital habits:

- “Multi-device apps”. It is the option for the users who want to mitigate a habit that consist of visiting too often or for too long an application on smartphone and/or the respective website with the PC.
- “Smartphone at PC”. This intention aim to mitigate habits that involve a excessive usage of a smartphone app while using PC. This is the case of “Multi-device context Habit” when the context involve the usage of the PC in a determined daily period. This intention includes also the subset category of “Multi-device app-context habits”.
- “Screen time”. As our interaction with technology is more and more pervasive, the ubiquity of devices represent a potential risk for overuse. Thus, I define a intention to form the good habit to make a break after a long multi-device session, and to control the overall daily screen time.

For each of them I tailor different intervention types, that are better explained in the following section, dealing with the FeelHabits architecture.

The main goal in the design of a new tool are:

- To prevent the unwanted non-conscious habits by letting the user choose a personal tolerance limit in terms of frequency and/or time duration of a determined multi-device habit, associated to a daily temporal context. This approach aims to encourage the formation of new self-regulation habits, by warning the user when the self-defined limit is reached. Referring to [38], the strategies related to habit formation are time and launches limit: I try to make them multi-device, by implementing aggregate (PC + smartphone) limits of usage time and number of launches. The interventions triggered in case of reach of a limit have the purpose to redirect the user activity to a alternative behaviour, without being too intrusive and restrictive. Thus, the severity of the intervention is again defined by the user: it can be a blocker or a notification. In case of blocker, the user has the opportunity to refuse it for that day, if he/she still needs to use the blocked resource.
- To provide a overview of the user-defined intentions and the usage data with regard to these intentions, just for the current day. FeelHabits avoids showing historical statistics and progress data that can provoke anxiety to the user, instead if focuses on the habit forming techniques.
- To collect in background usage data about multi-device sessions, for statistical purposes, to pave the way for modeling strategies to detect multi-device habits.

FeelHabits applies the chosen strategies to the three intention categories. In the next section, I provide a detailed description of the tool.

5.2 Architecture

This section deals with the detailed description of the FeelHabits architecture. With this tool, the user can define 3 main multi-device habit-mitigating intentions, that, as introduced in the previous section, I named:

- “multi-device apps”. With this intention, the user can set a usage time limit, or a maximum number of launches, for the multi-device apps (e.g. “WhatsApp” on smartphone, “web.whatsapp.com” at PC).
- “Smartphone at PC”. Choosing this intention, the user can set a usage time limit, or a maximum number of launches, for the smartphone apps, when using the PC in the meantime.

- “Screen time”. Here, the user can set a limit for his/her multi-device screen time.

The first two intentions are that are “app-level”, because they deal with the apps/websites usage, while the third one, independent from the details of usage, is “device level”. These limits are daily, and they are associated with a temporal context: they can be active for the whole day or part of it. At the end of the day, all the limits are reset. The multi-device architecture of FeelHabits is composed of 5 main components: 3 front-end tools, a server and a database. The tools are a Chrome Browser, a PC Windows app and a Android app.

Figure 5.1: FeelHabits project design

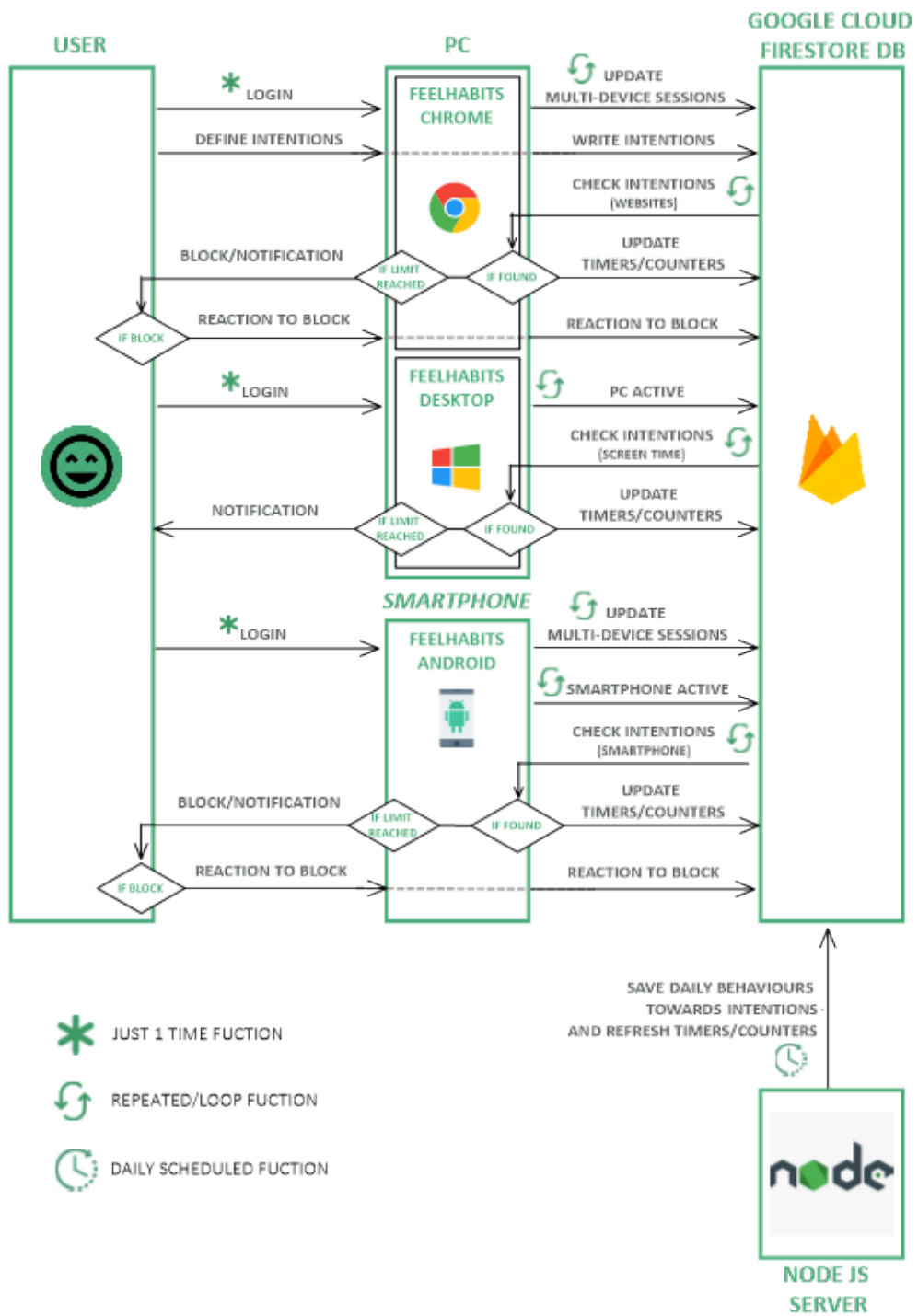


Figure 5.1 shows the FeelHabits system architecture. The left block represents the user, the central blocks represent the devices and the FeelHabits tools, while the right blocks provide a representation of the back-end part (the server and the DB). The arrows show the main communications among the components. In details:

- The FeelHabits Chrome extension provides the main user interface. From it, the user can set a new intention to control and improve multi-device habits, and if needed check and delete the already defined intentions. The intentions consist, as introduced, of:
 - limits of usage time or limits of number of launches associated to smartphone apps, websites accessible from PC, or multi-device apps.
 - a time limit for PC and/or smartphone usage, independently of the details about apps or websites.

When the Chrome browser is active, the extension works in background to track the internet usage on the PC browser, and manages the “multi-device app” intentions. If it finds a correspondence between the current opened website and an intention, the extension updates in real time the timers/launches counters set by the user for this website. When a limit is reached, the system reacts with an intervention. The severity of the intervention is chosen by the user in the definition of the intention and it ranges from a simple notification to an access blocker (giving the opportunity to accept or refuse it). The arrow named “reaction to block” in the architecture figure (5.1) represents the choice of the user in front of a block page, that will be saved in the DB.

- The FeelHabits desktop app for Windows works in background to track the usage of the PC, writing to the database a real time information about the status of the PC (active or not, “PC Active” arrow in Figure 5.1) and the timestamp of the last PC suspension/shutdown. Then, the application manages the third intention option (“Screen time”), updating the timers about multi-device sessions if they are currently active.
- FeelHabits for Android similarly works in background to update in real time the status of the smartphone (“smartphone active” arrow in Figure 5.1). Moreover, it checks the smartphone-related intentions, that can belong to all the three intention types (“multi-device apps”, “smartphone At PC”, “Screen time”). For the first two, if FeelHabits finds a correspondence between the currently launched smartphone app and an intention, for that temporal context, the app updates the timers/launches counters associated to that app. When a limit is reached, FeelHabits blocks the access to that application or sends a warning notification (again, depending on the chosen level of severity). In case of block, again, the user can accept or refuse it. To manage the third intention,

the app works when the smartphone is unlocked, and if it finds a “screen time” intention for the current context, it updates the timers independently of the launched apps. In this case, when a limit is reached, the severity of the intervention can be only a notification.

Furthermore, both the Chrome extension and the smartphone app, in background, collect and save in the DB the data about websites on PC browser and smartphone apps, accessed during multi-device sessions. Thus, when a website on PC or a smartphone app is visited, and the other device is active or was active in the last minute (the MTV2 defined in the previous chapter), the respective FeelHabits tool saves the information about the current timestamp and the opened URL/app (the “update multi-device sessions” arrows in Figure 5.1).

5.2.1 DB

The description of the database helps understand the interactions among the FeelHabits components, because it is directly connected with all the other parts. The cloud database¹ contains two root collections:

- **Apps&URLs.** It contains the list of the most popular multi-device applications, divided by category. The Chrome extension reads these information when the user defines a new intentions belonging to the “multi-device apps” category.
- **Users:** It contains a document for each user ID. Inside, there are 4 attributes and 3 subcollections. The attributes are:
 - “PCActive” (boolean). It is “true” if the PC is running, “false” if it is suspended/off.
 - “smartphoneActive” (boolean). It is “true” if the smartphone is unlocked.
 - “lastPCEventTime” (int). It contains the timestamp of the last PC suspension/switch off.
 - “lastSmartphoneEventTime” (int). It contains the timestamp of the last smartphone lock/switch off.

The collections are:

- “Apps”: inside, it contains the list of the most frequently opened smartphone apps. This list is written by FeelHabits for Android. The Chrome extension reads this list when the user is defining a new “Smartphone At PC” intention.

¹created with Google Cloud Firestore

- “Intentions”: it contains the list of user defined intentions, with the details about the context, the status (active or deleted). This is the most complex data structure: in the next paragraph (“Intentions”) I examine its content.
- “multiDeviceEvents”: it contains the information about the usage of smartphone apps and URL visited from the PC Chrome browser, during multi-device sessions. This means that the information is written if the other device is “active” or has been locked/suspended/switched off in the last 60 seconds. Inside “multiDeviceEvents” there are two collections, named “PC” and “smartphone”. These subcollection contains the multi-device session usage info, structured as key value pairs: the key contains the timestamp of the app launch, the value contains the opened smartphone app/website on PC.

Intentions The “Intentions” collection contains a document for each set intention, identified by a unique key. Each document is associated with a series of attributes that define:

- The temporal context: “workingDays”, “holidays”, “morning”, “afternoon”, “night”.
- The intention category: “choice”. It can be, coherently with the 3 intention categories: “multi-device apps”, “smartphone At PC”, “screen time”.
- The time/launches limit values: “smartphoneLunchesLimit”, “PCLaunchesLimit”, “smartphoneTimeLimit”, “PCTimeLimit”, “aggregateLaunchesLimit” “aggregateTimeLimit”.
- The status of the intention: “deleted” (boolean).

Inside each intention, if the choice is “multi-device apps” or “smartphone At PC”, there is a further collection that contains a document for every involved app or URL, with inside the detail about the user behaviour towards this intention. If the intention is aggregate, (a aggregate daily limit for a multi-device app) both the documents referred to the app and the website will be in that collection, separately. In details, inside each of these documents there can be some of the following fields, on the basis of the user’s choice:

- smartphoneTimeLeft (PCTimeLeft)
- smartphoneLaunchesLeft (PCLaunchesLeft)
- smartphoneTimeLeftIgnore (PCTimeLeftIgnore)
- smartphoneLaunchesLeftIgnore (PCLaunchesLeftIgnore)

- smartphoneLaunchesLeftIntervention (PCLaunchesLeftIntervention)

It is intuitive to understand that the fields that contains the word “smartphone” are inside smartphone apps, and analogously for the “PC” keyword for websites, and “timeLeft” and “launchesLeft” keep track of their usage. The fields with the “Intervention” suffix indicate the severity of the system intervention (it can be “block” or “notify”). Then, the fields with the “Ignore” suffix are boolean flags that indicate, if the set intervention is “block”, the user’s reaction towards the block page.

When the respective “timeLeft”/“launchesLeft” value is positive, the ignore flag is “false”. It means that the limit is still active. When a limit is reached and the intervention severity is a notification, then the “ignore” flag is set to true, i.e. the notification appears only once. Instead, when “timeLeft”/“launchesLeft” value is negative and the severity is a block page, then the block page appears every time the involved application is opened, unless the user decided to refuse the block. If the user accepts the restriction, he/she will be warned again if the limit is not respected in the future (until the end of the temporal context).

If instead, the choice is “screen time”, the attributes that denote the user’s behaviour are different. In fact, there are: the type of limit (overall or non stop session), its value, the time left, and the information about:

- The device and the timestamp when the user has reached the limit.
- The device and the timestamp when, after a reached limit, the session is reset. Thus, it means how much the user exceeded beyond the usage limit before taking a break from both devices for more than one minute. This can be a estimation of the effectiveness of the notification.

The aggregate limits In the cases of “multi-device apps” intentions, when the timer/counter is aggregate (for a multi-device app), there are some more fields inside the collection that contains the intention details:

- aggregateAppTimer (aggregateURLTimer)
- aggregateAppLaunches (aggregateURLLaunches)

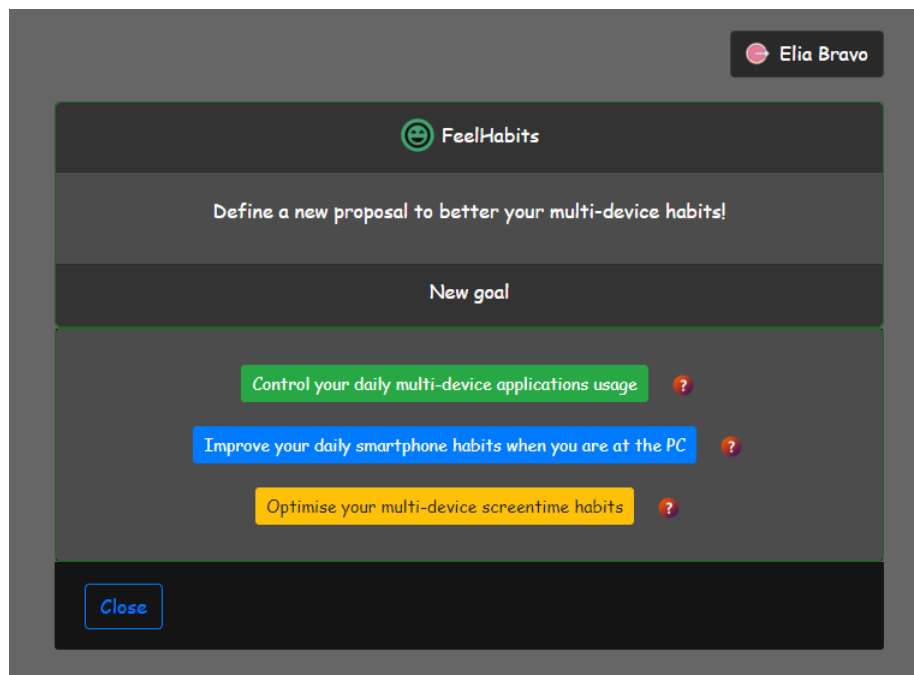
They contain the information about the name of the analogous app/URL to form the multi-device app pair, for which a certain limit has been set as “aggregate”. This information is exploited by the Chrome extension and the smartphone app, in their background functions. When they find a “active” intention that involves the current app/URL, and for that intention, on the DB, there is one of these fields, it means that the current limit is aggregate. So, the application reads from to the DB the timeLeft/launchesLeft value of the complementary app/URL, and computes

the difference between the aggregate limit and the usage data of both devices. If the difference is negative, the intervention is applied on the device(s) where the application is running.

5.2.2 FeelHabits Chrome Extension

The Chrome Extension represents the heart of the FeelHabits system, since from it the user can define the intentions to mitigate a digital habit. The main goal of this tool is to build an easy and comprehensive interface to easily define intentions. From the main window, the user can set a new intention, or check and edit the details of the already defined intentions. Figure 5.2 shows the Chrome extension main window, with the 3 previously described multi-device intention options.

Figure 5.2: Feel Habits Chrome: main window



First step: when

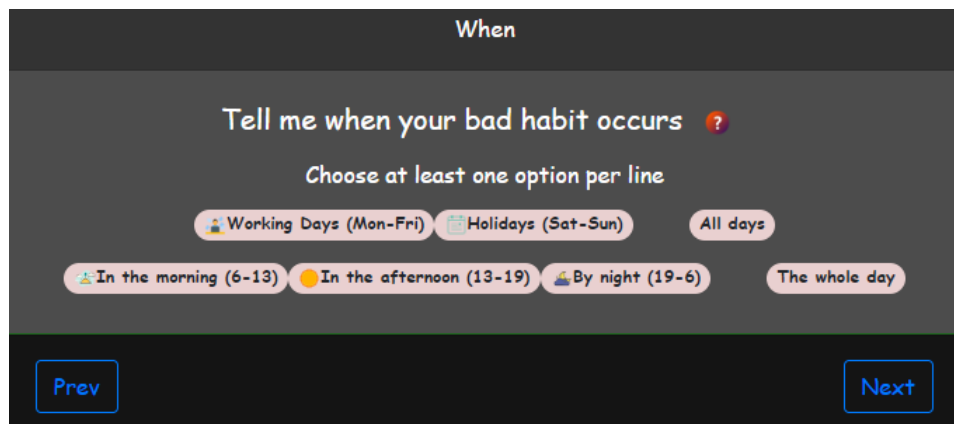
For each of the three possible intentions, the first step is the same and consists of selecting the temporal context when the habit occurs (“When” step, Figure 5.3). From here, the user can select the daily period(s) and the part(s) of the week when the habit is supposed to be checked by the system. The two categories for “part of the week” are:

- Working Days: from Monday to Friday
- Holidays: Saturday and Sunday

The possible options for the daily period are:

- morning: from 6am to 1pm
- afternoon: from 1pm to 7pm
- night: from 7pm to 6am of the next morning

Figure 5.3: Feel Habits Chrome: When



Second Step: What

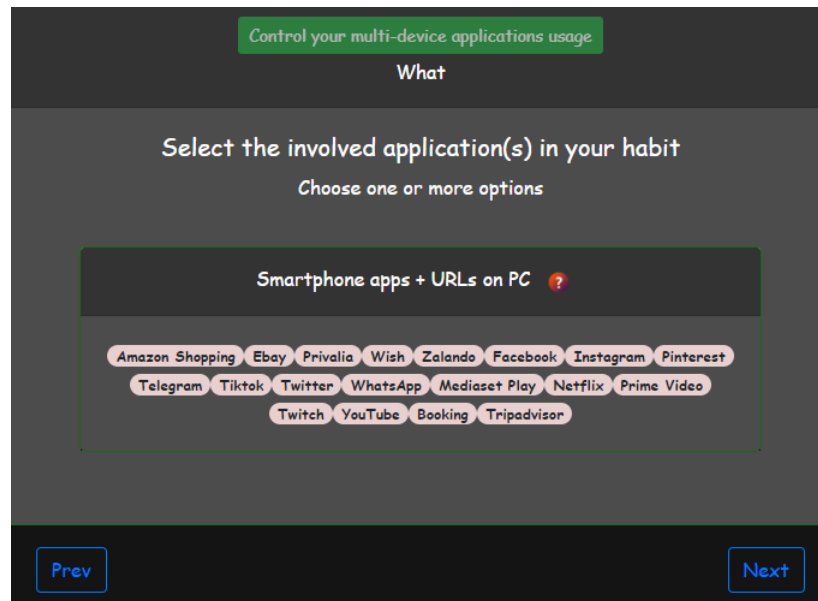
In this step, the user chooses the involved apps/URLs in the intentions. For the “Screen time” intention type, that is “device level” and doesn’t involve any apps/URLs, this step is skipped. Instead, for the other two intention types, there are some differences:

- “Multi-device apps” intentions. Here, the “What” step consists of selecting the multi-device apps for which the user wants to mitigate the usage in the daily periods they selected in the previous step. The interface shows a list of multi-device app names, so they are intended to be a pair composed of smartphone app + URL (accessed by the PC Chrome browser). For instance, if the user clicks on “Facebook”, he/she is considering the multi-device app that includes “Facebook” smartphone app, and the “www.facebook.com” website accessible from PC browser.

The multi-device apps are extracted from the DB and are the same for all

the users. The choice of the multi-device apps has been made by considering that the first user test of the FeelHabits system is conducted in Italy. Thus, I retrieved the most visited websites in Italy². The same approach has been performed for the most used Android apps³. Then, on these two lists, I extracted the applications that are present in both of them and on the basis of the analysed literature, are potential source of bad digital habits. Figure 5.4 shows the final list of multi-device apps: belonging to social networks, communication, video, ECommerce and travel categories.

Figure 5.4: Feel Habits Chrome: What step (multi-device app)

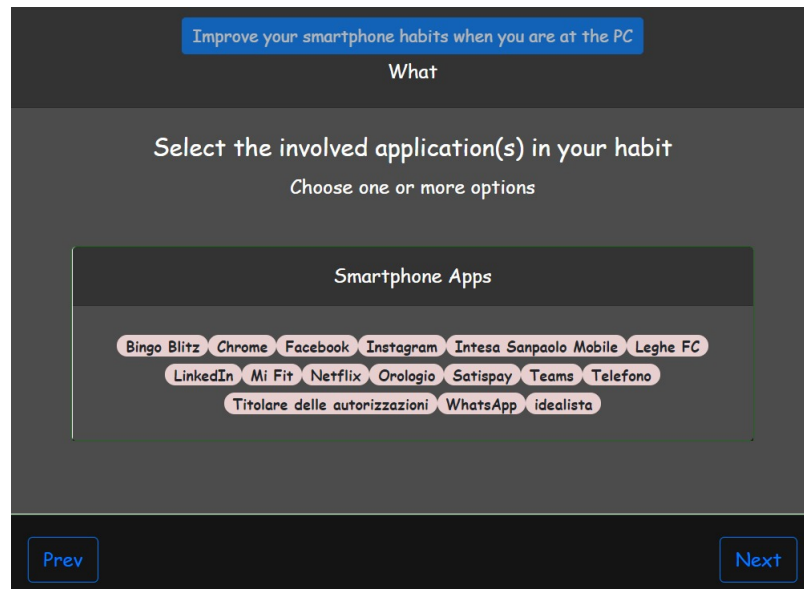


- “smartphone At PC” intention: the “What” step, differently, contains a customised list of the most visited smartphone apps (Figure 5.5). Those app names are read from the DB (and provided by FeelHabits smartphone app). The user can choose the smartphone apps for which he/she wants to mitigate the usage, when using the PC in the meantime (or in the last minute).

²from <http://www.alexa.com>

³from <http://www.similarweb.com>

Figure 5.5: Feel Habits Chrome: What step (smartphone At PC)

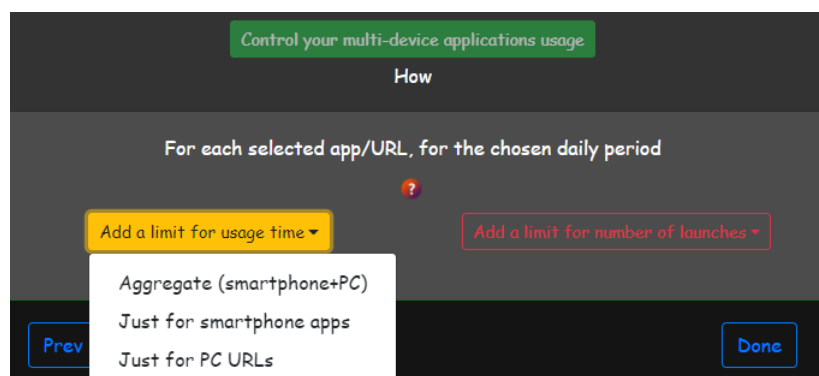


Third and Last Step: How

The “How” step consists of selecting the intervention types and its features. All the limits are daily, thus they are reset every morning. Again, the options are different for the three intention types.

- “Multi-device apps”. For this intentions, in the “How” step there are 2 buttons:
 - “Add a limit for usage time”.
 - “Add a limit for number of launches”.

Figure 5.6: Feel Habits Chrome: Apps and URLs - Limits



Each of these limit options contains 3 further choice options (Figure 5.6):

- “Aggregate”: the limit is aggregate, i.e. the chosen value for the maximum usage time/maximum number of launches is an overall daily threshold for that multi-device app (PC + smartphone).
- “Just For Smartphone Apps”.
- “Just For PC URLs”.

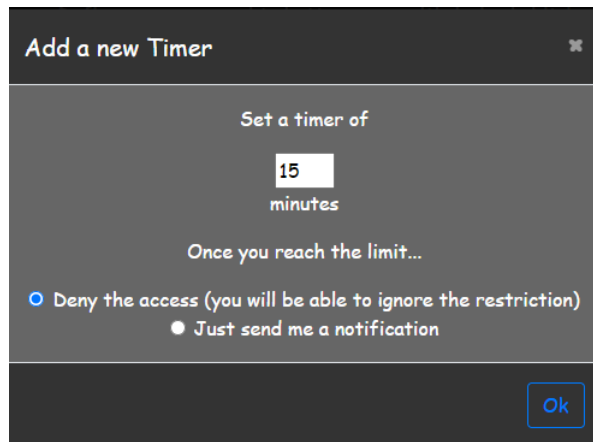
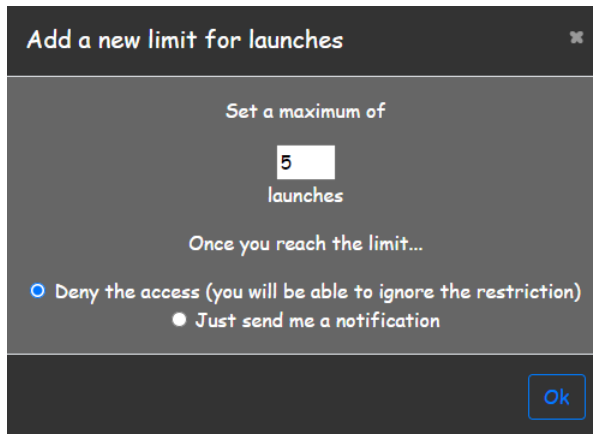
With regard to this limits, the user sets:

- The limit value, i.e. the maximum usage time (Figure 5.7) in minutes or the maximum number of launches (Figure 5.8).
- The level of severity: a access blocker for that app, or a simple notification.

When a limit is reached, during the chosen temporal contexts, for one of the involved apps/URLs, a notification or a block window appears on the last involved device.

- “Smartphone At PC” Even with this choice, the next step is called “How”, and the buttons are similar:
 - “Add a limit for usage time”.
 - “Add a limit for number of launches”.

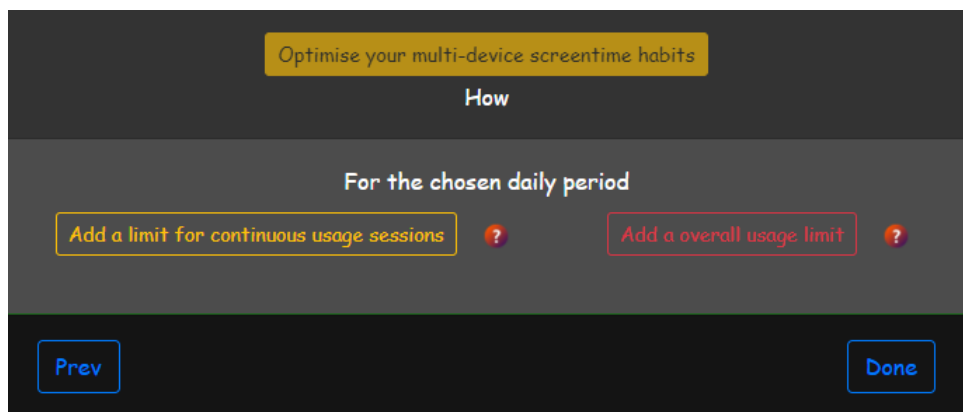
The difference is that in this case, these options do not contain other suboptions, because the only involved device is the smartphone. Again, the last choice to make is, the values for the limit (usage minutes: Figure 5.7/number of launches: Figure 5.8) and the strength of the system intervention.

Figure 5.7: Feel Habits Chrome: new timer**Figure 5.8:** Feel Habits Chrome: new counter

- “Screen Time” With this choice, the button options in the “How” step, as Figure 5.10 shows, are:
 - “Add a limit for continuous usage”. Here, the user can set, for the selected period, a time limit for the PC and/or smartphone continuous usage sessions. If both devices are not active for one minute or more, the timer will reset.
 - “Add a overall usage limit”. Here, the limit doesn’t refer to non-stop usage, but it is a overall usage limit for the daily selected period.

The intervention severity for the reach of a screen time limit is just a notification (the block of a device has been considered too drastic).

Figure 5.9: Feel Habits Chrome: screen time limits



Finally, the user clicks on the “Done” button and a new habit is defined (Figure 5.12)

Figure 5.10: Feel Habits Chrome: nonstop session timer

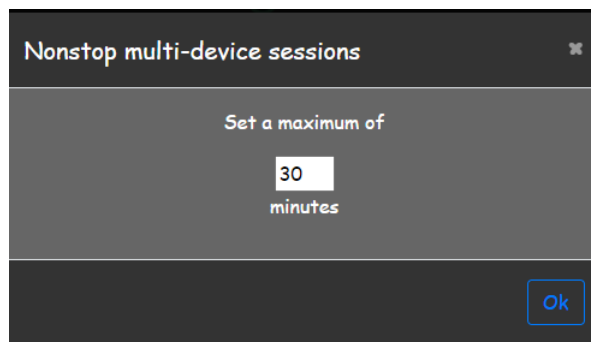


Figure 5.11: Feel Habits Chrome: overall session timer

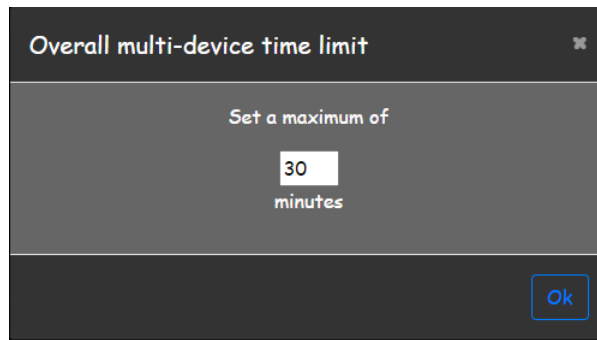
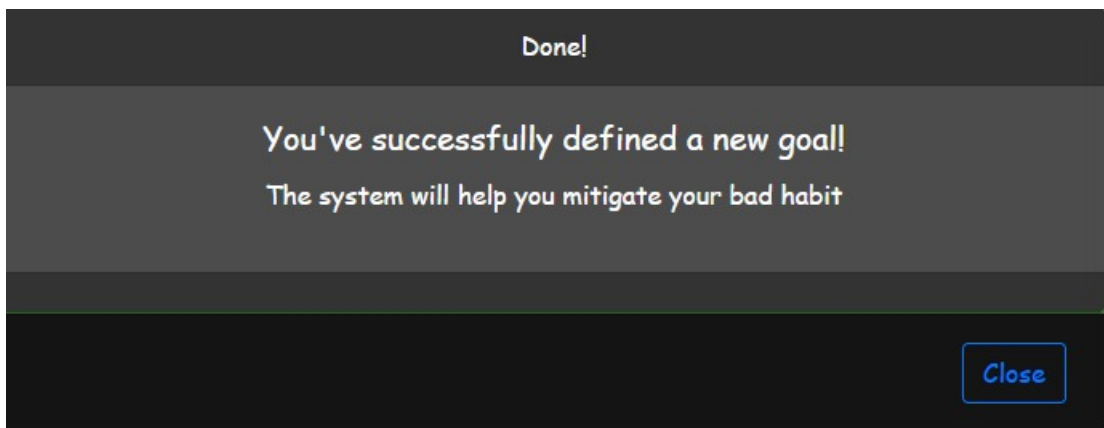


Figure 5.12: Feel Habits Chrome: new habit defined!



FeelHabits Chrome: notifications / block windows Every time the user changes tabs or updates the URL on the Chrome browser, a listener that handles these user’s actions triggers a function that checks the current URL, and reads from the DB the intentions of the first type (“multi-device apps” the only one that has to do with websites). If it finds a correspondence for that URL in the current context, the function manages the update of the timer/counter and if needed it sends the consequent notification/block page.

The notifications of a reached limit are not clickable and contain just the warning message, with the information about the end time of the restriction (Figure 5.13).

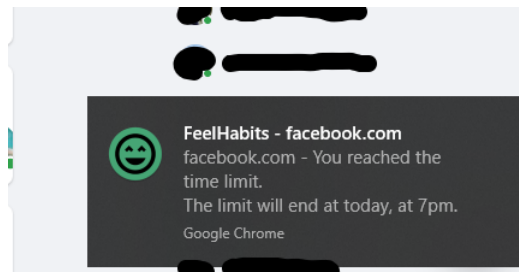
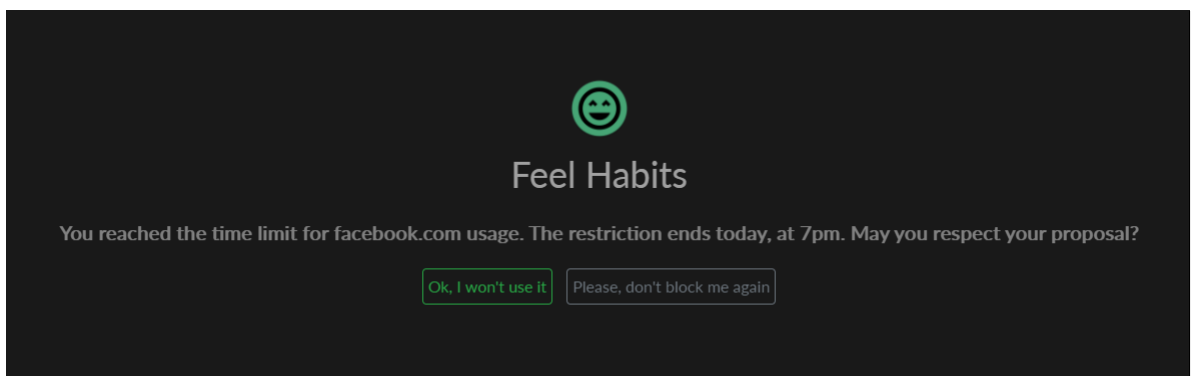
Figure 5.13: Feel Habits Chrome: notification example**Figure 5.14:** Feel Habits Chrome: Block example

Figure 5.14 shows a example of a block page on the browser triggered by the FeelHabits Chrome extension, when a limit is reached. The related message lets the user know about: the type of limit (time or launches), the URL, and the daily time when the restriction ends.

Here, the user can choose between two options:

- “Ok, I won’t use it”. It means that, if the users attempts again to access that website, and the time still belongs to the temporal context of that limit, the block page keeps appearing, for that day. By clicking on it, the browser tab will automatically close.
- “Please, don’t block me again”. This is the action that turns the “ignore” flag to true (“DB” section, 5.2.1). If the user attempts again to access that website, and the time still belongs to the temporal context of that limit, he/she won’t be blocked for that day. By clicking on it, the browser tab is redirected to the website, and the user is free to visit it.

Intentions overview

On the main page of the Chrome extension, the user is informed about the number of set intentions. By clicking on the “Show” button, the user can monitor their status for the current day, filter the currently active ones, delete them if needed. Figure 5.15 shows an example of intentions overview interface.

Figure 5.15: Feel Habits Chrome: Intentions Overview

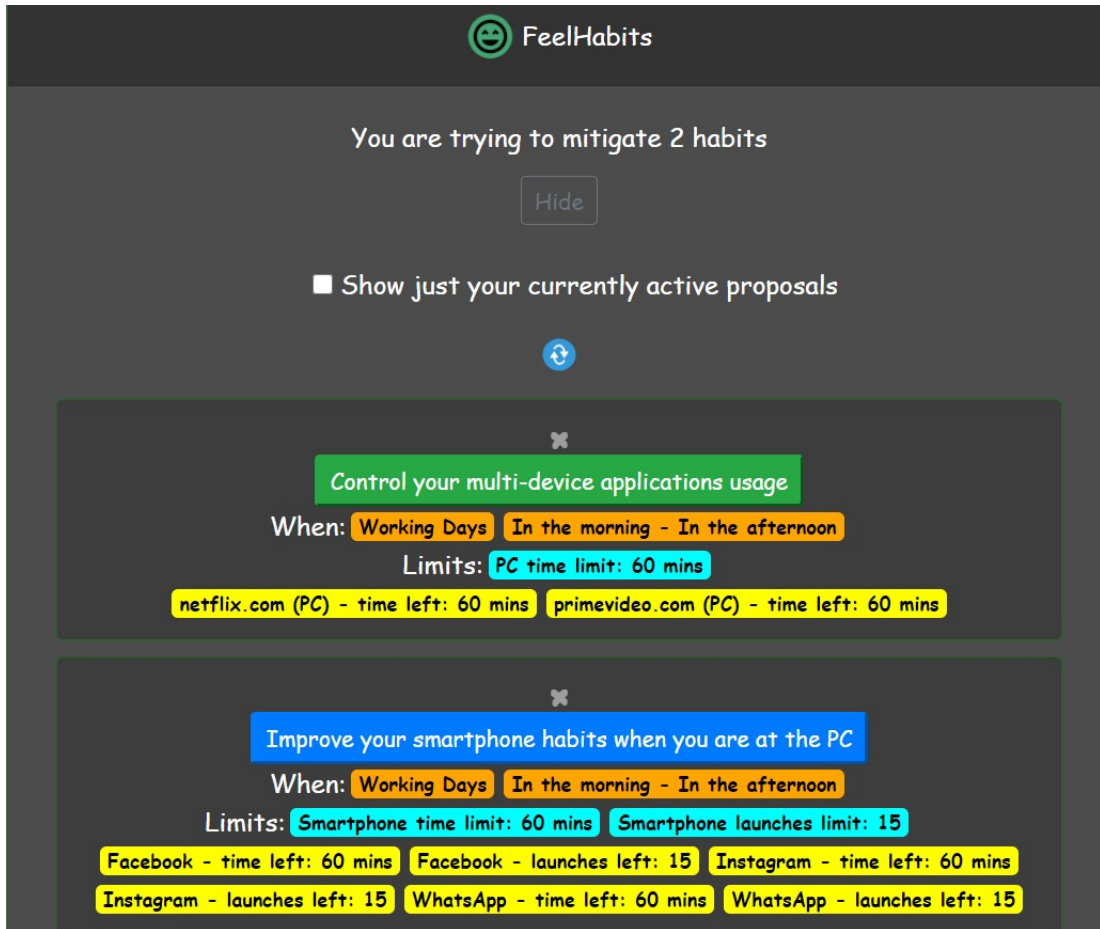
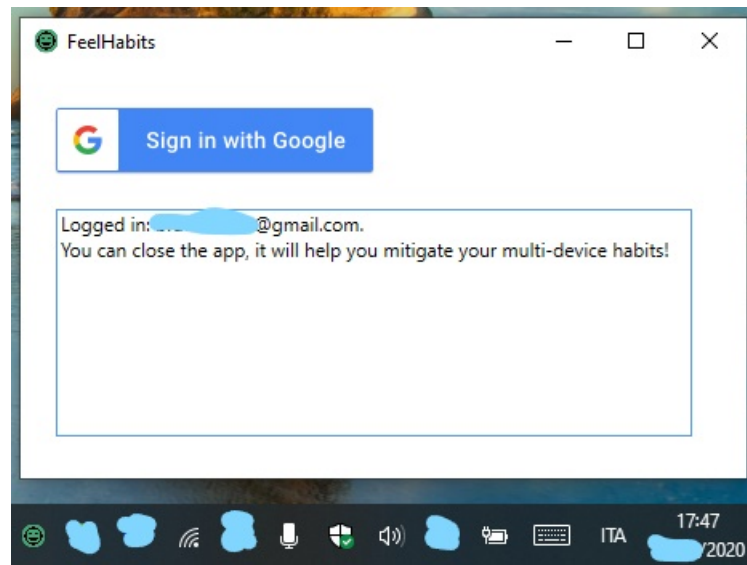


Figure 5.16: Feel Habits Desktop: main window

5.2.3 FeelHabits Desktop PC app

The FeelHabits PC is a Windows Presentation Foundation app, that basically consists of a login window interface (Figure 5.16). The PC is considered as active if the screen is on, no active if the PC is sleeping or off. Once logged in, the user can click on the close button, and the desktop app keeps running, with a active icon on the system tray. The application is designed to start automatically at Windows startup, and it cannot be closed unless the user decides to kill the process. The system works in background and sends to the DB the information about the status of the PC (active or not). At Windows startup, the system updates the status writing on the DB, on the field “PC active”, the value “true”. When the user suspends or turns off the PC, another function is triggered. This function puts the “PCactive” field to “false” and updates the “lastPCInputTime” to the current timestamp.

Additionally, the application manages the “screen time” intentions. A function, scheduled every 10 seconds, queries the DB looking for such set intentions, and if the current context is compatible, the timers are updated. In case of concurrent usage of PC and smartphone, the PC application has the priority for the managing of these intentions. When a limit for overall daily screen time is reached, a notification appears on the PC desktop, with a message that informs the user about the daily end time of the restriction (Figure 5.17). Until the end of the daily period associated to that intention, the user should not use any device. In case of reached limit for non-stop sessions, the notification message suggests, instead, to take a break

(Figure 5.18). This message provides a hint to form a good behaviour. If the user detach from all devices for more than one minute, then the timer is reset.

Figure 5.17: Feel Habits Desktop: notification for overall usage time limit reached

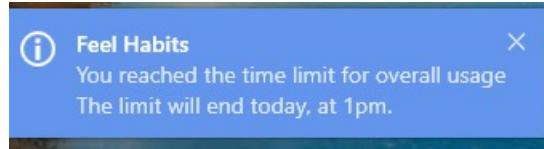
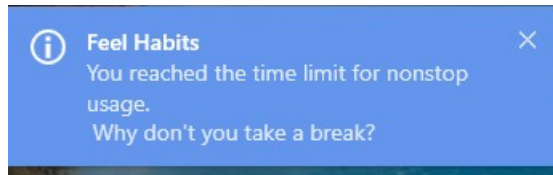


Figure 5.18: Feel Habits Desktop: notification for non-stop session usage time limit reached

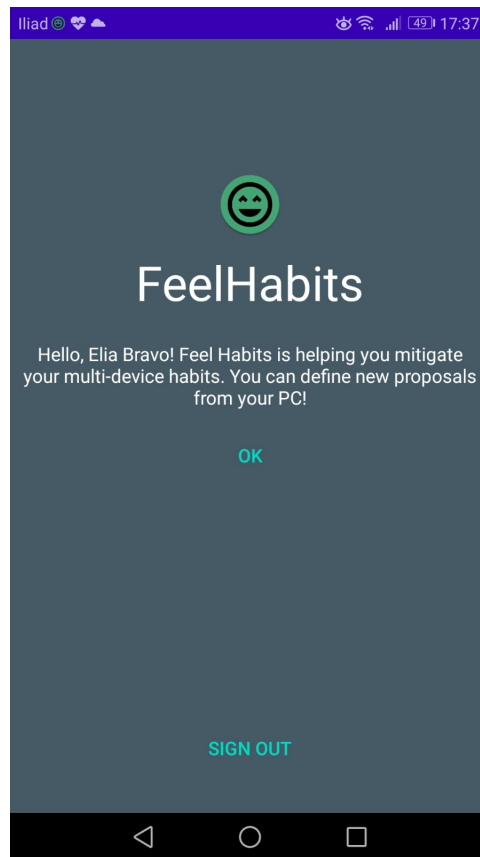


5.2.4 FeelHabits Android app

FeelHabits smartphone app works primarily as a background application that updates the usage data for the limits defined by the user in the Chrome extension. Figure 5.19 shows the main activity of the app. Everytime the smartphone is unlocked, a service named “AppMonitorService” is registered. This service reads from the DB all the intentions set by the users, and it consequently starts a timer that schedules a task which, every 5 seconds, until the next phone unlock, monitors the smartphone usage⁴. At every interval, the app verifies if a app has been just launched and/or is running. Then the background service queries the DB, looking for active intentions that involve that app or for screen time intentions. If so, the function updates the DB to the usage data about intentions (smartphoneTimeLeft, smartphoneLaunchesLeft, continuousUsageTimeLeft, overallUsageTimeLeft). For the aggregate limits, it computes the time/launches left taking into account the complementary PC values.

When a limit is reached, the app, on the basis of the chosen intervention severity, inflates a block activity/sends a notification. The message content of the block activities are similar to the block page triggered by the FeelHabits Chrome extension:

⁴exploiting the UsageEvents.Event class, available from Android API 21

Figure 5.19: Feel Habits Android app: main activity

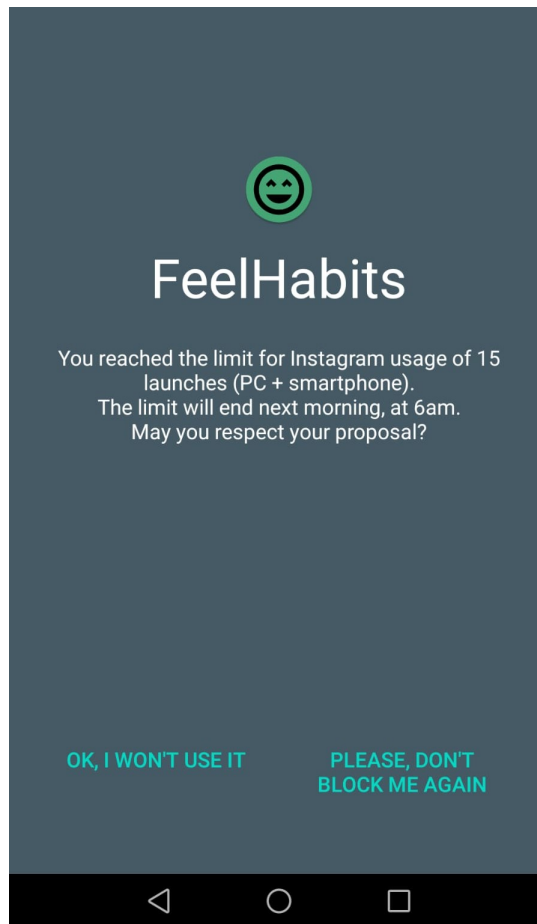
it let the user know about the reached limit type, the involved application, the end time of the restriction.

Figure 5.20 shows the block activity related to Instagram multi-device app, where a aggregate (PC + smartphone) launches limit has been reached. Again, the user can choose among two options, with similar functionalities:

- “Ok, I won’t use it”. By tapping on it, the user accept the restriction, and the involved app is closed. In case of a further access, the block page keeps appearing.
- “Please, don’t block me again”. With this choice, the involved application moves to foreground and can be accessed for the daily temporal context associated to the intention.

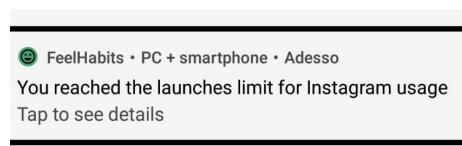
For the “smartphone At PC” limits, the blocker message is similar, except for the information about the limit type.

Figure 5.20: FeelHabits Android: block activity (multi-device app)



If intention belongs to “multi-device apps” or “SmartphoneAtPC”, but the intervention severity is a notification, the notification message will be as in figure 5.21. By tapping on it, the application shows the same activity of the respective block page, except for the absence of the “reaction” option, replaced by a unique “Ok” button.

Figure 5.21: FeelHabitsAndroid: notification for reached limit (multi-device app and smartphone at PC example)



In case of reach of a “screen time” limit, again a notification is shown, and if the user taps on it, a activity with a more detailed message is inflated. Figures 5.22 and 5.23 shows the notification and the activity for overall usage limit, while Figures 5.24 and 5.25 the cases of non-stop usage session limits reached.

Figure 5.22: FeelHabitsAndroid: notification for overall usage session limit reached

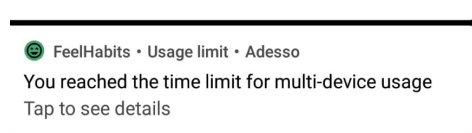


Figure 5.23: FeelHabits Android: for overall usage session limit reached

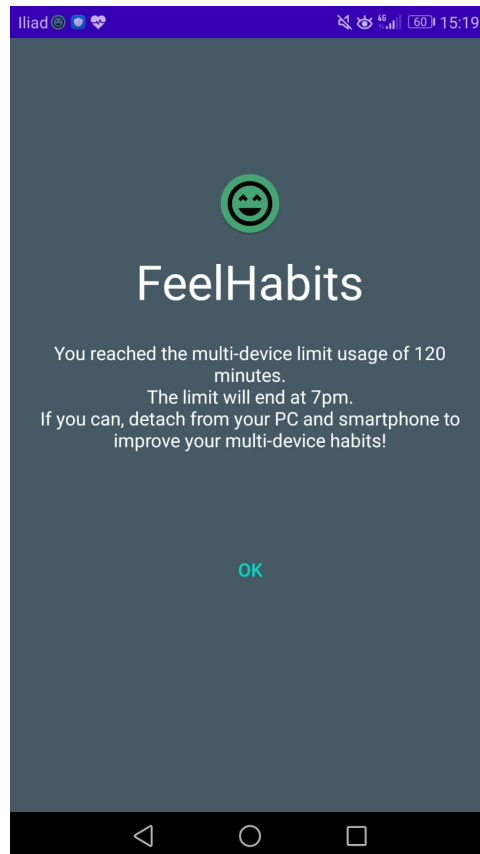


Figure 5.24: FeelHabitsAndroid: notification for non-stop session limit reached

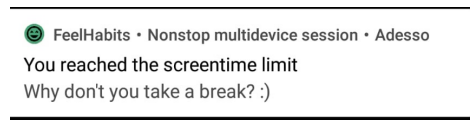
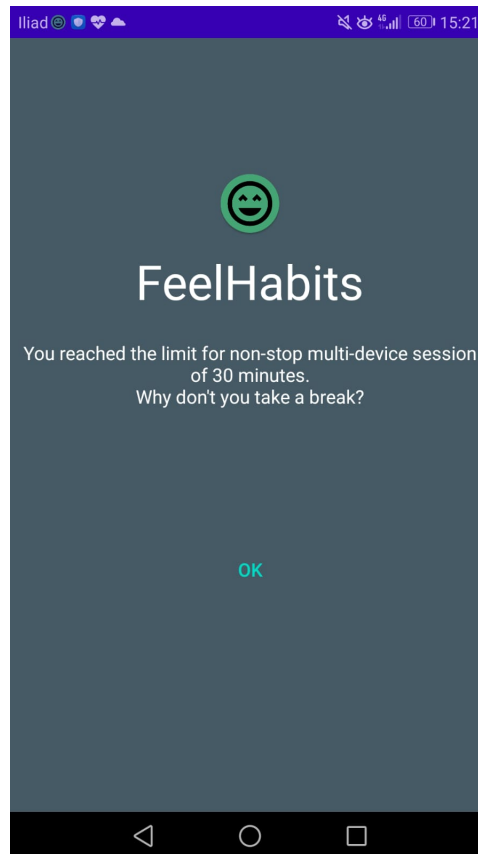
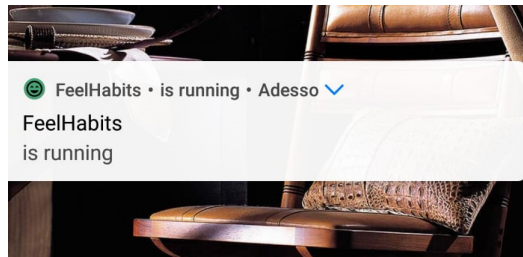


Figure 5.25: FeelHabits Android: block activity for non-stop session limit reached



To keep the service always active and let the user know about the app job, a fixed notification is shown (Figure 5.26).

When the smartphone is locked/unlocked, switched on/off, the app updates the “smartphoneActive” field. Additionally, when it is locked/switched off, the app saves in the DB the current timestamp (“lastSmartphoneEventTime”), to provide the information exploited for performing the functionalities of FeelHabits related to multi-device session: the multi-device app tracking and the multi-device nonstop session limits. To work correctly, a special permission need to be explicitly allowed

Figure 5.26: Feel Habits Android app: fixed notification

by the user⁵.

5.2.5 Server

A NodeJS server that communicates with the DB has been implemented for the refreshing of the daily limits every morning at 4am, with a backup of the usage data, for statistical purposes. Thus, we are able to know the behaviour of the user even when a limit has been reached. In details, the pieces of information needed for the first 2 intention types (multi-device app and smartphone At PC) are, for each daily set limit, the time left and the launches left fields, and the “ignore” flags (“timeLeftIgnore” and “launchesLeftIgnore”). If the time left or the launches left are minor than 0, it means that the user has exceeded the limit. In particular, when the limit is reached:

- if the intervention type is “block”, every time the user tries to open one of the involved application, the block appears, unless the users, during the previous analogous block, has decided to click on “don’t bother me again”. In this last case, the “ignore” flags turns from “false” to “true”. Otherwise, the last choice of the user is to try to respect the limit, and the “ignore” flags is still “false”. Thus, if the limit is less than 0, we can estimate the reaction of the user to the system blocker.

If the “ignore” flags is true, then we know that somehow the user has refused the restriction. If the negative number is close to 0, we know that the limit just passed the threshold, and we may suppose that the alert has been effective. While, if the negative number is far from 0, then the limit was definitely ignored.

Instead, if the “ignore” flag is false and the limit value is negative, we can suppose a willingness of the user to respect the limit, and we can know how many times the user fell into the bad habit, maybe without remembering the

⁵the android.permission.PACKAGE_USAGE_STATS

intention.

Here, the aim is to evaluate if a blocker strategy, especially when it is repetitive, have a positive effect and can be a effective tool for good habit forming, or it just conveys frustration to the user.

- if the intervention type is “notify”, we can make the same evaluations if the limits has been exceeded, but without considering the “ignore” flag, that in that case will be true for sure.

If the chosen limit involves a single device and the value of the counter is negative, its module represents the excess over the threshold set by he user. If the chosen intention is aggregate, we need to make the aggregate usage computation.

About the third intention type (“Screen time”), as said, the data about the timestamp of the reached limit are available in the DB. Moreover, just for the nonstop sessions, the system saves the usage time over the threshold before taking a break from both devices. These data give some useful indications about the user’s behaviour and the effectiveness of the tool.

Chapter 6

Evaluation

I recruited 7 people (4 male, 3 female) who habitually use the Windows PC for work or study purposes, and own a Android smartphone, to install the FeelHabits system and use it for 14 full days or more. I did not provide any suggestions about how to use the application: they were asked to use FeelHabits without any constraint during the test time. After the test period, I collected all the usage data to analyse them and extract pieces of information about:

- the number, the types of the chosen interventions, the type and the amount of limits, the chosen severity level for the interventions, in relations with the contexts.
- the behaviour of the users compared with the chosen intervention types, their reaction to the blockers/notifications.
- some general evaluations about the users behaviour, the links with the definitions of multi-device habits, through an analysis of the collected data about multi-device sessions.

6.1 Chosen intentions: overview

Table 6.1 shows a overview of the intention choices made by the test users. The total number of intentions ranges from a minimum of 3 to a maximum of 6. Considering the deleted intentions, at the end of the test time the remaining intentions were at minimum 2, at maximum 5 (on average 3). Most of the deleted intentions are followed by a definition of a new analogous intention in substitution of the old one, with a modification whether in the time context, or in the limit

user	set Intentions	deleted	Apps&URLs	SmartphoneAtPC	Screentime
“user1”	5	2	3	2	0
“user2”	6	1	1	5	0
“user3”	4	2	1	2	1
“user4”	3	0	3	0	0
“user5”	4	1	2	2	0
“user6”	3	1	3	0	0
“user7”	3	0	1	1	1
Total	28	7	14	12	2

Table 6.1: FeelHabits chosen interventions: overview

threshold. typically because the previous limit was too strict and the user reached it too many times.

6.2 User’s behaviour

In this section, I describe the details about the behaviours of the single users, comparing them to the personal statistics about the most visited smartphone apps on the PC (multi-device context habits), and the multi-device app habits. My analysis of multi-device app habits is limited to the apps/websites visited during multi-device sessions. Thus, I explore only a subset of the cases that belong to the definition of “multi-device app habits” adopted in this thesis.

User1 - an intensive interaction with FeelHabits It is interesting to observe the behaviour of user 1, who intensively used FeelHabits as a personal challenge to fight against multi-device digital habits. All the chosen interventions are in working days, in the morning or in the afternoon, never by night, and they are “multi-device apps” and “smartphoneAtPC”. All the associated interventions are blockers.

Among the “multi-device apps” intentions, one is related to video category, and it is a one hour timer for Netflix and Prime Video, just with PC browser. Apparently, this intention seems single device. However, the user set, in parallel, a “smartphoneAtPC” limit for launches (5), for the same context, associated to Prime Video and Netflix smartphone apps. The user motivated this choice saying that she watches videos with the PC for longer times during launch breaks, and in this context she wants to control the duration of these breaks, while during the day, she is used to opening videos with the smartphone while working on the PC. In this case, the intention is to mitigate the frequency of this habit. The user reached the time limit on PC 3 times (2 with Prime Video, 1 with Netflix), and she never exceeded the launches

limit with the smartphone.

The other two “multi-device apps” defined intentions are associated with social networks (Facebook and Instagram) and communication (WhatsApp). Anyway, these intentions have been deleted immediately, without reaching any limits. It suggests a first approach with the application, where the user changed her mind. In fact, a “smartphoneAtPC” intention that include Facebook and Instagram have been set in substitution of the last mentioned one. It consists of a limit of 10 launches and 30 minutes for each app. Even this one has been deleted in a few days, because the launches were reached too early (75% of limits reached). A new “smartphoneAtPC” limit for Facebook, Instagram and WhatsApp of 60 minutes and 15 launches has been set consequently: it is the only “smartphoneAtPC” limit that was maintained until the end of the test.

Nevertheless, even for this last intention, the user exceeded most of the limits of launches almost everyday, typically with more than a app (71.4% of launches limits reached).

The interesting aspect of the user’s behaviour is the frequency of blockers and the reaction to them. On average, the user got about 7 blockers per day, and about 3 blockers per day for each application. The reaction to blockers was, for the 92% of cases, the choice to respect them, but the tendency to forget the proposals is very high (with a peek of 7 blockers for a single app) and every time the user decided to respect the limit.

The user shows a comparable usage of WhatsApp, Facebook and Instagram with the smartphone, during multi-device sessions, both in term of frequency and time. In general, the threshold of 15 launches was reached in less than 10 minutes: this aspect suggests a behaviour referable to the “checking habit” [2]. The user looks aware of the frequent launches of these three apps, but not of the duration of their usage: the usage limit of 60 minutes significantly exceeds the actual use.

Figure 6.1 shows user 1 most launched smartphone apps during multi-device sessions. In this list, Netflix and Prime video are not present, suggesting the reason why the user never reached the 5 launches threshold for these apps. Figure 6.2 shows the most visited websites in multi-device sessions. The common applications in these two lists are Facebook, WhatsApp, and LinkedIn. Thus, the choice for multi-device apps intentions looks coherent with these data.

Figure 6.1: User 1 - most used smartphone app on PC

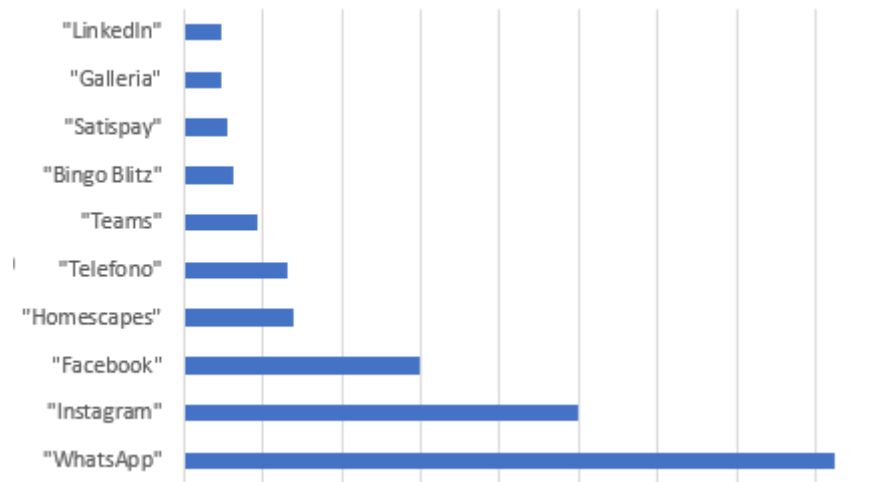
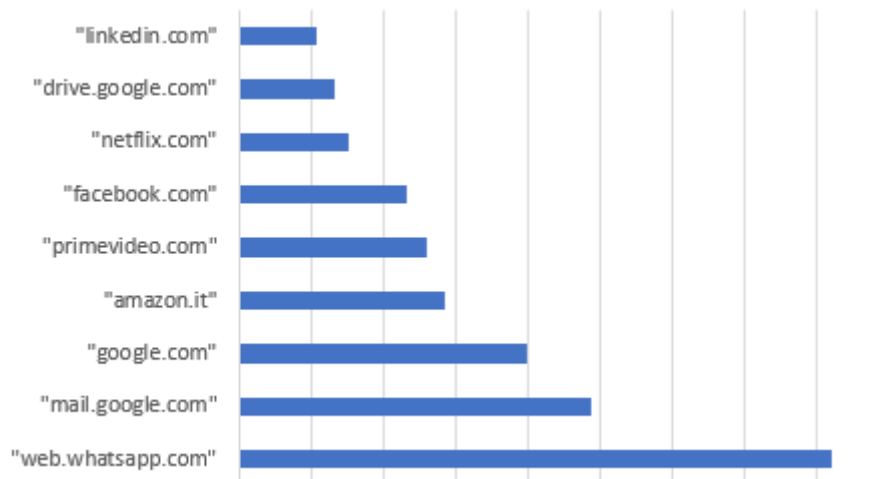


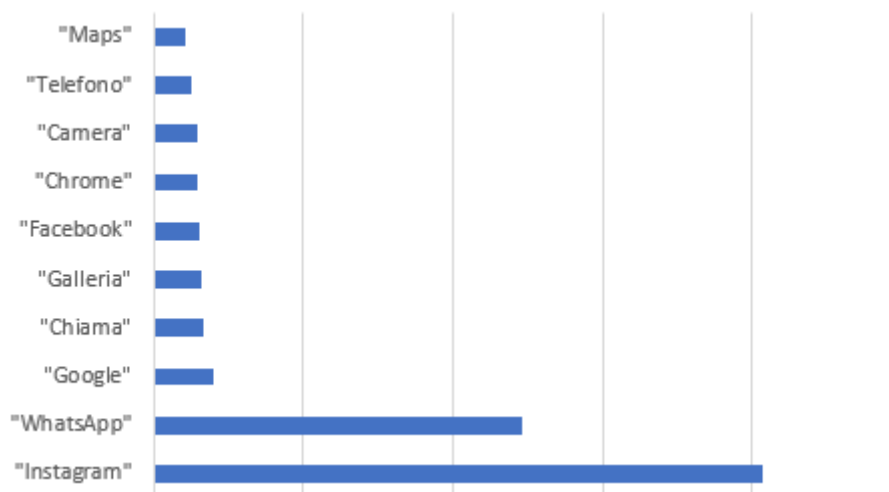
Figure 6.2: User 1 - most visited websites in multi-device sessions



User2 - FeelHabits to reduce the Instagram usage User 2 set 4 “multi-device apps” limits with “block” intervention, but 3 of them were actually single device, because associated to smartphone apps: a daily time limit of 15 minutes for WhatsApp in working days, and a daily time limit of 15 minutes for Instagram in the weekends, and a daily time limit of 2 launches for LinkedIn in working days. The limits for WhatsApp and LinkedIn have been exceeded for the 20% of cases, but the block was accepted and respected for LinkedIn, ignored for WhatsApp. This aspect suggests a minor necessity to use LinkedIn, compared with WhatsApp. The use of Instagram, in the weekend, exceeded the limit for 3 out of 4 days, and it

was always ignored, with a further usage, on average, of about 15 minutes per day. The “smartphone at PC” limits are related to Instagram: the first one, a 15 minutes limit for morning and afternoon during working days, has been deleted after 2 days, because the usage time has been always reached and ignored. During the rest of these two days, the user exceeded the limit by, on average, about 40 minutes. User 2 consequently set another “smartphone at PC” limit of 15 minutes associated to Instagram, just in the morning. This limit has been always respected, in total contradiction with the usage of the previous two days. The user demonstrated to remember her personal goal, considerably reducing the time spent on Instagram in the morning, feeling as a reward the lack of such constraint in the afternoon. She declared the usefulness of FeelHabits to control the Instagram usage both in working days (with an improvement in productivity), and in the weekends. Figure 6.3 shows the 10 most launched smartphone apps during multi-device sessions. WhatsApp and Instagram belong also to the 5 most visited websites in multi-device sessions.

Figure 6.3: User 2 - most used smartphone app on PC



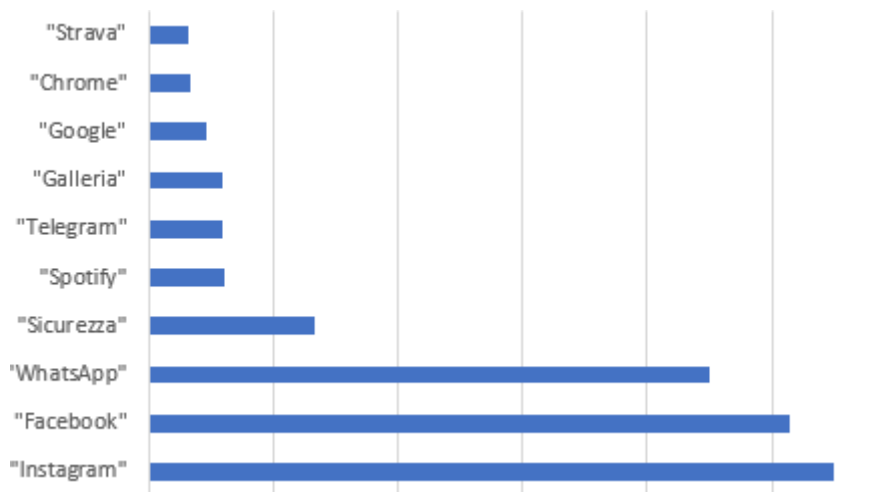
User 3 and user 7: non-stop sessions and notify interventions User 3 and user 7 both defined a multi-device non-stop session limit of 30 minutes and other intentions with a “notify” intervention. For both users, the computation of the non-stop sessions looks significantly overestimated (with a average of 64 minutes over the limit for user 3, and 124 minutes over the limit for user 7). When the limit was reached with the smartphone, users typically continued the session for few minutes (less than 10). Differently, when the session limit was reached with the PC, the system reveals a further non stop usage of hours. This means that

users deactivated the automatic standby, and they are used to leaving the PC on during breaks.

About the other intentions, user 3 defined two “multi-device app” and one “smartphone at PC” intentions for working days. A multi-device app limit of 10 launches, in the morning, including Facebook, Instagram, WhatsApp and Telegram has been deleted because some limits (Facebook and WhatsApp) were reached too early and they have been greatly exceeded, with a peak of 38 launches over the limit. However, even if the limits are multi-device, the user visited each app with a unique device: Facebook with the PC browser, WhatsApp and Instagram with the smartphone. The other defined intentions are limits of time. One is a 30 minutes limit, in the morning and by night, for the WhatsApp, Telegram, Twitter, Facebook, Instagram and Twitter multi-device app. The other one is a “smartphone at PC” limit of 20 minutes, in the morning and in the afternoon, for Instagram and WhatsApp. The time limit were exceeded very rarely: again the user is not aware of the frequency of his checking habits. Moreover, among the three most visited websites during multi-device sessions, in working days, during the day, there are Facebook and a sport betting website. These results suggest that the users tends to perform interruptions from work with the PC rather than with the smartphone. Moreover, among multi-device sessions data, I did not find any cases of multi-device app.

User 7 defined a daily time limit of one hour for different applications, with a “smartphone at PC” intention for Strava, Facebook, Chrome, Google and Whatsapp, and a “multi-device app” intention associated with Instagram, Telegram, WhatsApp. These two intentions, with regard to WhatsApp, overlap: in fact they are defined for the same temporal context: presumably, the “multi-device app” limit would be reached always before the “smartphone at PC” one, which looks unnecessary. Nevertheless, the user showed a very low usage of these apps, compared with the defined limits. Figure 6.4 shows the most opened smartphone apps during multi-device sessions. Among them, Spotify and Facebook appear as well in the list of the most visited websites during multi-device sessions. Spotify is typically accessed with the smartphone by night, with the PC during the day, while the usage of Facebook occurs during the day with both devices.

User 4: many refused blockers User 4 demonstrated a low awareness of his digital habits, especially regarding the Facebook usage time with smartphone. Among the 3 defined intentions, all of them belong to “multi-device app” category, but two of them are actually only smartphone related. One is a 10 minutes usage limit for Facebook and for Instagram, just in the morning, during working days. The other one is a 10 minutes usage limit for Facebook, for working days, in the morning and in the afternoon. These two intentions, again, overlap. The user always reached the related limits, tapping on the “Don’t bother me again” button all the times. On average, user 4 exceeded the Facebook limits by 22 minutes

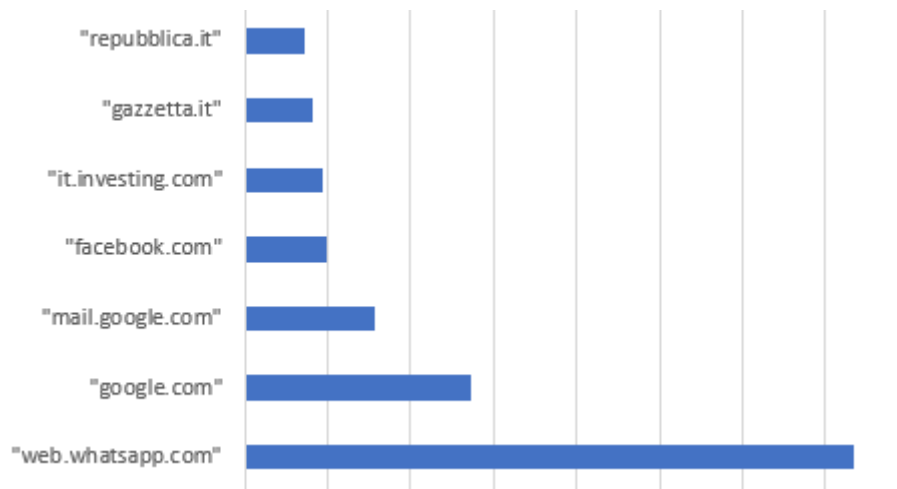
Figure 6.4: User 7 - most used smartphone app on PC

per day. Nevertheless, the user declared that the blockers had a positive effect in limiting the overall usage of Facebook. The other defined intention is a usage limit for the whole day, during working days, associated with Twitch multi-device app (visited almost only with the PC). User 4 reached the limit just once and the limit has been respected.

In general, the most visited website during multi-device sessions is YouTube. By night, in working days, the most opened websites in multi-device sessions are Netflix and Twitch.

User 5 and user 6: time limits and notifications User 5 set just limits of time associated with Facebook, Instagram and WhatsApp, with a notification as intervention. The thresholds, of 30 minutes (by night, in working days) and one hour (in the morning and afternoon, in working days and holidays), were exceeded rarely (just 2 times with WhatsApp multi-device app, during the day). In general, the usage of Facebook and WhatsApp is frequent with both devices during all day. For this reason, I suppose that a limit of launches for Facebook multi-device app would have been more effective. The access to potentially distracting websites on PC during multi device sessions is very common, as Figure 6.5 shows.

User 6 defined only usage time limits of one hour, for many multi-device apps, related to holidays in the morning and afternoon and by night in working days. The chosen apps for both intentions are many: Amazon Shopping, Ebay, Instagram, Mediaset Play, Netflix, Prime Video, Privalia, Telegram, Tiktok, Twitch, YouTube. During the period of the test, the user reached the limit for YouTube three nights, without exceeding them by too much (on average 10 minutes) and sometimes he almost reached the limit for Instagram. He declared that his expectation was

Figure 6.5: User 5 - most visited websites in multi-device sessions

to reach everyday the limit for youtube.com with the PC browser, because he is used to listening to music with YouTube while performing other tasks. The user did not reach these limits, since, in the described context, the PC browser window was minimised. In this situation, FeelHabits does not update any website-related counters. The only application that compares both in the most launched smartphone app and the most visited websites with the PC (in multi-device sessions) is YouTube: typically in the afternoon with the PC, by night and all day in the weekends with the smartphone. Most of the other applications included in the intentions are launched seldom or not at all.

6.3 Multi-device app-context habits

From the users data about multi-device sessions, I extracted all the transitions from a smartphone app to a website visited on Chrome, mapping them to the temporal contexts, and counting the occurrences of these patterns. The results are of interest: every user, even who reached few limits with FeelHabits, showed some significant correlations that can be identified as multi-device context app habits. Table 6.2 shows the patterns that may be linked with the topic of digital wellbeing. Most of the multi-device app context patterns are on working days, and this is an expected result, since the weekend days analysed in the test are only 4. A significant finding is related to the classification of app/website categories found among these correlations: in addition to social network, messaging and video categories, I found also gaming, news and sports betting services.

user	applications	context
user 1	Homescapes -> web.whatsapp.com web.whatsapp.com -> WhatsApp primevideo.com -> WhatsApp	afternoon - working days afternoon - holidays night - working days
user 2	web.whatsapp.com -> Instagram web.whatsapp.com -> Instagram Instagram -> google.com	morning - working days afternoon - working days night - working days
user 3	facebook.com -> WhatsApp bet365.it -> WhatsApp Telegram -> bet365.it	morning - working days morning - working days morning - working days
user 4	youtube.com -> WhatsApp Facebook -> youtube.com WhatsApp -> youtube.com	morning - working days morning - working days afternoon - working days
user 5	Facebook-> gazzetta.it Instagram -> repubblica.it	afternoon - working days afternoon - working days
user 6	YouTube -> netflix.com youtube.com -> Instagram	night - working days afternoon - working days
user 7	mail.polito.it -> Instagram Instagram -> youtube.com	afternoon - working days afternoon - working days

Table 6.2: FeelHabits: multi-device context-app habits

Chapter 7

Conclusions

7.1 Discussion

The most common app/websites categories in the defined intentions are social networks (Instagram and Facebook) followed by communication (WhatsApp and Telegram), and video (Twitch, Prime Video, Netflix, YouTube). Few users chose ECommerce applications, none selected the travel services. Users behaviours towards intentions are significantly varied. Among them, two users tended to reach the limits almost everyday, with a opposite reaction towards blockers: user 1 always tried to respect the limit, user 4 always refused it. User 2 managed to change consistently her behaviour with Instagram usage in a few days. Other users defined less restrictive limits of usage time, reaching them few times (user 5, user 6 and user 7).

Analysing the data about multi-device sessions and comparing them with the defined intentions, the findings suggest that the users are not fully aware of their digital usage, and sometimes the limits look inconsistent with the actual multi-device interactions: in general the launches limits were more easily reached, and the time limits were overestimated. Some users set a limit for many apps as an experiment, without caring about the real need to mitigate habits. Other users even set overlapping limits, showing that the FeelHabits features are not so easy to understand for everybody.

With regard to multi-device context habits, the smartphone apps usage in front of the PC is a common pattern for all users: in this context, both the “messaging” and “social network” categories belong to the top 3 launched apps for all the users. For this reason, among the designed intentions, the “smartphone at PC” category looks as the most “universal” and the most effective one for multi-device habits mitigation. Differently, the collected data suggest that not all the users have multi-device app habits. The “multi-device apps” intention choices contained

limits associated with a single device, other included aggregate limits, but their usage was more commonly performed with a unique device.

The extracted data about multi-device app-context habits reveal some context-related correlations that include apps/websites targeted as source of bad habits. This observation suggests a great potentiality for the automatic modeling of this category of multi-device habits. Both user 1 and user 2, who habitually use WhatsApp with both devices, defined a limit for WhatsApp just related to the smartphone app. They justified this choice saying that their usage of WhatsApp for work purposes is habitually performed with the PC, while the usage of WhatsApp smartphone app is dedicated to non-work tasks. Moreover, at work, switching from the PC to the smartphone can be generally a cause of distraction. Thus, the users argue that this separation enhances their self control over this multi-device app. This is a typical example of multi-device app habit, where two different contexts trigger the use of the same app with different devices. Similarly, user 6 demonstrated to have a multi-device app-habit related to YouTube: during the day for listening to music with the PC, by night for watching videos.

I found some cross-device patterns, especially related to WhatsApp. However, some of them are due to the constraints imposed by FeelHabits. For instance, user 2 declared to use Instagram with the PC to escape from the smartphone blocker, without tapping on the “don’t bother me again” button. The motivation of this choice is that the user, in these cases, needed to use Instagram for performing a “useful” task (accessing to the chat), while she still wanted to be blocked for the unnecessary usage of Instagram (watching the stories). Thus, I believe that this aspect can be considered as a positive effect of FeelHabits.

In general, all the users evaluated FeelHabits as a valid tool for controlling and mitigating digital habits.

7.2 Limitations

There are some limitations to be considered with regard to the FeelHabits system, and the conducted test.

- First of all, the simplification in the definition of multi-device apps (smartphone app + PC URL) excludes all the Windows apps. This means that if the users habitually use, for instance, Whatsapp on the smartphone, and instead of web.whatsapp.com, the Whatsapp Windows app, the actual FeelHabits multi-device app usage data are inaccurate.
- The number of users involved in the study is low. Thus, the statistics may significantly deviate from the average usage of PC and smartphone. Nevertheless, the findings of this work are significantly varied, suggesting that a

multi-device DSCT must grant a degree of flexibility and customisation to be suitable for the different multi-device users.

- The duration of the test, limited to 2 weeks, does not give the possibility to analyse the user behaviour in the long term. The user can assume virtuous behaviours towards blocks or notifications in the first weeks and then ignore or delete the constraints, or, worse, uninstall the system. Monitoring the interaction with a multi-device DSCT in the long term is fundamental to understand the efficiency of the tool in terms of habit forming.
- The implementation choice for device session has proven to be inaccurate in the detection of non-stop sessions, for the users who disabled the automatic PC standby and always leave the PC on during breaks. In these cases, the system provide misleading warnings. To solve this problem, a alternative is to update periodically the status of the PC, by detecting the user keyboard and mouse inputs.
- As we said, the evaluation of the multi-device app habits is limited by the fact that FeelHabits does not detect usage data about single device sessions, unless they belong to a intention. Thus, the estimation of these habits excludes the cases when the user interacts with an app using only the smartphone and in another context he/she uses the relative website interacting only with the PC.
- The FeelHabits system is not designed to control efficiently the multi-device patterns where the user listens to music with a device and performs another task with a different device, because when the PC browser is minimized or the smartphone is unlocked, the system do not update any timers.

7.3 Future work

This thesis has the aim to explore the topic of digital wellbeing considering the multi-device ownership of the modern users. The related findings are a further proof of the need to continue along this path, improving some of the functionalities designed in FeelHabits and integrating them with supplementary tools to involve all the user's devices. The first steps for future work should consider the presented potentialities and limitations. An improvement over FeelHabits could be a more precise detection of the PC usage, that is able to distinguish the effective interactions from the cases when the user is taking a break, leaving the PC on. Then, a suggestion is an upgrade of the PC software, to mitigate the habits related to Windows desktop app usage. Furthermore, a ideal tool should include features for controlling the other digital devices, such as the smartwatch and the tablet, but also the smart TV. A smartwatch integration may provide further information about the

effectiveness in reducing the external interruptions triggered by notifications and the consequent frequency of distractions. In general, a more efficient assistance to the user, provided by an automatic system able to detect the multi-device habits and consequently suggest the most adapt interventions for the user, would be the optimal features for the design of future multi-device DSCTs.

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